SOFT COMPUTING METHODS FOR DESIGN APPLICATIONS IN MICROWAVE DOMAIN

A THESIS

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by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **SOFT COMPUTING METHODS FOR DESIGN APPLICATIONS IN MICROWAVE DOMAIN** in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Electronics and Computer Engineering of Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from January 2006 to January 2009 under the supervision of Dr. Ankush Mittal, Associate Professor and Dr. M. V. Kartikeyan, Associate Professor, Department of Electronics and Computer Engineering of Indian Institute of Technology Roorkee, Roorkee, India.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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The Ph.D. Viva–Voce Examination of **Mr. Chauhan Narendrasinh Chandrasinh**, Research Scholar has been held on ....

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Signature of External Examiner

To

The Almighty,

My Guru,

My Teachers,

My Family Members, and

My Friends

Abstract

The growing commercial market of wireless communication systems/devices over the past decade has led to the explosion of interests and opportunities for the design and development of microwave components. The wireless industry emphasizes on the development of components in shortest possible time and at low development cost [1]. There is also a class of critical design applications such as design of high power devices and components where the accuracy requirement is the prime goal. The design of the most microwave components require the use of commercially available electromagnetic (EM) simulation tools for their analysis. In the design process, the simulations are carried out by varying the design parameters until the desired response is obtained. The optimization of design parameters by manual searching is a cumbersome and time consuming process, and the chances to get local minima are very high. Moreover, increasing number of design parameters or widening the search range makes it difficult to converge to the global optima.

Soft computing methods play important role in the design and optimization of many engineering disciplines including microwave domain. The aim of these methods is to tolerate imprecision, uncertainty, and approximation to achieve robust and low cost solution in a small time frame [2]. Soft computing methods such as Genetic Algorithm (GA), Artificial Neural Network (ANN) and Fuzzy Logic (FL) have been widely used by EM researchers for microwave design since last decade [1, 2, 3]. However, these methods suffer from certain drawbacks.

GA is a powerful optimization tool, but it requires a large number of iterations to achieve convergence and to arrive at an optimum solution. ANN has proved its efficiency in modeling microwave components, but it has also suffered with generalization problems. Moreover, due to very small wavelengths involved in microwave design, which requires high precision, it is not easy to model components using conventional methods. In all, modeling and optimization are essential parts and powerful tools for the microwave design task but they must be applied judiciously.

Our present research work deals with the development and use of soft computing based methods for tackling challenging design problems in microwave domain. Our aim in the development and investigation of these methods is to obtain the designs in small time frame while improving the accuracy of the design for a wide range of applications. In order to achieve this goal, a few diverse design problems of microwave field, representing varied challenges in the design, such as microstrip antennas, microwave filters, a microstrip-via, and also some critical high power components such as nonlinear tapers and RF-windows have been considered as case-study design problems. Different design methodologies are developed for these applications. The first chapter of the thesis presents introduction and motivation behind the work. It also presents the scope of the overall work.

In chapter two of the thesis, a state-of-the-art review on the use of soft computing methods for the design of microwave components is presented. In this chapter, we have described the conceptual background of five important soft computing methods namely GA [4, 5], Particle Swarm Optimization (PSO) [6, 7], Bacterial Foraging Optimization (BFO) [8], ANN [9, 10] and Support Vector Machine (SVM) [11]. Although each description is followed by the review of microwave designs based on these methods, the emphasis is made on covering design works using recently developed techniques such as PSO, SVM and BFO.

Microwave designs obtained using hybridization of these soft computing methods are also discussed.

Chapter three presents a modified particle swarm optimizer and demonstrates its applicability for the design of a specific microwave filter. Commercial growth in the use of wireless communication products necessitates the efficient design of components in a smaller and realistic time frame. A Computer-Aided Design (CAD) approach is adopted to minimize the time required to obtain best possible design parameters and reduce the experimental iterations as far as possible. Though GA and PSO can be directly used for microwave filter design problems, an inherent limitation of these algorithms is that they require a large number of iterations to converge to an optimum solution. Therefore, the researchers on PSO have also been continuously working for improving the convergence speed and accuracy of the standard PSO [12]. In this work, we present a novel modification to PSO algorithm, PSO with Multiple Subswarms (PSO-MS), which aims to offer faster convergence while improving quality of solution. The solution is generic as it can be applied to the cases when the design process is complex, computationally expensive and time consuming. In the proposed modification, we have introduced a new paradigm of multiple sub-swarms for searching parameter space with the PSO algorithm. The social component of PSO's velocity update equation is modified to consider the effects of multiple sub-swarms. Five benchmark functions have been considered for testing the proposed algorithm. The approach is implemented and tested for two basic variations of PSO, namely, PSO with inertia weight [13] and PSO with constriction factor method [14]. The experimental results illustrate that the PSO-MS algorithm has the potential to converge faster, thus reducing the computational expenses, while improving the quality/accuracy of the solution. The PSO-MS is also used for the design of coupled microstrip-line band-pass filter which is a computationally expensive process when EM tool is invoked in iterative loop of PSO. The results of the proposed algorithm show improvement over the design results obtained using standard PSO.

Chapter four deals with support vector driven evolutionary algorithms for the design of specific microwave components. Full-wave EM simulation techniques provide accurate solution. However, the accuracy, computational time and convergence of the solution using EM simulators are dependent on the number of constraints to be handled. Since, these constraints have to be handled manually in full-wave EM simulators, they do not guarantee convergence and also require long run time especially when optimization-based design automation is considered. In order to overcome these obstacles, either closed-form expressions or mathematical curve fitting techniques, which use data obtained from measurements or EM simulators, can be employed to compute the output response. Various meta-modeling techniques such as ANN, response surface method, kriging, etc., can be used to create approximate model from the empirical data [15, 16]. Most of these models have inherent limitations of accuracy and validity over a restricted range of parameter values. ANN has been used by many EM researchers to model microwave components and balance the trade-off between computation time and accuracy [1]. However, the generalization accuracy achieved by the ANN based models of microwave components needs improvement to increase the effectiveness of CAD. In this chapter, we have presented a more accurate model of microwave components using SVM. Similar to ANN, SVM is also a learning technique to learn from empirical data to deal with the accuracy and complexity trade-off, by minimizing upper bound on the generalization error [11, 17]. A detailed description for SVM based microwave modeling is presented and models for specific microwave components such as a one-port microstrip via and two microstrip antennas are developed. The accuracy of the SVM models is compared with other meta-models developed using ANN. Another contribution of the chapter is in presenting a hybrid approach combining SVM with evolutionary algorithms such as PSO/GA. In this approach, the model of microwave component obtained using SVM is invoked in the optimization loop of evolutionary algorithms. The significant advantage obtained with SVM model is that it responds quickly (approximately in milliseconds) compared to iterative parametric analysis using EM simulation tools for which the response time is large (approximately in minutes depending upon the complexity of the problem). The hybrid method, support vector driven genetic algorithm, is demonstrated for the design of circular polarized microstrip antenna at 2.6 GHz band, while another similar hybrid method, support vector driven particle swarm optimization, is demonstrated for the design of a simple aperture coupled microstrip antenna.

Chapter five of the thesis deals with the design of a nonlinear taper using swarm intelligence based algorithms. The design of high power microwave sources and their components belong to a class of problems in which high precision is required with very less tolerance. Vulnerability of one component may cause the failure of the entire system and spell catastrophic damage. Nonlinear taper is one such component which is used in the output system of high power gyrotrons to connect output section of cavity with the main waveguide system. For high power applications, the design of a nonlinear taper requires very high transmission (above 99%), with minimum spurious mode content. In this work, the design optimization of a nonlinear taper to be used in a specific gyrotron (42 GHz, 200 kW, CW gyrotron operating in the $TE_{0,3}$ cavity mode with axial output collection) has been taken as a case study. The taper synthesis has been carried out considering a raised cosine type of nonlinear taper and the analysis is done using a dedicated scattering matrix code as it is very fast and accurate for taper analysis [18]. The design of nonlinear taper is carried out using two swarm intelligence based algorithms, namely, PSO and a modified BFO. The classical BFO ignores the effects of swarming, and all the bacteria are assumed to have the same swim length. However, varying the swim length according to the fitness

may give better convergence speed. In order to improve the convergence and quality of solution, the BFO algorithm is modified such that it includes memory of the bacteria, global swarming effect and variable swim length. The modified BFO (MBFO) is tested on a set of benchmark functions. The optimization of a nonlinear taper is carried out using both the PSO and MBFO algorithms, which show very good agreement with the desired objective. The best optimized taper design shows excellent response with very high transmission (99.86%) indicating the effectiveness of these methods.

In chapter six, the design of disc-type RF-windows is presented using Multi-Objective Particle Swarm Optimization (MOPSO) method. High power microwave and millimeter-wave sources such as gyrotrons, klystrons, and other gyro-devices produce very high output power at wavelengths in microwave and millimeter-wave ranges [19]. RF-window is a critical component in the output system of these devices. The design requirement of the window is that it should withstand high power, mechanical and thermal stresses, be leak tight and lossless. Therefore, the challenge is to select a proper window material, and obtain an optimized design that minimizes power reflections and absorption for a better transmission [19]. Hence, these components have to be designed carefully. Many real time design problems require optimization of more than one objective. In this case, it is desired to find a solution that optimally balances the trade-off between multiple objectives. Multi-objective optimization is implemented with PSO by several researchers[7]. In this work, the design of two types of RF-windows, namely, double disc window [19, 20] and pillbox-type window [21] for use in high power devices is presented using a specific implementation of MOPSO [22], which uses the mechanism of crowding distance and found to be highly competitive in converging towards Pareto front. The role of MOPSO is to find physical dimensions for both the types of windows while optimizing the trade-off between matching of desired resonant frequency and maximizing bandwidth around the

resonant frequency. The design of double-disk window is carried out for a specific 42 GHz, 200 kW, CW gyrotron (with two different disc materials) and for a 170 GHz, 1 MW, CW gyrotron, while the design of pillbox-type window is carried out for a 2.856 GHz, 5 MW, pulsed klystron. The results show the best resonance matching for each window design and prove the applicability of MOPSO to wide range of high power microwave devices/components.

Finally, in chapter seven, the contributions made in the thesis are summarized and scope of the future work is outlined. In summary, the thesis contributes towards improvement of the efficiency and accuracy of the design problems in microwave domain by proposing and investigating soft computing methods, their modifications and hybridizations.

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Narendrasinh C. Chauhan

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Chapter 1

Introduction

For the past few decades, the engineering design and optimization problems have proved to be promising and form much potential and important areas of research [23, 24]. Many researchers and engineers in academics and industry face difficulties in understanding the role of optimization in engineering design. The goal of optimization is not only to achieve a feasible solution, but also to meet a design objective. In most engineering design applications, the objective is to minimize the cost or maximize the efficiency of production. The goal of the over all design process is also to address the issues such as modeling the process, handling the constraints (which may be linear or nonlinear), forming objective, and some times handling multiple objectives which may be conflicting in nature. With the advent of high speed computers, the optimization process has become a part of Computer-Aided Design (CAD) methodology. In a nutshell, *optimization is a very powerful tool but it must be applied judiciously.* Our research deals with soft computing methods for the design applications in microwave domain.

1.1 Microwave design and soft computing: An overview

Microwave engineering is a discipline which is full of design problems. There are various types of design problems available and each is having different challenge with it. The growing commercial market of wireless communication devices over the past decade has led to the explosion of interest and opportunities for design and development of microwave components. The industry emphasizes on the development of components and systems in shortest possible time and at low development cost [1]. This places the demand on various CAD tools for the development of microwave components. There is also a class of critical design problems where the reliability and accuracy are the prime requirements.

Soft computing is defined as a collection of computational techniques in computer science, artificial intelligence and machine learning, which attempt to study, model, and analyze very complex phenomena for which more conventional (hard computing) methods have not yielded low cost, analytic, and complete solutions. The term soft computing was first coined by Zadeh [2]. The aim of soft computing is to tolerate imprecision, uncertainty, and approximation to achieve robust and low cost solution in a small time frame. Much of the soft computing techniques are inspired from biological phenomena and the social behavior of biological populations. Earlier in most literature, the term of soft computing was confined to Artificial Neural Network (ANN), Genetic Algorithm (GA), and Fuzzy Logic (FL). But, the major elements of soft computing include neural network, evolutionary computation, fuzzy logic, machine learning, and probabilistic reasoning [2]. The recently developed methods based on swarm intelligence, and foraging behavior of natural and biological populations such as birds, fishes, ants, and bacteria are also considered to be part of the growing field of soft computing.

1.2 Motivation

The steps of a conventional microwave design process consists of problem identification, specification generation, concept development, electromagnetic analysis, evaluation, initial design, final design, fabrication, and testing [1]. At present, the design of most microwave components is carried out using commercially available Electromagnetic (EM) simulation tools. Many new EM simulation tools are being developed to automate the design process. EM simulation techniques help to produce analysis for microwave components. In the design process, the role of EM simulator is to obtain responses such as S-parameters, standing wave ratios, gain, current distributions, power transmission and reflections, etc., for the component to be designed. In the conventional design methodology, once an initial design is obtained, the EM analysis and evaluation is performed iteratively until the desired specifications are met. In this process, one has to change the design parameters by modifying its geometrical structure and apply expert domain knowledge to make the design feasible, and to move towards desired objective. This process is repeated till a tolerable solution is achieved. But it does not guarantee for the optimum solution. This approach may, sometimes, degrade the performance of the component after its fabrication in the desired subsystem. Moreover, these methods of designing and optimizing them by hand are laborious, time intensive, and require designers to have significant knowledge about electromagnetics, microwave engineering, and other specialized subjects concerning the design. Eventually, it is necessary to use various optimization algorithms to reach the optimum parameters. Some of the present EM simulators use conventional optimization methods [24] like golden search method, steepest descent method, conjugate gradient method, quasi-Newton method, and other random search methods for optimization of the design parameters. The difficulties with these local search methods are that they require a proper initial guess; otherwise the chances of getting local optimum solutions are very high. Moreover, they can only handle a few number of design parameters. In addition, handling of many design constraints at the same time is very difficult. This conventional way of microwave design has also achieved a certain level of maturity in recent years. To make the efficient use of EM simulation techniques in the development of microwave components is still a topic of research. New techniques are required in order to search from a large design space and reach an optimum solution.

Soft Computing (SC) methods offer unique advantages for the design applications in microwave domain. They are listed as follows:

- The SC methods can be easily interfaced with EM simulators due to which the laborious task of optimizing design parameters in manual mode can be converted to computer simulations. So, faster results can be obtained. Moreover, the use of global optimization methods can avoid the chances of obtaining local optima.
- Handling many design constraints simultaneously is easy for SC methods.
- The use of SC methods does not require extensive mathematical formulation of the problem. Thus the requirement on the necessity of exclusive domain specific knowledge can be reduced.
- Since most of the SC methods come under "GNU general public license" (open source), they provide low cost solutions to the designer. Moreover, effective hybridization of SC methods may also reduce the dependency on costly EM simulators up to some extent.
- SC methods are adaptive and scalable. Though in this thesis we discuss SC methods for microwave design applications, they are applicable to the design of many other engineering disciplines.

Soft computing methods such as GA and ANN have been widely exploited by EM researchers for microwave design since last decade [1, 3, 25, 26, 27, 28, 29, 30, 31, 32, 35, 36, 37, 38, 39, 40]. Though these techniques are effective, they suffer from certain drawbacks. Evolutionary algorithms such as GA, particle swarm optimization (PSO), etc., are effective in finding optimum solution from a multivariate feature space, but they are iterative and require large amount of computation to reach an optimum solution. ANN has been widely used for fast microwave modeling but it has also suffered with generalization problems. This has created the need to develop novel modifications and hybridizations of SC methods in order to solve microwave design problems effectively. Moreover, during the recent past, several new soft computing methods such as Bacterial Foraging Optimization (BFO) [41], Ant Colony Optimization (ACO), Support Vector Machines (SVM), Artificial Immune System (AIS) [42], etc., have emerged along with their applications in engineering design and optimization problems. Most of these recent SC methods have not been yet investigated or very few works have been reported on these methods for microwave design tasks. This also motivates us to investigate these methods for the design tasks in microwave domain.

1.3 Design challenges

Although there are various EM simulation tools and soft computing methods, the following design issues and requirements make the field of microwave design a true challenging aspect:

Sensitivity: The key challenge in the design of microwave components is to deal with sensitivity. Due to very small wavelengths involved in the microwave region, any small variation in the physical aspects of the components may result in huge variation in the output response. This makes the design surface extremely non-smooth. Thus, modeling and finding an optimum solution make the design task challenging. It necessitates fine tuning of design parameters in the feature space. Moreover, increasing number of design parameters make the feature space too large to explore. Hence, in order to achieve high precision requirements, unconventional methods have to be employed in the design process.

Size reduction and low weight: Due to emerging technologies and miniaturization of the components, optimization is required with high precision.

Time-to-market: The recent trend in industry suggest the design and manufacturing of components in small time-frame to satisfy the need of growing commercial market. Therefore, the design and development should be as fast as possible.

Low cost: The EM simulators available in the market for designing components are very costly. It is not possible for an industry or institute to purchase all the tools. This also demands the use of efficient alternative solutions for the design of components. The process adopted should be such that it reduces the cost of production.

Reliability: RF/microwave components are extensively used in critical areas such as communications, radar, defense, and some specific industrial–scientific–medical (ISM) applications where the reliability of the component is the prime requirement. Malfunctioning of one component may cause the failure of the entire system and spell catastrophic damage. It is required to develop and investigate soft computing methods that provide accurate and reliable designs.

1.4 Research objectives, problem statement, and scope

Research objectives:

The objectives of our research work can be stated as follows:

- To develop soft computing based methods that lead to faster design of microwave components.

- To develop soft computing based methods that lead to accurate design for certain critical applications such as design of components for high power microwave sources.
- To develop effective hybridization of soft computing methods to solve design problems in microwave field.
- To learn effectively from empirical data and develop empirical models of microwave components via support vector machine framework.
- To prepare a state-of-the-art review on the present use of soft computing methods for microwave design tasks and to investigate recent soft computing methods for microwave design.

In order to meet the above mentioned research objectives and demonstrate the potential strength of the presented soft computing based methods, a pack of diversified problems with varied challenges have been considered and solved.

These design problems are as follows:

- Design of a coupled microstrip-line band pass filter
- Efficient modeling of a simple one-port microstrip via
- Design of a circularly polarized microstrip antenna and a simple aperture coupled microstrip antenna
- Design of a nonlinear taper for a specific high power gyrotron
- Design of disc type RF-windows for high power microwave and millimeter-wave sources

The examples of microstrip antennas, and microstrip filter are considered to demonstrate different optimization approaches for faster design. Again, the efficiency of SVM based modeling is demonstrated by a microstrip via, and two microstrip antennas. Whereas, the critical components - nonlinear taper and RF-windows - are chosen to show the ability of different soft computing methods to obtain precise and accurate designs where the tolerance is very less. It should be noted that the applications considered here are case-study design problems, but the methods presented can well be applied to many other microwave design problems.

Problem statement:

The problem statement for the present research work is to develop and investigate soft computing based methods for tackling challenges in the design applications of microwave domain. Our aim in the development and investigation of these methods is to obtain the designs in small time frame while maintaining or improving the efficiency of the design process for a wide range of applications. Our goal is also to learn effectively from empirical data, and to provide a framework for efficient modeling of microwave components.

Thus the research work here emphasizes on dealing with challenges in solving diversified design problems of microwave field using soft computing based methods. The work presented here addresses the engineers, designers, and researchers in the field of soft computing, modeling and optimization in engineering, and RF/microwave design.

Scope:

A typical microwave design process consists of problem identification, specification generation, concept development, EM analysis, evaluation, initial design, final design, fabrication, and testing. Out of these steps, our research work in the thesis is focused on converting initial design to final design which includes steps such as modeling, computer-aided analysis, and optimization. Thus, the assumption is made that the initial designs and some information about the design parameters (such as specifications, ranges, etc.) are available. In the present work, this information is obtained from previous published works and expert knowledge. Moreover, as the present research work emphasizes on soft computing methods for microwave design problems, the fabrication of the components is not considered. It may be noted that the term 'experiment' or 'experimental' is used to refer 'simulation' and not the physical experiment. It should also be noted that the soft computing methods presented here do not aim to replace the use of EM simulators from microwave design, but they overcome the shortcomings present in the conventional design methodology.

1.5 Organization of the thesis

The organization of the later chapters is as follows. Chapter two presents a state-of-the-art review on the present use of soft computing methods for design applications in microwave domain. In chapter three, a modified particle swarm optimization algorithm with a novel concept of multiple sub-swarms is presented and its applicability is demonstrated by the design of a specific microwave filter. Chapter four of the thesis presents efficient modeling of microwave components using SVM and also presents a hybrid approach - support vector driven evolutionary algorithm - for designing microwave components such as a microstrip via, and two microstrip antennas. Chapter five presents the design and optimization of a nonlinear taper for a specific high power gyrotron using two swarm intelligence based algorithms namely a modified bacterial foraging optimization and a standard particle swarm optimization. Chapter six presents the design of disc-type RF-windows using multi-objective particle swarm optimization methodology. Finally in chapter seven, the contributions made in the thesis are summarized and scope of the future work is outlined.

Chapter 2

Preliminaries and Review

2.1 Overview

In this chapter, we present a state-of-the-art review on the present use of soft computing methods for the design applications in microwave domain. Since long time, the literature on soft computing was confined to the methods such as genetic algorithms, artificial neural network, fuzzy logic, and their variations and hybridizations. During last decade, few other swarm intelligence based algorithms such as particle swarm optimization, ant colony optimization, and bacterial foraging optimization have emerged. Microwave researchers also observe these techniques and try to adopt them for various microwave design applications. In this chapter, we present a review of microwave design using five soft computing methods namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFO), Artificial Neural Network (ANN), and Support Vector Machine (SVM). Out of these methods, ANN and GA have been widely exploited by microwave researchers. Though efforts have been made to review related works of all five methods used for microwave design applications, emphasis is given on recent methods, namely, PSO, SVM and BFO. For BFO and SVM, no much has been reported in literature for microwave design.

For convenience, we have divided the discussion of the review into three parts: microwave design using evolutionary algorithms, microwave modeling using soft computing methods such as ANN and SVM, and hybridization of soft computing methods used for microwave design. The list of references covered in this review is by no means exhaustive, but it is fairly representative of present usage of these techniques.

The organization of the chapter is as follows. Section 2.2 presents microwave design using three evolutionary and swarm intelligence based algorithms[1] namely GA, PSO and BFO. Section 2.3 discusses microwave modeling using two techniques, namely, ANN and SVM. Section 2.4, presents a review on the usage of hybrid soft computing techniques for microwave design.

2.2 Microwave design using evolutionary algorithms

Currently used methods of microwave design suggest the use of full-wave analysis of EM simulation tools. Many new EM simulation tools are being developed by industry to automate the design process. Some of them are embedding local search methods for optimizing the design parameters. Evolutionary Algorithms (EAs) are reliable alternatives to these methods for getting optimum designs.

There are many advantages of using EAs for engineering design including microwave field, some of them are as follows:

- EAs are derivative free methods for design optimizations.
- Unlike conventional local search methods, EAs can optimize many variables

[1]Eventhough PSO and BFO are swarm intelligence based algorithms, they are referred under the category of evolutionary algorithms to maintain simplicity of the presentation.

simultaneously.

- Due to population based approach, EAs search simultaneously in different parts of the search space.

- EAs can be easily implemented on parallel architectures.

- EAs can be easily interfaced with various EM simulation tools in order to optimize design parameters. The inherent mechanisms of EAs overcome local minima in most cases.

In this section, we review microwave design applications using three evolutionary algorithms: genetic algorithm, particle swarm optimization, and bacterial foraging optimization.

2.2.1 Genetic Algorithm

Overview

Genetic algorithm was introduced by John Holland [43] and it was applied to many practical problems by Goldberg [4]. It is one of the promising ways of searching for optimum solution from multivariate nonlinear feature space. It is based on the principles of natural evolution and natural genetics [43, 4]. The power of GA resides in its three basic operators namely reproduction, crossover, and mutation. Due to population based approach, these algorithms have been able to obtain global optimal solutions in complex optimization problems. The applicability of binary GA and its modifications have been proved in many realtime applications [44, 45, 46, 47, 48]. A brief working of GA is described in Appendix A of the thesis.

Micorwave design using genetic algorithm

Many modifications to the simple binary coded GA have been proposed and used by the researchers for the design of microwave components since last decade. Though it is not possible to summarize all works of GA in microwave designs in this chapter, we have tried to cover them briefly and for the in depth knowledge readers are requested to refer [3, 25, 26, 27, 28, 29, 30, 31, 32, 49] and the references therein.

An initial review of microwave designs obtained with GA since 1992 to early 1997 was presented by Weile and Michielssen [25]. They covered electromagnetic design applications in four categories: antennas, stratified medium structures, static devices, and miscellaneous. A review on evolving wire antennas such as Yagi and crooked-wire antenna designs using GA was presented by Linden and Altshuler [26]. Johnson and Rahmat-Samii [3] also presented the use of GA in engineering electromagnetics. They collected the works of GA in applications such as design of microwave absorbers, reduction of array sidelobes, designs of shaped-beam antenna arrays, radar target identification, and broad-band patch antennas. Haupt and Werner [27] also described various electromagnetic designs obtained with GA. They used genetic algorithms mainly for the design of antennas, synthesis of array patterns and optimization of scattering patterns.

Many advancements and modifications of GA have been proposed and they have also been used for electromagnetic designs. Johnson and Rahmat-Samii [28] introduced a technique of combining GA and Method of Moments (MoM) for integrated antenna designs. In this technique, GA optimization was combined with a tailored MoM analysis, which involves removal of rows and columns from the Z-matrix instead of refilling the Z-matrix in each iteration of the GA. Their method was used for the design of wide band and dual band patch antennas.

GA has also been used for wireless communication applications. Hong and Dong [29] have proposed two different GA-based efficient searching approaches and applied them to maximum likelihood decoding and distance spectrum techniques to reduce computational complexity for Multiple-Input Multiple-Output (MIMO) systems. Villegas, *et al.* [30] described Electromagnetic Genetic Optimization (EGO) that combines accuracy of full-wave EM analysis with the robustness and speed of parallel computing GA on the cluster supercomputing platform. The EGO was used to design a dual-band antenna element for wireless communication applications.

GA has also been used for problems like array pattern synthesis, array failure detection, and array failure correction. Yan and Lu [31] presented simple and flexible genetic algorithm for pattern synthesis of antenna array with arbitrary geometric configuration. Their approach presented the array excitation weighting vectors as complex number chromosomes and used decimal linear crossover without crossover site. Their method suggested the advantage of avoiding binary coding and decoding, and using simplified approach of chromosome construction. GAs have also been used for the design of oversized waveguide components. Plaum *et al.* [32] optimizes bends for oversized waveguides using GA. In the design of waveguide bends, they optimized curvature function and for corrugated waveguides, the corrugation depth of a bend.

Despite of GA's success and wide use in finding optimum designs, it consumes huge computational time to reach an optimum solution. Moreover due to stochastic nature, sometimes GA may converge prematurely leading to local optima, especially, when the search space is huge and highly nonlinear.

2.2.2 Particle Swarm Optimization

Overview

Particle swarm optimization, developed by Kennedy and Eberhart [6, 50], is a simple and effective swarm intelligence based method for optimization of wide range of functions. Fundamental hypothesis to the development of particle swarm optimization is social sharing of information and collaborative behavior of biological swarms [6, 7, 33, 51]. A detailed description of PSO is covered in Chapter 3. In next subsection, we present a review of works performed for design applications in microwave domain using PSO and its modifications.

Microwave design using Particle Swarm Optimization

The use of PSO for electromagnetic & microwave design applications was initially justified in [52, 53]. Rahmat-Samii [52, 54, 55, 56] has studied and applied PSO and its modifications to many electromagnetic design applications, especially for the design of various antenna structures and arrays. Robinson and Rahmat-Samii [52] introduced conceptual overview of PSO for electromagnetic community. They indicated the use of invisible wall technique over absorbing and reflecting wall techniques for applying boundary conditions. They showed the use of PSO to the optimization of profiled corrugated horn antenna. Recently, Jin and Rahmat-Samii [54] presented a review on PSO for antenna designs. They illustrated the effectiveness of applying swarm intelligence to design antennas with desired frequency response and radiation characteristics for practical EM applications. They demonstrated the flexibility of PSO to handle both binary and real parameters, and in solving multi-objective problems by applying it to three design problems: design of dual-band patch antenna, artificial ground plane of surface wave antenna, and low-sidelobe antenna array, respectively.

In other modifications to PSO, Ciuprina, *et al.* [53] presented Intelligent PSO (IPSO) that offered more intelligence to particles by using concepts of group experiences, unpleasant memories, local landscape models based on virtual neighbors, and memetic replication of successful behavior parameters. They tested IPSO on a test function and on Loney's solenoid. Wang *et al.* [57] presented a combined approach of PSO and Finite-Element Method (FEM) for the design of compact planner microwave filter. They suggested the use of PSO-FEM approach to be useful in wide range of novel filter design. In an another modification to PSO, Mikki and Kishk [58] presented a new physical formalism of PSO technique based on quantum mechanics. They applied this newly developed PSO, known as Quantum PSO (QPSO), to electromagnetic problems such as synthesis of antenna array, and finding equivalent circuit model for dielectric resonator antenna that predicts parameters like Q-factor. The authors proved this algorithm to outperform improved version of classical PSO in convergence speed as well as in obtaining better solution.

One of the drawbacks in performing microwave designs with PSO, due to its iterative nature, is that the overall design process becomes computationally intensive and time consuming. To reduce overall computation time of the design process, PSO can be implemented on parallel clusters. As each particle in PSO acts as an independent agent, it is an inherent characteristic of the algorithm that enables it to be parallelized easily. Jin and Rahmat-Samii [55] presented a method combining PSO and Finite Difference Time Domain (FDTD) method for the design of multi-band and wide-band antennas. They also implemented this method on a parallel cluster to reduce the computational time introduced by full-wave analysis of FDTD method.

It is also observed that many real-time problems have more than one objective. In this case, it is desired to find a solution that optimally balances the trade-off between multiple objectives. Similar to GA, multi-objective optimization is possible to implement with PSO. Xu and Rahmat-Samii [56] shows the use of Multi-Objective PSO (MOPSO) by applying it to two electromagnetic problems: synthesis of 16-element antenna array which is optimized for trade-off between beam efficiency and half-power beam width, and optimization of shape reflector antenna for high gains of multiple feeds.

Researchers have also compared the concepts and performances of PSO with

GA. The conceptual difference between PSO and GA is described by Kennedy and Eberhart [6]. According to them, PSO lie between GA and evolutionary computation. The adjustment of particle towards its individual best, and towards global best is conceptually similar to crossover operation used in GA. The benefit with PSO is that it converges in less number of iterations than GA, and requires few parameter settings. PSO has been demonstrated in certain instances to outperform GA [6]. A comparison between PSO and GA on test problems is carried out by Hassan *et al.* [59]. Boeringer and Werner [60] compared PSO and GA for phased array synthesis problem. They obtained good performance with both the methods. According to them the cost function budget for electromagnetic optimization dominates, and book-keeping requirement for both the algorithms becomes negligible. They also found a simpler implementation and reduced book-keeping appeal of PSO. Despite advantages of PSO such as faster convergence, simple approach, and reduced book-keeping over GA, it may also lead to premature convergence and local minima similar to GA.

2.2.3 Bacterial Foraging Optimization

Overview

Bacterial foraging optimization is an optimization technique introduced by Passino in 2002 [8]. It is inspired from the imitation of the food-ingesting (foraging) behaviors of Escherichia (E.) coli bacteria, which are present in our intestines. In this method, a group of bacteria move in search of rich nutrient concentration and away from noxious elements. The algorithm proceeds by selecting or eliminating bacteria based on their good or poor foraging strategies. This process either eliminates the poor strategies or refines them in to better ones. The foraging process in BFO algorithm involves four main steps which include chemotaxis, swarming, reproduction, and elimination-dispersion. The detailed description of BFO and few of its variations is given in Chapter 6 and Appendix-C of the thesis. The investigation and use of BFO has been started by microwave researchers since past two to three years and very few works on BFO for microwave design have been reported in the literature. The works on the use of BFO in microwave design and for other engineering applications are discussed in the next subsection.

Microwave design using Bacterial Foraging Optimization

The works reported in literature [61, 62, 63] show that BFO has been used mainly for antenna and array designs. Gollapudi, *et al.* [61] used bacterial foraging optimization technique for calculating resonant frequency for rectangular microstrip antenna of arbitrary dimension and substrate thickness. They also determined the feed point of the microstrip patch antenna using the same technique. Datta, *et al.* [62] presented an improved adaptive approach to bacterial foraging algorithm and used it for optimizing both the amplitude and phase of the weights of a linear array antenna, for maximum array factor at any direction and nulls in specific direction. They used principle of adaptive delta modulation to make the algorithm adaptive. Guney and Basbug [63] used bacterial foraging algorithm to achieve null steering in radiation pattern of a linear antenna array by controlling only the element amplitudes. BFO and its improvements have also been used in few other design applications such as job shop scheduling [64], stock indices prediction [65], and optimizing multivariate PID (Proportional-Integral-Derivative) controller [66].

2.3 Soft computing methods for microwave modeling

An inherent and important part of the design process is modeling. Conventional method suggests the use of EM simulation tools for modeling and analysis of microwave components. A typical design problem in EM simulator sometimes takes much computation time even on up-to-date processors. Various regression techniques such as neural networks, response surface methods, kriging, and regression splines can be used as metamodels [15]. A *metamodel* is defined as 'model of the model'. The advantage of these methods is that they respond very fast, and sometimes it is also possible to design components when its closed-form formulas are not available. In this section, we present conceptual overview and a brief review of EM modeling using two soft computing methods namely ANN and SVM. ANN has been widely used for EM modeling, while the SVM is relatively new and is not explored as effectively by EM researchers.

2.3.1 Artificial Neural Network

Overview

An artificial neural network (also called neural network) is a parallel distributed processor made up of simple processing units. It has the capability to learn from empirical data, store experimental knowledge and make it available for use in desired application [9]. It has long been used as a machine learning tool in many research and commercial applications to learn the underlying function, mapping the input and output data from a large data set [34]. ANN has been proven to be fast and effective technique for modeling microwave components. It can be used as a tool for predicting device behavior when no mathematical model is available. A brief conceptual background on the working of artificial neural network is presented in Appendix-B. Current state-of-the-art ANN based modeling for microwave design can be found in detail in [1, 35, 36, 37, 38, 39, 40, 67]. Although this is not an exhaustive list, it tries to include different ANN models for various microwave components. For detailed study reader may refer to the references presented here and the further references there in.

ANN based microwave modeling

A thorough review of ANN applications in microwave CAD is presented by Burrascano, *et al.* [35]. The authors there showed the role of ANN in replacing most CPU intensive part of microwave CAD, namely, yield optimization, tolerance analysis, and manufacturing-oriented design. They illustrated few significant applications, and presented issues for practical implementation. They also introduced self-organizing maps for enhancing model accuracy and applicability. Neural network has been studied and applied widely for the design of RF and microwave components by Zhang and Gupta [1]. After discussing neural network structures and training methods, they provided a general methodology for the development of accurate and efficient Electromagnetically-trained Neural Network (EM-NN) models for use in microwave CAD. They showed ANN-based modeling for various RF and microwave components such as transmission line structures, active devices, microwave circuits, antennas, and systems. At last they described an exciting method - knowledge based neural network by combing microwave knowledge with neural networks and showed its use in RF and microwave design.

Various modifications were performed to simple multilayer perceptron type neural network by researchers according to EM design requirements. Wang and Zhang [36] developed a novel neural network structure, namely, Knowledge-Based Neural Network (KBNN) by combining microwave experience and learning power of neural network. They also developed new error backpropagation training scheme utilizing gradient based $l2$ optimization. They applied KBNN to different microwave modeling problems like circuit waveform modeling, transmission line modeling and MESFET modeling problems, and proved that KBNN gives less testing errors than multilayer perceptrons and it is also efficient when training data is insufficient. Marinova, *et al.* [37] presented a model by employing neural network inverse algorithm and two feed forward neural networks for solving electromagnetic design problems. The model was applied for the design of magnetic simulation coil and gradient coil. An ANN based approach for modeling of linear and nonlinear circuits was presented by Suntives, *et al.* [38]. They described a modified hybrid approach for computing S-parameters of microstrip discontinuities based on equivalent circuit extraction and ANN. Ding, *et al.* [39] presented ANN approach to EM based modeling and optimization in frequency and time domains and used them to nonlinear circuit optimization problems. They presented EM-based time domain neural modeling approach combining available knowledge of equivalent circuits with state-space equations and ANN. Recently, a state-of-the-art review on microwave filter modeling, optimization, and design using ANN techniques is presented by Kabir, *et al.* [40]. The review included application of ANN on different types of filters such as waveguide cavity filters, simple lower order filter, waveguide dual-mode simple elliptic filters, coupled microstrip line filters, and microwave filters on PBG structure. They demonstrated through results that ANN techniques can produce fast and accurate results and can reduce computational cost compared to conventional and time consuming EM simulations.

Despite their wide use, ANN has also certain drawbacks. It is difficult to find a structure of neural network which includes number of layers, number of nodes in each layer and transfer mapping functions at each layer. There is no general rule to set parameters such as learning rate, momentum, and to find number of training samples for desired accuracy. Although neural networks are capable of achieving high degree of training accuracy in approximating the underlying design process, their generalization ability (error in predicting data not present in training set) is not as accurate. The reason is that neural network tries to minimize the empirical risk (error on training data). Moreover, neural network serves as a black box (i.e., it does not answer how a particular output is obtained). A promising alternative to neural network, which overcomes many of its drawbacks is SVM.

2.3.2 Support Vector Machine

Overview

Support vector machine is a machine learning technique developed by Vapnik [11]. It is based on the principle of statistical learning theory. SVM was developed for pattern recognition task but later on its application was extended to regression problems. Support Vector Regression (SVR) is found to give robust and effective model of the process under consideration [68, 69]. The models developed using SVR are simple and their evaluation is very fast. No prior knowledge about input/output mapping is required for the model development. An increasing number of engineers and researchers from diverse fields have begun to take a serious interest in this emerging technology. The hypothesis generated using SVM involves both Structural Risk Minimization (SRM) and Empirical Risk Minimization (ERM). This makes SVM much more powerful in generalizing than traditional neural network which only minimizes empirical risk. The key ideas of SVM are: nonlinear mapping from input space to high-dimensional feature space using a kernel trick, and find an optimum hyperplane that maximizes generalization ability [11, 70].

Similar to ANN, the SVR can learn from data allowing it for model development even when component formulas are unavailable. It has been proved to generalize well and marks the birth of another unconventional approach to modeling and design problems in RF/microwave CAD. Even though with its wide popularity, very few works have been reported on SVR for microwave design problems. One of our aims in this thesis is to introduce SVM to electromagnetic community and show how it can be used for effective microwave modeling in general. A detailed conceptual description of SVM is given in Chapter 4. In the next subsection, a review on using SVR for microwave design applications is presented.

Use of SVM in microwave modeling

Though very few works have been reported in literature, we present here a brief review on microwave modeling using SVM. In [17], Angiulli, *et al.* discussed the use of SVR for modeling microwave devices and antennas. They reported that SVR-based model gives better prediction accuracy in less computational time compared to ANN-based modeling approach. Angiulli, *et al.* [71] also used SVR-based approach for electromagnetic inverse scattering problem. Wu, *et al.* [72] used SVR for extracting electromagnetic parameters such as complex permittivity and permeability for magnetic thin film materials. Güneş, *et al.* [73] adapted SVR to the analysis and synthesis of microstrip lines on all isotropic/anisotropic dielectric materials. They found SVR superior to ANN for regression applications due to its higher approximation capability and much faster convergence with sparse solution technique. Güneş, *et al.* [74] also developed SVM model for small-signal and noise behavior of microwave transistor and compared it with ANN model. Martínez-Ramón and Christodoulou [75] introduced a set of novel techniques based on SVM, and applied them to antenna array processing and other problems in electromagnetics. Particularly, SVM was used for linear and nonlinear beam forming, parameter design for arrays and estimating the direction of arrival problems. Modifications to SVR and combination of electromagnetic analysis with SVR have also been tried by some of the researchers. Xu, *et al.* [76] presented an approach for modeling microwave devices based on combination of conventional equivalent circuit model and SVR. They found this approach to be fast and accurate for developing model of SiC MESFET.

Despite SVR's smaller errors and superior generalization capabilities, there are certain challenges in using SVR for microwave design. The accuracy of prediction in SVR depends on selection of hyperparameters. These include deciding values of penalty trade-off parameter C, kernel function and its parameter, and parameter ε of regression tube. Few methods have been suggested in literature but none is guaranteed to give best selection with minimum computational expenses. Moreover, simulation response of microwave components is very sensitive to small changes in its design parameters. So it is challenging for microwave designers and researchers to develop effective models using SVM. Microwave designers may have expert domain knowledge in addition to data sets. Inclusion of this domain knowledge may lead to higher accuracy of the components.

2.4 Hybrid soft computing methods for microwave design

All the individual soft computing techniques are powerful and contribute in the design process, but each of them also have certain drawbacks. ANN and SVM are efficient modeling techniques but they are not in much use for optimization purpose. GA and PSO are useful in optimization but they require interface with EM full-wave analysis codes. Moreover, due to their iterative nature they are computationally intensive and time consuming. Researchers have also tried to develop hybridization of different soft computing methods by combining two or more methods by removing drawbacks and using advantages of each method [77, 78, 79, 80]. This section reviews few works on hybridization of two or more soft computing techniques used for the microwave design applications.

Yang, *et al.* [81] presented a hybrid approach combining PSO with Least-Square SVM (LS-SVM) to improve computational efficiency of FDTD (Finite-Difference Time Domain) method. In this approach, PSO was used to optimize hyperparameters of LS-SVM. Researchers have also tried to combine GA and PSO algorithms exploiting the advantage of both algorithms. A very simple hybridization of GA and PSO was investigated by Robinson, *et al.* [82] and it was tested for profiled corrugated horn antenna. After investigating both algorithms individually, they tested two combinations: GA followed by PSO and PSO followed by GA in which the result of previous algorithm was used as starting point for the later algorithm. According to their results PSO-GA hybrid combination returned the best horn. Gandelli, *et al.* [83] presented a hybrid evolutionary algorithm - Genetic Swarm Optimization (GSO) - by integrating main features of GA and PSO. After performing preliminary studies, GSO was applied to the design of planer reflectarry antenna and found reliable and effective for applications in electromagnetics. Researchers have also developed hybridization of bacterial foraging optimization with GA and PSO, but they have not been investigated for microwave design applications. A hybrid approach combining PSO with BFO was presented and used to optimize multi-modal and high dimensional benchmark functions in [84]. The hybrid method was found to be better than standard BFO and comparable to PSO and its variations on benchmark functions. Kim, *et al.* [85] presented another hybrid approach combining GA and PSO and demonstrated it for solving optimization benchmark problems. They also successfully used it for tuning PID controllers of automatic voltage regulator.

Chapter 3

PSO with Multiple Subswarms and its Application to the Design of Microwave Filter

3.1 Introduction

In recent trends, most of the electromagnetic problems and design of microwave/millimeter wave components employ different EM simulation tools. At the outset, initial design is carried out with coarse and approximate analytical and circuit models. This initial design will farther be perfected to obtain a final design by making use of suitable EM simulators. But, this procedure is manual, tedious, time-consuming and chances of getting local minima are very high.

EM researchers are using various evolutionary and, in recent years, swarm intelligence based algorithms such as genetic algorithm, and particle swarm optimization for the optimization of design parameters [3, 52]. The advantage of this technique is that it reduces manual and laborious task of getting desired response with EM simulations, but there are certain drawbacks of this method. The major drawback in using Evolutionary Algorithms (EAs) is that they require large number of iterations, and invoking EM simulation tools in their iterative loops makes the design process computationally expensive and still time consuming. Moreover, increasing design parameters or widening the search range makes them sometimes difficult to converge to global optimum.

Researchers have been working continuously on Particle Swarm Optimization (PSO) for the improvement of its convergence speed and accuracy [12, 13, 14]. In this chapter, we present a novel concept of multiple subswarms in PSO algorithm with a hope that searching the feature space in a distributed manner may lead to faster convergence towards global optima. This motivates us to apply the above mentioned approach to complex design processes that are computationally expensive and time consuming. The proposed algorithm is tested on five benchmark functions. At last we have shown the applicability of the algorithm for the design of a specific microwave filter. Though the algorithm presented here can be applied for the design of a variety of microwave components, a microwave filter is considered as a case study.

The organization of the chapter is as follows. In section 3.2, standard PSO algorithm, and its two basic variations are presented. In section 3.3, we present a modified PSO algorithm with multiple subswarms. Section 3.4 presents the experiment with benchmark functions. Section 3.5 demonstrates the application of the proposed algorithm for the design of a specific microwave filter. Finally, section 3.6 presents concluding remarks.

3.2 Partilce Swarm Optimization

3.2.1 Standard PSO

The standard PSO is a population based algorithm. Each potential solution in the population is known as *particle*, which is represented by position and velocity vectors. The particles fly through the multidimensional search space in order to get the best solution. These particles adjust their velocity according to their own flying experience and according to the experience of their companions. Let, the position and velocity of each particle in the *swarm* (a population of particles) are represented as $X_i = (x_{i1}, x_{i2},..., x_{iD})$, and $V_i = (v_{i1}, v_{i2},..., v_{iD})$ (where D is number of decision parameters of an optimization problem) respectively. The best previous position of each particle is represented as $P_i = (p_{i1}, p_{i2},..., p_{iD})$. The global best position of all particles is represented by $P_g = (p_{g1}, p_{g2},..., p_{gD})$. The velocity and position of each particle are updated using relations:

$$v_{id} = v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{3.1}$$

and

$$x_{id} = x_{id} + v_{id} \tag{3.2}$$

where c_1 (cognitive constant) and c_2 (social constant) are two positive constants, r_1 and r_2 are two random numbers uniformly generated between [0, 1]. The values of c_1 and c_2 are considered to be equal in most PSO literatures to balance movement of particle in both cognitive and social components. The velocities of particles are clamped by maximum velocity vector V_{max} on each dimension. The pseudo-code for standard PSO is shown in Fig. 3.1. The global best version (GBEST) of standard PSO is considered for the experiments in this work.

3.2.2 Variations of PSO

There are several variations to the standard PSO algorithm, a comprehensive summary of which is given in [7]. In this section, we discuss two basic variations of PSO. The first is PSO with Inertia Weight Method (IWM) which is proposed by Shi and Eberhart [13, 86], while the second is PSO with Constriction Factor Method (CFM) which is proposed by Clerc [14].

Shi and Eberhart [13] introduced Inertia Weight (IW) parameter into original particle swarm optimizer. The purpose was to balance exploration and exploita-

```
Initialize positions and velocities of all particles in the swarm randomly
Repeat
    For each particle in the swarm
        Calculate the fitness value f(X_i)
        If f(X_i) < f(P_i) then P_i=X_i
    End for
    Update P_g, if the best particle in the current swarm has lower f(X) than f(P_g)
    For each particle in the swarm
        r_1=rand(); r_2=rand();
        Calculate particle velocity according to equation (3.1)
        Restrict the velocity of particles by [-V_max, V_max]
        Update particle's position according to equation (3.2)
    End for
Until maximum iteration or minimum error criteria is attained
```

Figure 3.1: Pseudocode of standard PSO algorithm

tion abilities of PSO. Basically, IW controls the momentum of the particle by weighing the combination of previous velocity. The velocity update Eq. (3.1) is modified to,

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}), \tag{3.3}$$

where w represents inertia weight which is used to balance local and global search abilities. Different ways of selecting value of inertia weight are given in literature [7], which include linearly decreasing IW, nonlinearly decreasing IW, linearly increasing IW, and fuzzy adaptive IW. In this work, we consider a common choice of considering linearly decreasing inertia weight from an initial value of 0.9 to final value 0.4.

In another variation, Clerc [14] proposed a different approach to balance the trade-off between exploration and exploitation. He introduced a constant which is referred as *constriction coefficient* to constrict the velocity of particles. The velocity update Eq. (3.1) is modified to,

$$v_{id} = \chi[v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id})], \tag{3.4}$$

with constriction factor χ defined as

$$\chi = \frac{2\kappa}{|2 - \phi - \sqrt{\phi(\phi - 4)}|}, \phi = c_1 + c_2, \phi > 4, \tag{3.5}$$

where $\kappa \in [0,1]$ is a positive constant. Here parameter κ controls the exploration and exploitation abilities of the swarm. A comparison of IWM and CFM is given in [87]. It was concluded that CFM has relatively better convergence abilities than IWM.

In the next section, we present a modified PSO considering multiple subswarms and apply it to both the above variations of PSO. The proposed algorithm (after adapting above modifications) is tested with five benchmark functions commonly used in PSO literatures. The results of modified PSO with above two variations (IWM and CFM) are compared with standard PSO with same variations respectively.

3.3 Particle Swarm Optimizer with Multiple Subswarms

In this section, a new implementation of PSO algorithm considering multiple subswarms is presented. This modification is inspired from human knowledge acquisition process. It can be realized in a society, that an individual obtains information of a particular thing or event based on his own experience (which is stored in his own memory) and the information available from global information sources such as TV, internet, newspaper, etc. These two information sources can be correlated with the local best and global best positions utilized by the particles. But, humans (we) also gain information from our local environment (i.e., from the persons with whom we are in contact). This specifies that every individual is also part of a local group from which he/she also gains information. Inspired by this aspect of an individual in the society, we present a new modification to PSO algorithm in which a swarm is divided into multiple subswarms. Each particle also considers best information available to the subswarm (local group) in which it belongs. The velocity update equation in the proposed method is modified to consider the effects of multiple subswarms. The proposed modified PSO algorithm, which we call PSO with Multiple Subswarms (PSO-MS), is shown in Fig. 3.2. The major changes in the proposed algorithm from standard PSO algorithm (Fig. 3.1) are highlighted.

In the proposed algorithm, first we initialize number of subswarms. The number of particles in each subswarm is defined by total number of particles in the original swarm divided by number of subswarms. In every iteration of the modified algorithm, we also find the subswarm's best (P_{gs}), in addition to the

Initialize number of subswarms

Initialize positions and velocities of all particles**in each subswarm** randomly

Repeat

  For each subswarm

    For each particle in the **subswarm**

      Calculate the fitness value

      If $f(X) < f(P_i)$ then $P_i = X_i$

    End for

    Update P_{gs} **, if best particle inthe subswarm has lower** $f(X)$ **than** $f(P_{gs})$

  End for

  Update P_g, if the best particle in the swarm has lower$f(X)$ than $f(P_g)$

  For each subswarm

    For each particle in the **subswarm**

      r_1=rand(); r_2=rand(); r_3=**rand();**

      Calculate particle velocity according to equation **(3.6)**

      Restrict the velocity of particles by $[-V_{max}, V_{max}]$

      Update particle's position according to equation (3.2)

    End for

  End for

Until maximum iteration or minimum error criteria is attained

Figure 3.2: Pseudocode of PSO with Multiple Subswarms (PSO-MS)

swarm's global best (P_g). To consider the effect of subswarm's best, we modify the velocity update Eq. (3.1) as,

$$v_{id} = v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2' r_2 (p_{gd} - x_{id}) + c_3' r_3 (p_{gsd} - x_{id}). \qquad (3.6)$$

Here, the cognitive component is not changed, and the c_1 still represents cognitive coefficient as in standard PSO. We divide social component into two parts: one representing the effect of swarm's global best (P_g), while the other representing the effect of subswarm best (Pgs). The social coefficient c_2 is modified to c_2' and a new coefficient c_3' is added to the equation along with a new random number r_3. Here, we suggest to select the values of c_1, c_2' and c_3' in such a way that $c_1 = c_2' + c_3$ and $c_2' = c_3'$. These restrictions have been imposed in order to keep the trust of particles equal on cognitive and social components. By keeping equal values of c_2' and c_3' will lead particle equally towards global and subswarm best positions.

Our modification also holds true when we do not divide swarm into multiple subswarms. If we consider the number of subswarms to be one, then P_g and P_{gs} will produce the same values and the velocity update Eq. (3.6) will reduce to Eq. (3.1) of standard PSO algorithm, provided the value of r_3 is same as the value of r_2 and the values of c_2' and c_3' are chosen as suggested above. In this case, the algorithm of Fig. 3.2 will reduce to standard PSO algorithm as shown in Fig. 3.1. In this work, we test our algorithm (Fig. 3.2) with number of subswarms varying from one to five.

The concepts of IWM and CFM (as described in previous section) are applied to velocity update Eq. (3.6) in similar way as they were defined in Eq. (3.3) and (3.4) respectively. The values of c_2' and c_3' are selected following the restrictions described earlier. Useful suggestions for parameter selection for both these variations are obtained from [88] and [89] respectively. Finally, the positions of particles are updated similar to standard PSO algorithm according to Eq. (3.2).

3.4 Experiment with benchmark functions

3.4.1 Benchmark functions

To compare the performance of proposed algorithm with standard PSO algorithm, five nonlinear benchmark functions commonly found in the PSO literature [12, 13, 89] are employed. These benchmark functions are shown in Table 3.1. Among these functions, De Jongs' sphere function and Rosenbrock's functions are unimodal, while rest of the functions are multimodal. To test these functions the fitness value was taken equal to the function value.

3.4.2 Experimental settings

In addition to the selection of benchmark functions, there are many experimental settings to be determined such as the swarm size, maximum number of iterations for each run, the search space size, etc. To keep these settings as standard as possible, we follow the simulation settings given in [12] whenever possible. However, the swarm size of 30 is considered for all experiments on test functions in this work. In order to check the performance with increasing complexities, the simulations were performed on these functions with three dimensions 10, 20, and 30 except for Schaffer's f6 function which is of two dimensions. Maximum iterations are kept at 1000 for Schaffer's f6 function. Maximum iterations for sphere function are 1000, 2000, and 3000 for dimensions 10, 20 and 30 respectively. For rest three benchmark functions maximum iterations are 3000, 4000, and 5000 for dimensions 10, 20 and 30 respectively. The maximum tolerance limit for Schaffer's f6 function is 0.00001, while for rest of the functions tolerance limit is considered to be 0.01. The range of search and initializations for test functions are shown in Table 3.2. As the optimum objective function value for all benchmark functions are near origin, initializing particles uniformly random in the search range would allow the particles to be distributed around origin. So

Table 3.1: Benchmark functions

Function name	Function
De Jongs's sphere function	$f_1 = \sum_{i=1}^{n} x_i^2$
Rosenbrock function	$f_2 = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
Generalized Rastrigrin function	$f_3 = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$
Generalized Griewank function	$f_4 = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$
Schaffer's f6 function	$f_5 = 0.5 + \frac{(\sin\sqrt{x_1^2 + x_2^2})^2 - 0.5}{(0.1 + 0.001(x_1^2 + x_2^2))^2}$

Table 3.2: Initialization range, search range, and error tolerance

Test function	Range of search	Range of initializations
f_1	$[-100, 100]^n$	$[50, 100]^n$
f_2	$[-100, 100]^n$	$[50, 100]^n$
f_3	$[-10, 10]^n$	$[2.56, 5.12]^n$
f_4	$[-600, 600]^n$	$[300, 600]^n$
f_5	$[-100, 100]^n$	$[15, 30]^n$

to avoid such biasing, asymmetric initializations as suggested in [12] and [90] are used in the experiments. The maximum velocity V_{max} is considered equal to half the range of search i.e., $V_{max} = \gamma X_{max}$ [89] where the value of γ is considered to be 1 (remember the search range is [-X_{max}, X_{max}]). Eberhart and Shi [87] also suggest limiting the maximum velocity V_{max} to dynamic range of the variable X_{max} on each dimension.

3.4.3 Experimental results and discussions

In this section, comparison of PSO-MS is made with standard PSO for both the variations IWM and CFM respectively. Table 3.3 shows the performance of PSO-MS and PSO with IWM for all five benchmark functions, while Table 3.4 shows the performance of PSO-MS and PSO with CFM. To neutralize the randomized effects due to probabilistic nature of EAs, the results presented in the tables are average of 50 simulations (runs) for each function. In the tables, when the number of subswarms is one, no division of particles in the swarm takes place and it refers to standard PSO, while the number of subswarms two to five refer to PSO-MS. In the tables, results are shown considering three performance metrics [12]: average achieved optimum value out of 50 runs, number of successful runs out of 50 runs, and average generation of success from the set of successful runs. The best results, considering all three metrics in all cases, are highlighted with bold faces in both the tables.

It is observed from Table 3.3 and Table 3.4 that PSO-MS with two subswarms outperforms standard PSO in terms of number of successes and average obtained optimum value. Moreover, it is observed from Table 3.3 and Table 3.4 (in most cases) that PSO-MS with two subswarms obtains similar or better performance in less number of iterations. This leads to reduction in computational expenses. It is observed from both the tables that average generation of success is lower for PSO-MS than PSO for all subswarms. It is also observed for both PSO variations that for generalized Rastrigrin's function with dimension 20 and 30 and Rosenbrock's function with dimension 10, PSO-MS obtains higher average optimum value than PSO. The comparison of Table 3.3 and Table 3.4 shows that for most of the cases PSO-MS and PSO with CFM obtain better performance in less number of iterations than PSO-MS and PSO with IWM respectively which is also a conclusion in [87]. Finally, a comparison of total number of successes for IWM and CFM shows that PSO-MS with two subswarms obtains more number of successes than standard PSO in both the variations. Here, we also observe the classic case of time-accuracy trade-off. It can be seen from the tables that as the number of subswarms increases, keeping the swarm size same, faster convergence is obtained while decreasing the number of successes. Now, if we need greater accuracy, the swarm size should be increased accordingly, which again results in larger computational time due to more Function Evaluations (FEs) that have to be performed. Hence, in our experiments, two number of subswarms are found to give optimum performance in most test cases. Here, the values of c_1, c_2' and c_3' were considered to be 2, 1 and 1 respectively for IWM. For CFM, it was observed that performance is sensitive to the values of c_1, c_2', and c_3' (the similar conclusion is also drawn empirically in [89]). Therefore values of these parameters were manually optimized in CFM for each test case.

3.5 Experiment

3.5.1 Design of coupled microstrip line band pass filter

In this section, as a case study of microwave components, we have considered the design of microstrip filters. Microstrip filters have become popular due to their small size, low cost, and good performance. Various topologies available for implementing microstrip filters are end coupled, parallel coupled, hairpin, interdigital and combined filters [91, 92, 93, 94, 95]. Parallel coupled microstrip lines have been selected for implementation of microstrip filters in this experiment. We have considered the design of Chebyshev band pass filter for approximately 1 GHz bandwidth centered at 2.5 GHz frequency. The specifications for the problem are given in Table 3.5.

The general layout of the coupled microstrip line filter considered for the problem is shown in Fig. 3.3. It is made of cascaded coupled line sections. Skew-mirror symmetry has been used in developing the structure (i.e., structure

Table 3.3: Performance comparison of PSO-MS and PSO with IWM

Fn.	Dim.	Average achieved optimum value (Standard deviation)					Number of successes (Average generation of success)				
		Number of subswarms									
		1	2	3	4	5	1	2	3	4	5
f_1	10	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(566)	**50(391)**	50(403)	50(419)	50(428)
	20	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(1291)	**50(851)**	50(878)	50(915)	50(934)
	30	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(2081)	**50(1344)**	50(1394)	50(1453)	50(1479)
f_2	10	25.19 (62.34)	**32.85 (84.40)**	55.48 (135.11)	66.78 (122.03)	69.06 (139.94)	1 (2365)	**2 (1997)**	1 (1620)	0 (–)	0 (–)
	20	131.94 (269.92)	56.05 (83.92)	**49.75 (72.59)**	121.24 (210.96)	167.31 (301.86)	0 (–)	0 (–)	**0 (–)**	0 (–)	0 (–)
	30	186.85 (370.73)	**89.27 (141.64)**	103.99 (16.43)	252.12 (394.40)	241.79 (388.54)	0 (–)	**0 (–)**	0 (–)	0 (–)	0 (–)
f_3	10	2.30 (1.55)	**2.20 (1.18)**	2.54 (1.27)	2.74 (1.82)	2.84 (1.44)	3 (1904)	**4 (1349)**	4 (1531)	3 (1943)	2 (1958)
	20	**14.20 (4.68)**	15.79 (5.98)	16.35 (5.82)	15.62 (5.20)	13.69 (4.76)	**0 (–)**	0 (–)	0 (–)	0 (–)	0 (–)
	30	**31.44 (7.15)**	35.32 (10.23)	37.70 (9.06)	39.36 (9.75)	36.01 (8.70)	**0 (–)**	0 (–)	0 (–)	0 (–)	0 (–)
f_4	10	0.075 (0.035)	**0.054 (0.030)**	0.073 (0.042)	0.08 (0.045)	0.075 (0.041)	0 (–)	**2 (1182)**	1 (1092)	1 (1928)	0 (–)
	20	0.026 (0.026)	**0.021 (0.015)**	0.024 (0.021)	0.022 (0.016)	0.034 (0.027)	22 (2339)	**24 (1511)**	22 (1614)	19 (1612)	17 (1646)
	30	0.02 (0.015)	**0.015 (0.011)**	0.018 (0.015)	0.020 (0.018)	0.027 (0.027)	27 (3222)	**30 (2032)**	25 (2076)	27 (2152)	24 (2177)
f_5	2	0.00097 (0.0029)	**0.00078 (0.0026)**	0.0013 (0.0033)	0.0025 (0.0042)	0.0038 (0.0047)	45 (532)	**46 (417)**	43 (482)	37 (453)	30 (490)
Total successes (Total iterations)							248 (14300)	**258 (11474)**	244 (11090)	237 (10875)	223 (9112)

Table 3.4: Performance comparison of PSO-MS and PSO with CFM

Fn.	Dim.	Average achieved optimum value (Standard deviation)					Number of successes (Average generation of success)				
		Number of subswarms									
		1	2	3	4	5	1	2	3	4	5
f_1	10	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(66)	**50(48)**	50(81)	50(94)	50(182)
	20	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(221)	**50(132)**	50(283)	50(348)	50(387)
	30	0.01(–)	**0.01(–)**	0.01(–)	0.01(–)	0.01(–)	50(385)	**50(364)**	50(464)	50(663)	50(953)
f_2	10	**22.12 (48.18)**	27.77 (65.89)	30.04 (72.22)	53.99 (97.27)	25.81 (83.83)	**6 (2547)**	4 (1968)	1 (2636)	1 (1428)	1 (2435)
	20	43.36 (89.99)	**38.32 (75.41)**	46.28 (84.60)	70.97 (115.01)	89.17 (121.25)	2 (3116)	**3 (3266)**	3 (3784)	0 (–)	1 (3930)
	30	54.29 (84.64)	**41.33 (65.62)**	65.11 (149.2)	148.26 (399.28)	120.20 (199.99)	1 (3712)	**1 (3331)**	0 (–)	1 (4859)	0 (–)
f_3	10	2.30 (1.48)	**2.32 (2.05)**	2.38 (2.10)	3.10 (2.05)	4.34 (2.81)	4 (1920)	**7 (2085)**	5 (2533)	4 (2494)	1 (2760)
	20	**11.44 (4.15)**	12.07 (5.65)	14.65 (5.33)	15.84 (5.35)	14.78 (7.51)	**0 (–)**	0 (–)	0 (–)	0 (–)	0 (–)
	30	**26.34 (8.17)**	30.0 (10.65)	35.04 (11.94)	35.26 (10.18)	38.02 (14.42)	**0 (–)**	0 (–)	0 (–)	0 (–)	0 (–)
f_4	10	0.069 (0.034)	**0.059 (0.029)**	0.066 (0.035)	0.073 (0.042)	0.079 (0.051)	1 (1376)	**2 (894)**	0 (–)	2 (353)	1 (554)
	20	0.032 (0.059)	**0.026 (0.020)**	0.028 (0.023)	0.030 (0.030)	0.069 (0.083)	18 (263)	**21 (305)**	19 (350)	20 (399)	8 (453)
	30	0.037 (0.063)	**0.017 (0.016)**	0.035 (0.039)	0.13 (0.21)	0.44 (2.14)	23 (419)	**30 (413)**	25 (493)	7 (686)	5 (741)
f_5	2	0.0013 (0.0033)	**0.00039 (0.0019)**	0.0013 (0.0013)	0.0013 (0.0031)	0.00244 (0.0041)	40 (326)	**47 (432)**	43 (456)	38 (592)	33 (517)
Total successes (Total iterations)							245 (14351)	**264 (13138)**	243 (11094)	223 (11916)	200 (12912)

Table 3.5: Design specifications of coupled microstrip line band pass filter

Center frequency f_0	2.5 GHz
Bandwidth ($\triangle f$)	1.0 GHz
Pass-band ripple (L_a)	0.3 dB
Source and load impedance (Z_0)	50 Ω

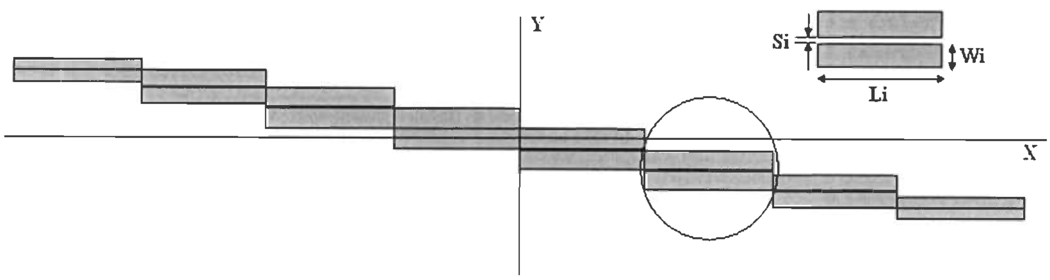

Figure 3.3: Geometry of coupled microstrip line band pass filter

on the left side of Y-axis is obtained by rotating right side structure 180° about Z-axis). In this problem, for each coupled stripline section, we have considered length of stripline (L_i), width of stripline (W_i), and separation between striplines (S_i) as design parameters as shown in Fig. 3.3. The number of coupled stripline sections is considered to be 4 on either side of vertical axis, thus making total number of design parameters 3*4=12. The range of values considered for the design parameters are shown in Table 3.6. The goal here is to get optimum combinations of these parameters that obtain bandwidth of 1.0 GHz resonanced at 2.5 GHz while minimizing reflection coefficient S_{11} within the band.

3.5.2 Experimental results

The design of filter was carried out using PSO-MS with both variations IWM and CFM considering two subswarms. To compare the output response of PSO-MS,

Table 3.6: Range of values for the design parameters

Name of design parameter	Range (mm)
Length of stripline (L_i)	[20.5, 23.0]
Separation between striplines (S_i)	[0.1, 0.4]
Width of stripline (W_i)	[1.0, 3.5]

the design optimization was also carried out using standard PSO, again with both the variations IWM and CFM. The design problem considered here has equality constraint of maintaining center frequency at 2.5 GHz. In this design with PSO-MS and PSO, a well-known penalty based approach as described in [7] is adopted for constraint handling. For handling boundary constraints, a three wall method (i.e., reflecting wall, absorbing wall, and invisible wall) is suggested in [52]. In the absorbing wall method, when the particle violates the boundary constraint in any dimension, the velocity in that dimension is made zero. In our experiments, we used a method similar to absorbing wall, but with small variation. In our method (which we refer to it as *sticky wall* method), when the boundary constraint is violated, the velocity is not reduced to zero, but the cut-off limit is imposed to the position of particle in that direction so that particle sticks to the wall and do not cross the range. This method is helpful, particularly, when the optimum value for that dimension is at the boundary. If the optimum is not at the boundary, then the particle will eventually come into the design space again with the effect of individual best and global best positions. The fitness function considered for the design in this problem is given as,

$$FitnessFunction = a_1(|BW - 1.0|) - a_2(nf_{s11}/nf) + a_3(|CF - 2.5|) \quad (3.7)$$

where BW is the bandwidth obtained in GHz (BW is obtained at 10 dB level from the graph of S-parameters), nf_{S11} is number of frequencies within the desired band for which $S_{11} < -15\ dB$, nf is total number of frequencies considered during simulation in the desired band, CF is the frequency at which resonance is obtained. The weights a_1, a_2, and a_3 are constants and can be chosen as per the requirement of larger BW, lower reflection (S_{11}) or resonance matching. In this experiment the values of a_1 and a_2 were considered to be 1, while the value of a_3 was considered to be 2.

In this work, a MoM based EM simulator IE3D [96] was used to obtain filter response. A typical simulation using this simulator takes few minutes (approx. 3-4 min.) of time to give the response on a latest workstation. A program interface was prepared and the EM simulator was invoked in iterative loop of the optimization algorithms. As evolutionary algorithms such as PSO require many iterations to converge to a desired objective, the resultant problem becomes computationally expensive if simple PSO is used.

In the design optimization process, PSO-MS (with two subswarms) and PSO were executed with 10 particles for fixed 50 iterations. The convergence graph for all four simulations is presented in Fig. 3.4. It is observed from the graph that PSO-MS converged faster towards better fitness value than PSO for both the variations (This can be concluded from the graph that at any time, the value obtained by PSO-MS is closer to the desired objective than the value obtained by PSO in both variations). The optimum filter response (S-parameters) for IWM is shown in Fig. 3.5.2, while for CFM is shown in Fig. 3.5.2. The BW of 1.01 GHz and 0.75 GHz were obtained with PSO-MS and PSO respectively for IWM, while the BW of 1.02 GHz and 0.99 GHz was obtained with PSO-MS and PSO respectively for CFM. It is seen from the figures that for IWM, PSO-MS obtains higher BW and produce the design which is near to the desired objective than PSO with same number of iterations, while in case of CFM, both PSO-MS and PSO obtain desired results.

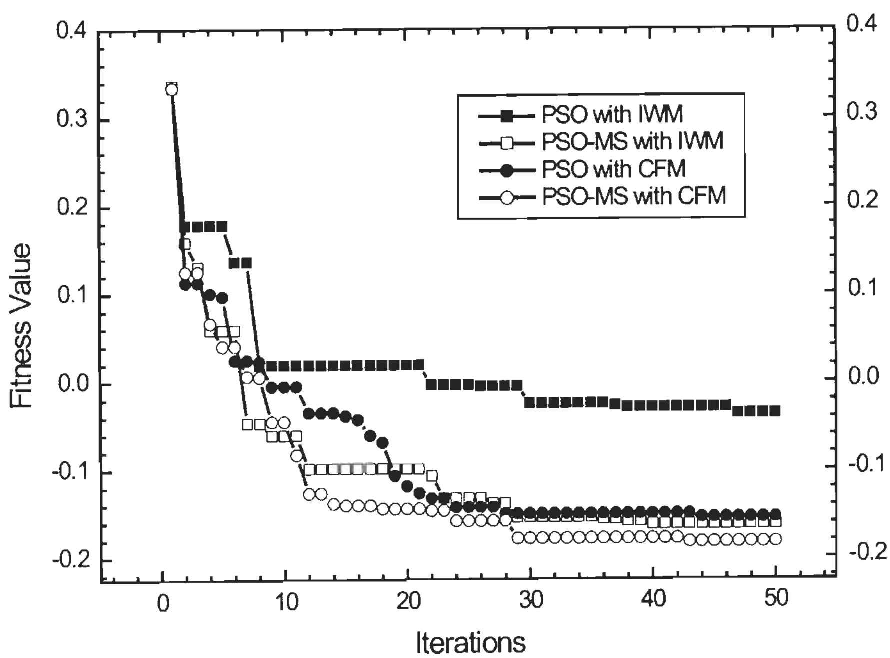

Figure 3.4: Convergence of PSO-MS and PSO for IWM and CFM

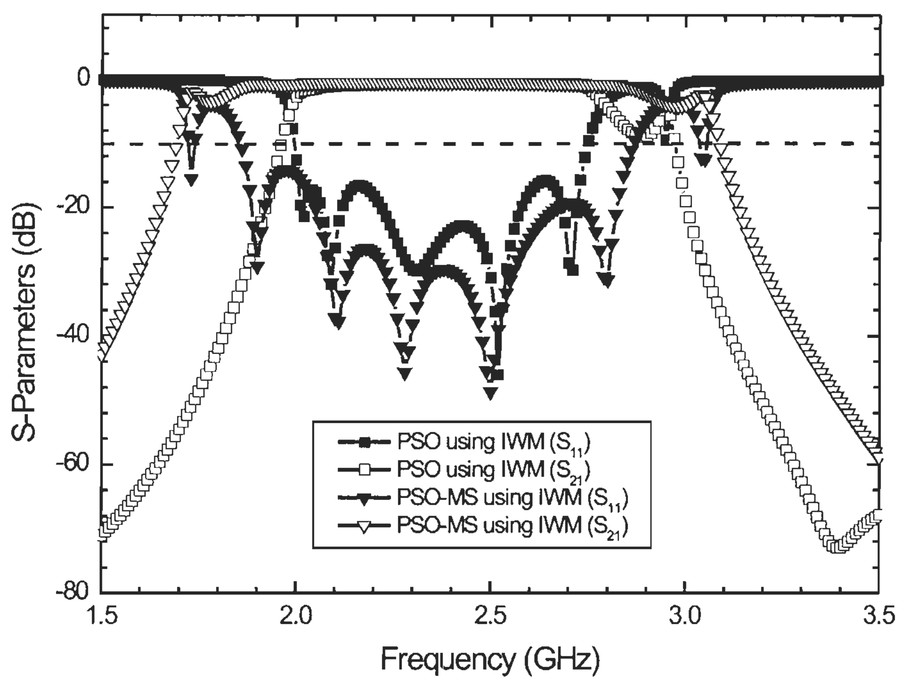

Figure 3.5: Comparison of filter response using PSO-MS (with two subswarms) and standard PSO with IWM

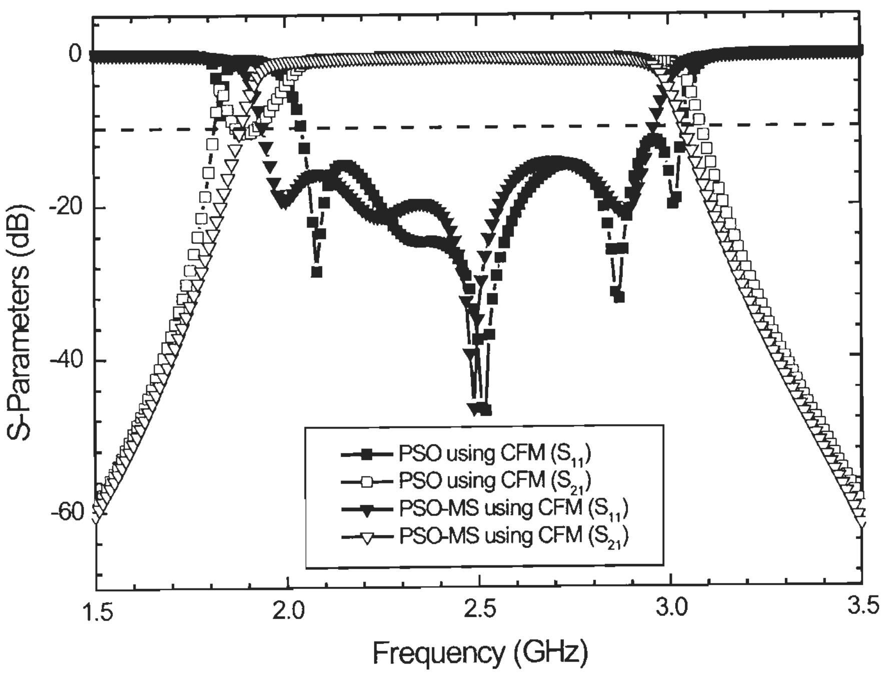

Figure 3.6: Comparison of filter response using PSO-MS (with two subswarms) and standard PSO with CFM

3.6 Concluding remarks

In this chapter, we introduced a new paradigm of multiple subswarms for searching parameter space with PSO algorithm. The social component of PSO's velocity update equation was modified to consider the effects of multiple subswarms. The concept was implemented for two basic PSO variations - IWM and CFM. The results show that the modified PSO with two subswarms leads faster convergence while improving the quality of solution compared to standard PSO. It was also observed that PSO-MS gives desired results within the framework of time-accuracy trade-off. We have also observed that parameters c_1, c_2' and c_3' in CFM are critical for the convergence of the algorithm and have to be chosen carefully. All simulations on test functions were carried out with swarm size 30. Yet improved performance can be obtained by using swarm size 50 or greater but it would also increase number of FEs.

At last the modified PSO was used for the design of coupled microstrip-line band-pass filter and its result was compared with the design results obtained using standard PSO. The comparison of results for the microstrip filter design problem proves the applicability of proposed approach in real time design problems where computational time is an important factor. Another advantage of this algorithm is that it can be parallelized easily as each subswarm's computation can be done on a separate processor.

Chapter 4

Support Vector Driven Evolutionary Algorithms for the Design of Microwave Components

4.1 Introduction

Commercial growth in the use of microwave products necessitates efficient design of components in a small time frame. A Computer Aided Design (CAD) approach is adopted to minimize the time required to obtain an optimized design. In order to use CAD models, the results predicted by them should be consistent with the actual results [97, 98]. However, due to very small wavelengths involved in microwave design that require high precision, it is not easy to model components of RF/microwave domain.

Full-wave EM simulators are widely employed for the analysis of microwave components. These simulators give desired solutions and are called *fine models*. A limitation of these models is that they are computationally expensive, especially when they are invoked in the optimization algorithms such as GA, PSO, etc. [99]. Besides this, a proper design may not be obtained using EM simulators alone, when the number of constraints are more. In order to remove these drawbacks, we may use mathematical curve fitting techniques that obtain data from experimental measurements or EM simulators. These models are referred to as *coarse models* [100]. However, these models have inherent limitations of accuracy and validity over a restricted range of parameter values.

ANN models trained by EM simulated data have been used to balance the trade-off between computation time and accuracy since last decade [1, 100, 101]. ANN models, once trained with a data set, have provided models that are almost as accurate as fine models and as fast as coarse models. However, the generalization accuracy achieved by the ANN based models of microwave components needs improvement to increase the effectiveness of CAD. A strong competitor of ANN which has gained popularity due to its generalization ability in recent years is Support Vector Machine (SVM). SVM is a machine learning tool designed to automatically deal with the accuracy-time trade-off by minimizing an upper bound on the generalization error [11]. In this chapter, we present an efficient modeling of microwave components using SVM framework. We also present a hybrid approach combining SVM with evolutionary algorithms and use it for the design of specific microwave components. Three different examples are presented showing the effectiveness of SVM based modeling and the proposed hybrid approach. These examples include: effective modeling of a one-port microstrip via, design of a circular polarized microstrip antenna, and design of a simple aperture coupled microstrip antenna.

The chapter is organized as follows. Section 4.2 presents a comparison between ANN with SVM, conceptual background of SVM, and framework for SVM based microwave modeling. The hybrid approach combining SVM with evolutionary algorithms is presented in section 4.3. Section 4.4 presents modeling and design of three microwave components mentioned earlier. Finally, concluding remarks is given in section 4.5.

4.2 Support Vector Machine and microwave modeling

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4.2.1 Comparison of ANN and SVM

Before discussing conceptual background of SVM, let us first compare it with traditional neural network. Artificial Neural network (ANN) has long been used as a machine learning tool in many research and commercial applications to learn the underlying function, mapping the input and output data from a large data set [9, 102]. Although it is capable of achieving any degree of training accuracy in approximating the underlying nonlinear function its generalization ability (error in predicting data not present in training set) is not as accurate. The reason is that ANN tries to minimize the empirical risk (error on training data). SVM on the contrary tries to minimize the upper bound on the expected risk. The direct consequence is that ANN may end up finding the local minima in minimizing the generalization error, whereas SVM is always guaranteed to find the global minima.

ANN, as mentioned earlier, is based on minimizing the empirical risk and, hence, it is data intensive. Without proper quality and quantity of data, the generalization achieved by ANN would be very poor. SVM however relies on minimizing the structural risk. Therefore, for a given training set, SVM generalizes better compared to ANN. Moreover, the time required for developing a SVM model of a microwave component is much lower compared to that of an ANN model because of the need for fewer data in training. This is very exciting feature of SVM over ANN when generation of data using EM simulations is expensive.

The prediction of unseen data in ANN is done based on weights modified during the training process. The presence of outliers in training set influence the final state of ANN after training. However in case of SVM, prediction of unseen data is done by considering only few training data which are known as *support vectors* (explained in section 4.2.2) and hence presence of outliers in the training set may not influence the generalization accuracy of SVM. Data for developing a model for microwave components is obtained usually from experimental setup, and the probability of presence of erroneous data is high. Since prediction of output in SVM is based on support vectors, probability of the erroneous data influencing the model obtained is minimal as compared to ANN.

The performance of ANN heavily depends on the structure of the network (i.e., the number of hidden layers, the number of neurons in each layer etc.). However there is no well defined methodology to determine the optimal network structure for a particular problem. The possible network structure is obtained by trial and error basis. Therefore, obtaining the best network structure requires expertise. In case of SVM, recent works [103] suggest that the structure of SVM can be pre-decided using training data analysis. Hence, developing a SVM based model of a component is much simpler as compared to ANN.

In ANN, the mechanism to predict the output after training, is encoded in the weights and threshold. Therefore, it acts like a black-box and theoretical explanation of why a particular value was predicted is very difficult to arrive at. In case of SVM, the results obtained can be analyzed theoretically using concepts from computational learning theory.

4.2.2 Support Vector Machine

Conceptual background

Support vector machine (SVM) is a machine learning technique developed by Vapnik [11]. It is based on the principle of statistical learning theory. SVM was initially developed for pattern recognition task but later on its application was extended to regression problems. Support Vector Regression (SVR) is found to give robust and effective model of the process under consideration [69]. The models developed using SVR are simple and their evaluation is fast. No prior knowledge about input/output mapping is required for the model development. An increasing number of engineers and researchers from diverse fields have begun to take a serious interest in this emerging technology. The hypothesis generated using SVM involves both structural risk minimization (SRM) and empirical risk minimization (ERM). This makes SVM much more powerful in generalizing than traditional ANN which only minimizes empirical risk. The key ideas of SVM are: nonlinear mapping from input space to high-dimensional feature space using a kernel function and finding an optimum hyperplane that maximizes generalization ability [11, 69].

Support Vector Regression

Learning systems for SVR estimation is described in [69, 104, 105]. Given a set of input-output training data $(x_i, y_i) \in R^n \times R$, i=1 to l, we need to estimate a function $f : R^n \rightarrow R$ that will correctly predict unseen examples generated from the same underlying probability distribution as the training data. The hypothesis of SVM maps the original input space into a high dimensional space via a kernel. This higher dimensional space is called *feature space*, in which an optimal hyperplane is determined to maximize the generalization ability [106]. The generic support vector regression estimation function takes the form:

$$f(x) = (w\Phi(x) + b) \tag{4.1}$$

where, $w \in R^n, b \in R$ and Φ denotes a nonlinear transformation from R^n to a high dimensional feature space. Our goal is to find the value of w and b that minimize the regression risk defined as:

$$R(f) = \frac{1}{2}||w||^2 + C\sum_{i=0}^{l}\Gamma(f(x_i) - y_i) \tag{4.2}$$

where Γ is the cost function, C is a constant, and vector w can be written in terms of data points as:

$$w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\Phi(x_i). \tag{4.3}$$

The ε-insensitive loss function [106] is the most widely used cost function. This function is of the form:

$$\Gamma(f(x) - y) = \begin{cases} 0, & \text{for} \quad |f(x) - y| \leq \varepsilon \\ |f(x) - y| - \varepsilon, & otherwise. \end{cases} \tag{4.4}$$

The regression risk in Eq. (4.2) and the ε-insensitive loss function in Eq. (4.4) can be minimized by maximizing the following dual optimization problem with respect to α and α^*,

$$W(\alpha, \alpha^*) = \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) - \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) \tag{4.5}$$

with constraints

$$\sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0, \quad where \quad \alpha_i, \alpha_i^* \in [0, C], \; i = 1, .., l. \tag{4.6}$$

Here, α_i and α_i^* are Lagrange multipliers which represent solutions to the above quadratic problem. Only the nonzero values of the Lagrange multipliers in Eq. (4.5) are useful in forecasting the regression curve and are known as *support vectors.* The constant C introduced in Eq. (4.2) determines penalties to estimation errors. A large C assigns higher penalties to errors so that SVM is trained to minimize error with lower generalization, while a small C assigns fewer penalties to errors. This allows the maximization of margin with errors, thus higher generalization ability.

The approximation for nonlinear data set is accomplished with the use of kernel functions. According to Christianini and Shawe-Taylor [104], one of the most important design choices for SVM is the kernel-parameter, which implicitly defines the structure of the high dimensional feature space where a maximal margin hyperplane is found. Too rich a feature space would cause the system to overfit the data, and conversely the system might not be capable of approximating the data if the kernels are too poor.

4.2.3 Framework for modeling microwave components using SVR

The steps in modeling microwave components using SVR are described as follows.

Identification of input and output: The preliminary step towards developing an SVR model is the identification of inputs and outputs of the problem to be modeled. Inputs for this work are the variable design parameters of the microwave component being modeled. Model outputs are determined based on the purpose of the model. This is typically the metric (e.g. S-parameters, bandwidth, etc.) that is used for evaluating the performance of the component being modeled.

Generation of training and test data: Training data for modeling the component is obtained by performing experiments or simulations for a set of sample

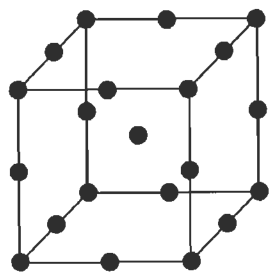

Figure 4.1: Hypercube illustrating the selection of initial design parameters. The three dimensions of the hypercube represent the three variable design parameters. The edges along a dimension represent the operating range for which the model of the component needs to be prepared. Circles indicate the initial design parameters that are chosen.

inputs. The sample inputs are chosen in such a way that the behavior of the component with respect to design parameters is completely obtained. The initial structures (training data) for simulation are identified based on Design Of Experiments (DOE) methodology [98]. This method is generally used to study and model the input-output relationship for a given process or component. The range of all input parameters of the component being modeled are identified. The range of an input parameter forms a line segment in single dimension, and if the all the input parameters are considered simultaneously in N-dimensional space, it would form a hypercube as shown in Fig. 4.1. The initial value of the design structures are chosen as the corners of the hypercube, the midpoint of the edges of the hypercube, and the center of the hypercube. To generate test data, sample inputs are generated randomly from the range of design parameters. The experiments or simulations are carried out on these training and test inputs to get actual training and test outputs.

Input scaling: In input scaling, we scale each input parameter values in the train data set between +1 to -1. This form of normalization prevents one of the variables to dominate in the prediction of output variables.

Kernel function selection: Various kernel functions such as linear, polynomial, RBF (Gaussian and exponential), sigmoid, splines can be used for mapping of input space to high dimensional feature space and they are elaborated briefly in [15, 105]. The popular choices for kernel functions are,

$$\text{RBF(Gaussian) Kernel: } K(x, x') = \frac{exp(-\|x - x'\|^2)}{2\sigma^2} \tag{4.7}$$

$$\text{Polynomial Kernel: } K(x, x') = (< x + x' > +c)^p \tag{4.8}$$

where $1/(2\sigma^2) = \gamma$ (gamma) of Gaussian-RBF kernel and p (degree of polynomial kernel) are critical parameters, while c in polynomial kernel is a constant.

Model selection: One of the important choices in developing an SVR model is the selection of model parameters (also known as *hyperparameters*) which include kernel parameters, the penalty of estimation error (C), and the value of ϵ. The value of kernel parameter implicitly defines the structure of the high dimensional feature space where a maximal margin hyperplane is found. Too rich feature space would result in over-fitting of data and if the kernels are too poor, data would not be predictable. Parameter selection thus involves obtaining the optimal values of C, ϵ and σ which would maximize the generalization ability. One of the model selection techniques commonly employed in literature is grid search. The elementary step in grid search is *cross validation* [107]. In a v-fold cross-validation, training set is first divided into v subsets of equal size. Sequentially each subset is tested using the SVR, which is trained on the remaining v-1 subsets. Thus, each instance of the whole training set is predicted once. The cross-validation accuracy is a measure of error in prediction of the data. The goal of model selection is to determine which combination of C, ϵ and σ has the maximum cross validation accuracy (minimum error). Various combinations are tried for the three parameters by sampling the search space at discrete intervals. Once the combination with minimum mean squared error is found, the search is performed around the combination with a reduced sample interval. This procedure is repeated until there is no significant improvement in the cross validation accuracy. Few other methods for tuning hyperparameters of SVM are suggested in literature [81, 108].

Training: Once the optimal parameters for the kernel are chosen, we train the SVR. This involves identifying the support vectors in the train data. Support vectors are input points which are closest to the optimal hyperplane. The output of training is an SVR model. The regression model obtained is then used to predict the output values (performance) for various inputs (design parameters). If the accuracy of the model is not within the acceptable limits (indicated by high value of cross-validation mean squared error) the process is repeated with simulations performed using more variations in design parameters.

Testing: The accuracy of model in predicting unseen data is verified by predicting the performance of an independent data set (test data set). The test data set is scaled between +1 and -1 using the same scaling parameters as used in the *input scaling* step. The output field of the test data set is predicted using the model file obtained after training SVR. The accuracy of prediction is defined in terms of Mean Squared Error (MSE) and Average Relative Error (ARE). MSE and ARE are computed as follows:

$$Error = PredictedValue - ActualValue, \tag{4.9}$$

$$MSE = \frac{\sum_{i=1}^{n} Error_i^2}{n}, \tag{4.10}$$

$$ARE = \frac{\sum_{i=1}^{n} \left(\frac{Error_i}{ActualValue_i}\right)}{n}, \tag{4.11}$$

where n is the number of sample points in test data set. After computing the accuracy on the test data set, it is determined if the accuracy of the model is acceptable by comparing it with a threshold value. The threshold is chosen based on how much accuracy can be obtained while making a physical design of the actual structure.

Step for improving the accuracy: As SVR is not data intensive compared to ANN, we may start with fewer training samples to model the component. If the generalization accuracy is below the acceptable level, additional training data are included. The dimensions of the additional structures are chosen as the midpoints of the points chosen during first iteration. The modeling process is repeated with additional training data. The need for this iterative process is due to the number of structures that have to be simulated for obtaining an accurate model can not be predetermined for a specific component.

4.3 Support Vector driven Evolutionary Algorithms: A hybrid approach

In recent years, the EM analysis of most microwave components is performed using EM simulation tools. Evolutionary algorithms (EAs) such as genetic algorithm and particle swarm optimization algorithm can be used for optimizing design parameters of microwave components. This requires invoking EM simulation tools in the optimizing loop of EAs. Due to iterative nature of EAs, the entire process becomes computationally expensive. A modified method with PSO was discussed in chapter 3 of this thesis. It reduced the number of iterations up to some extent in order to reduce the computational expenses. An alternative way of solving this problem is to make use of *metamodel.* A metamodel is a 'model of the model'. The number of metamodeling techniques such as ANN, SVR, response surface methodology, regression splines, etc., [15] can be used to create model of the time consuming EM simulation process. We use here support vector regression method for creating metamodel (model henceforth) of the process.

In this section, we present a hybrid approach combining SVR with EAs such as GA and PSO for the design of microwave components. We call this approach as Support Vector driven Evolutionary Algorithms (SVEA). In this method, we first create SVR model for getting response of the component to be designed. The data for training SVR can be obtained using experiments with EM simulators by varying design parameters in a pre-decided range. The range of design parameters are decided based on the simulation response of initial geometry and expert domain knowledge. The data generated empirically are used to create SVR model following steps specified in previous section.

The SVR model, thus created, is used as a metamodel replacing the complicated and time consuming parametric analytical procedure carried out by the EM simulator. The SVR model is invoked in the optimization loop of EAs as a fitness function for optimizing design parameters of microwave components. The exciting advantage obtained with SVR model is that it responds quickly (approximately in milliseconds) compared to iterative parametric analysis of EM simulator response (approximately in minutes and generally it depends on the complexity of the structure). Here, we use two EAs - GA and PSO to optimize the design parameters by invoking SVR model as its fitness function. As SVR model responds quickly, it is easy for EA to perform large number of iterations to optimize design parameters. A simple block diagram for the proposed approach along with conventional approach of using EM simulator, and the design approach using EA (which invokes EM simulator directly as its fitness function) is shown in Fig. 4.3. It should be noticed here that number of simulations required to generate training data to prepare SVR model are far less than number of simulations required if the optimization would have conducted by directly invoking the EM simulation tools in the fitness function of EA (see (b) of Fig. 4.3).

In the next section, we present three experiments demonstrating the effec-

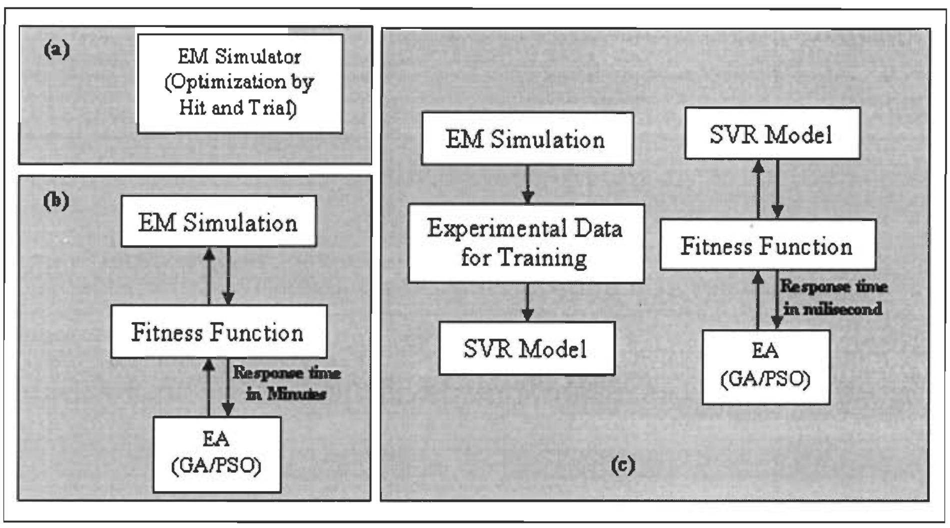

Figure 4.2: (a) Traditional approach of design using EM simulator (Using expert domain knowledge, and hit-and-trial method) (b) Design using EA by directly invoking EM simulator as its fitness function (c) Design using proposed approach SVEA

tiveness of SVR based modeling and efficiency of the presented hybrid approach in designing microwave components.

4.4 Experiment

4.4.1 Modeling of one-port microstrip via using SVR

Problem description

The first component we considered for modeling is a broadband GaAs one-port microstrip via. The top view of the via structure is shown in Fig. 4.3 [1, 100]. It consists of two planes, the ground plane and the substrate plane. The ground plane is placed at a height 0 and the substrate plane is placed at a height H_{sub} above the ground plane. The excitation signal is supplied to the component by means of a feedline through a port in the ground plane. The structure shown in Fig. 4.3 is a metal sheet on top of the substrate. Via is a hole drilled from the metal plate to the ground plane. ε_r is the dielectric constant of the substrate medium. The height of the substrate (H_{sub}), the dielectric constant (ε_r), and all loss parameters are considered constant for this experiment. The width of the incoming microstrip line (W_l), the side of the square shaped via pad (W_p) and the diameter of the via hole (D_{via}) are the three variable geometrical parameters. The component is characterized in terms of its S-parameter (S_{11}) which specifies the proportion of input energy that is reflected back.

While using this component in a microwave circuit, different combinations of the variable design parameters are tested to obtain the optimal performance of the overall circuit. Thus, the objective of the modeling in this problem is to predict the performance of the component for a particular design specification. This is done by obtaining a relationship between particular values of the variable design parameters and the S-parameter corresponding to those particular values.

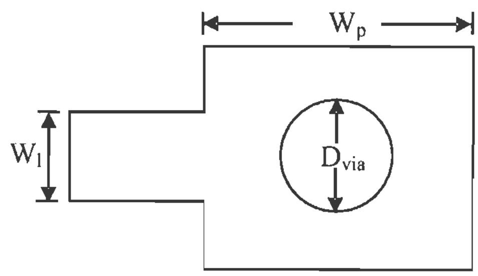

Figure 4.3: GaAs microstrip ground via geometry [1]

Table 4.1: Range of input parameters for modeling of one port GaAs Microstrip Via

Input Parameter	Range
Frequency	[5-55] GHz
W_l/W_p	[0.3-1.0]
W_p/D_{via}	[0.2-0.8]
W_l/H_{sub}	[0.1-2.0]

The characterization of the component at various frequencies is also required, since the circuit in which the component is used may be operating at various frequencies. The input variables we consider for modeling are three ratios of geometrical parameters W_l/W_p, W_p/D_{via}, and W_l/H_{sub}, and the frequency is also considered as fourth parameter. The range of these parameters considered for modeling are shown in Table 4.1. Output variable is the magnitude of S_{11} (S-parameter for one port) referenced at 50 Ω port termination.

Experiment and Results

Training data was obtained by performing simulations on the IE3D simulator [96]. Simulations were performed with frequency varying from 5 to 55 GHz.

Each simulation is performed by varying the values of input parameters in the range shown in Table 4.1. In order to minimize the number of simulations that need to be performed as well as capture the complete behavior of the component the initial structures that are to be used for training need to be carefully chosen carefully. The procedure used for selecting the initial training set is discussed in section 4.2.3 If it is found that the input-output relationships of the component have not been sufficiently captured (when cross validation error is high), additional simulation points are added to fit the higher order nonlinearities.

After obtaining the training data, the SVR model of the component was obtained using the procedure described in section 4.2.3. In order to compare the performance of SVR based model, a Feedforward ANN (FF-ANN) model was designed. Best results for the feed forward ANN were obtained using 10 neurons in the hidden layer. TanSigmoid was used as the activation function of the hidden layer, while a linear function is used for the output layer. The ANN model was designed using MATLAB Neural Network toolbox. Over-fitting of data during training is prevented by using simultaneous testing. The overall data set was divided into train data and simultaneous test data. Neural network was trained using the train data and accuracy of training is determined by predicting the simultaneous test data. The training iteration was repeated as long as the error in predicting simultaneous test data is non-increasing. The training accuracy is also verified on an independent test data set. Fig. 4.4 illustrate the plots of the actual values with the values predicted by FF-ANN and SVM respectively. The comparison of S-parameters (magnitude) using SVM, FF-ANN and actual values for two independent test cases are shown in Fig. 4.5 and Fig. 4.6 respectively. The accuracy of modeling for the various models is given in Table 4.2. It can be noticed that SVM provides significant improvement in performance over ANN model.

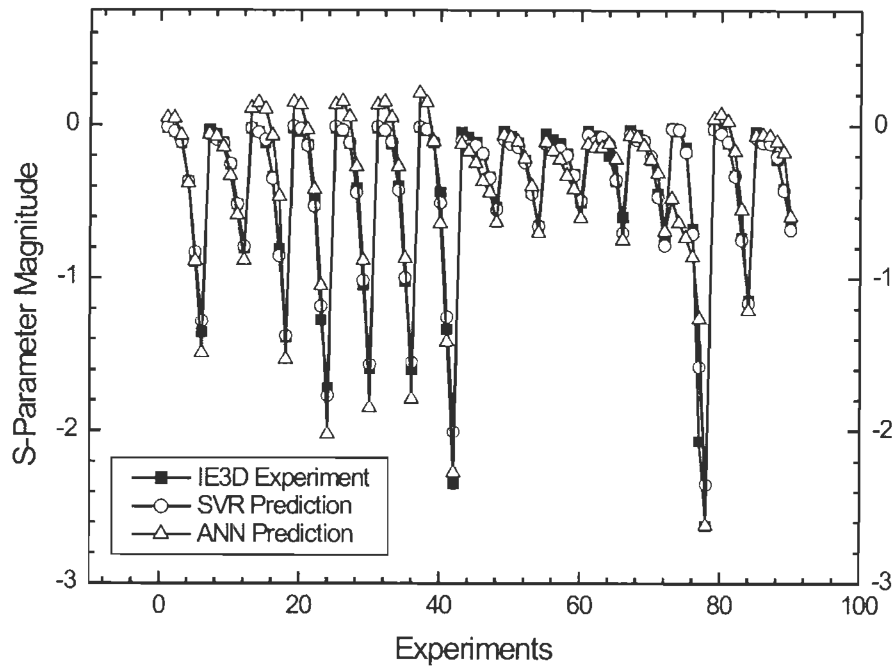

Figure 4.4: Plot of actual values vs. predicted values using SVR and Feedforward ANN

4.4.2 Design of circularly polarized microstrip antenna using Support Vector driven Genetic Algorithm

Problem description

Aperture coupled Microstrip Antennas (MSA) are widely used in wireless applications [93, 109, 110, 111, 112, 113, 114]. The circular polarization of antenna is required to make the devices independent of orientations. A method for improving axial ratio bandwidth of circular polarized microstrip antenna is given in [115]. In this experiment, we used the presented hybrid soft computing approach for improving the bandwidth of the circular polarized microstrip antenna. The

Table 4.2: Accuracy of modeling one-port microstrip via

Models	MSE	ARE
Feedforward ANN	0.0012	0.0290
SVM	5.836e-5	0.005164

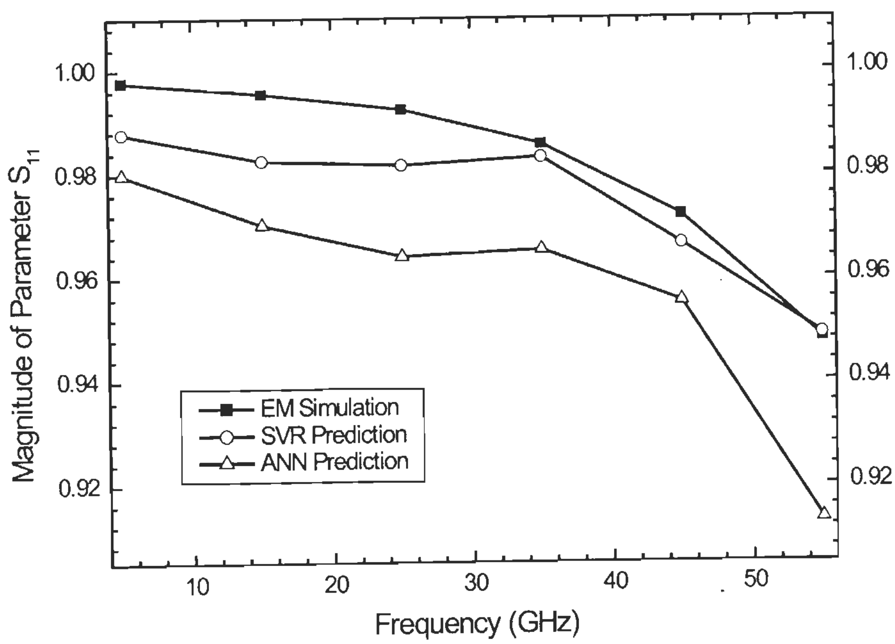

Figure 4.5: Plot of magnitude of S-parameter against frequency for dimension: $W_1/W_p = 0.4$, $W_p/D_{via} = 0.3$ and $W_1/H_{sub} = 0.2$.

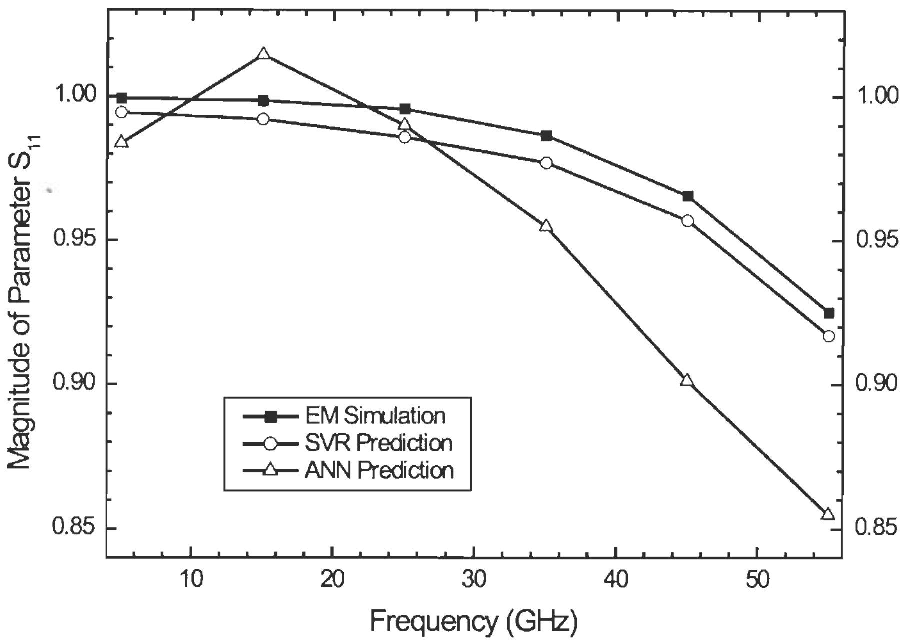

Figure 4.6: Plot of magnitude of S-parameter against frequency for dimension: $W_1/W_p = 0.75047$, $W_p/D_{via} = 0.34897$ and $W_1/H_{sub} = 1.0$

geometry of the MSA considered for the design here is shown in Figure 4.7. It consists of two dielectric layers both having same dielectric constants and loss tangents. The antenna design employs air gap between two substrate layers. The top layer is of dielectric sheet which supports patch. The bottom layer is a dielectric sheet which supports microstrip feed line on one side and slot on other side. In the proposed design, antenna patch is perturbed by inserting different length slits (horizontal and vertical, see Fig. 4.7(a)) for the generation of circular polarization [109]. The right circular polarization is obtained here by maintaining length of horizontal slit less than the length of vertical slit [111].

Our aim in designing Circular Polarized Microstrip Antenna (CPMSA) is to maximize its Axial Ratio (AR) bandwidth (for AR ¡ 3 dB) with resonance at 2.6 GHz. The Axial Ratio Bandwidth (ARBW) of microstrip antenna is given as,

$$ARBW(\%) = (\frac{f_H - f_L}{f_c}) \times 100 \tag{4.12}$$

where f_H and f_L are upper and lower frequencies considered at 3 dB from AR vs. frequency plot respectively and f_c is the resonant frequency. The constraints considered for the optimization are to maintain Voltage Standing Wave Ratio (VSWR) in its feasible range (A VSWR ≤ 2 ensures good performance for wide band operation), to maintain right circular polarization, and to maintain working frequency at 2.6 GHz. Four design parameters of microstrip antenna (see Fig. 4.7) namely horizontal slit length, vertical slit length, patch length (squared patch is considered), and slot length are considered for optimization. The objective function considered for optimization is defined as,

$$fobj = -a(ARBW) + b|CF - 2.6| + c(VSWR - 2.0) \tag{4.13}$$

where $ARBW$ is defined in Eq. (refEq4p8), and CF is the resonant frequency. The coefficients a, b and c are user defined constants.

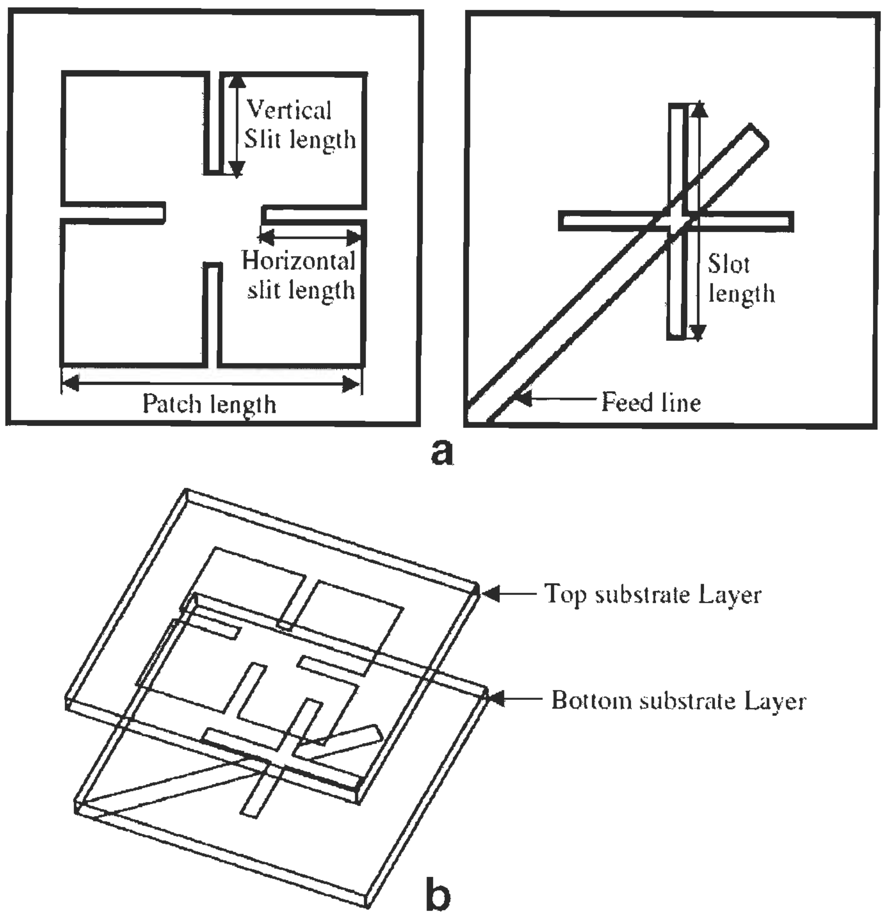

Figure 4.7: Geometry of the MSA (a) Patch shape and feed arrangement, and (b) 3D view

Experimental results

Two experiments considering different dielectric constants and air gaps were conducted to optimize the *ARBW* of CPMSA at 2.6 GHz band. The material dielectric constants in both experiments were fixed at 7.2 and 2.33 respectively. The air gap in both experiments was kept 3 mm and 4 mm respectively. The stub length for both experiments were manually optimized to 9.005 mm and 10.5 mm respectively. Two sets of training data (42 and 75) were generated from IE3D for two experiments respectively. The first experiment was conducted by considering all four design parameters while the second experiment was conducted by considering only three design parameters namely length of horizontal slit, length of vertical slit, and patch length. The parameter slot length was optimized manually prior to the experiment. This was done to reduce the search space and thus improve the model accuracy. Apart from design parameters, the parameters of support vector regression such as type of kernel, parameter of the kernels (σ for RBF kernel, order of polynomial for polynomial kernel), trade-off parameter C, and ε parameter of loss function were optimized manually by measuring their Cross Validation accuracy (CVacc) and Root Mean Squared Error (RMSE), which are defined as,

$$CVacc = \frac{c}{t} \times 100 \tag{4.14}$$

and

$$RMSE = \sqrt{\sum_{i=1}^{n}(y_i - f(X_i))^2}. \tag{4.15}$$

Here, c indicates number of test data that fall under regression tube (i.e., within the desired predefined prediction limit), and t indicates total number of test data. Here, y_i is the experimental value using IE3D and $f(X_i)$ is the predicted value. In the experiment, RBF kernel (with value of σ = 0.5, 0.4 respectively for two experiments) was found to give best performance. The optimum values of C and ε are kept ∞ and 0.02 respectively for both the experiments. The Matlab

Table 4.3: Performance of the SVR and NN models

Experiment	SVR Model		NN Model	
	CVacc	RMSE	CVacc	RMSE
Experiment 1(7-fold)	74.8	0.4623	66.67	0.6073
Experiment 2(5-fold)	82.33	0.3583	79.0	0.5587

toolbox of SVR [116] was used to implement the algorithm. The 7-fold and 5-fold cross validation was used to measure the performance in both the experiments respectively. Here, we define the CVacc (which is considered as performance metrics for this example) as,

In this example, we used GA for optimizing SVR model of CPMSA, hence we name the hybrid approach as Support Vector driven Genetic Algorithm (SVGA). To compare the results of proposed approach, similar experiments were conducted for the same datasets using another hybrid approach of Neural Network driven Genetic Algorithm (NNGA). In this method, the empirical approximation model was generated using neural network [9]. Three layer feed forward back-propagation neural network with Levenberg-Marquardt transform function and 0.1 learning rate was used to create model. The number of hidden neurons to create ANN model were 4 and 5 respectively for both the experiments. The predictions using SVR and ANN models are presented in Fig. 4.8 and Fig. 4.9 respectively for both the experiments. The performance of the models is presented in Table 4.3 using both CVacc and the corresponding RSME as defined in Eq. (4.14) and Eq. (4.15) respectively.

The GA with 50 population size, roulette wheel selection, 0.8 crossover and 0.01 mutation was simulated for 2000 generations to get the optimized values of each experiment. The optimized parameters and optimum ARBW for both the experiments are summarized in Table 4.4. The ARBW was calculated at 3 dB

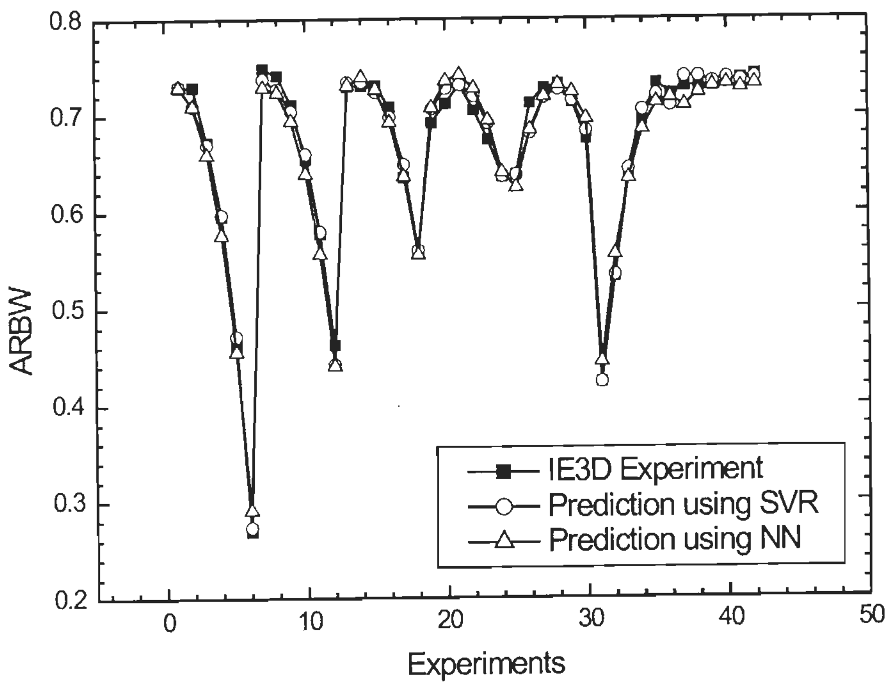

Figure 4.8: Predictions using SVR model and ANN model with IE3D experiment for Experiment 1

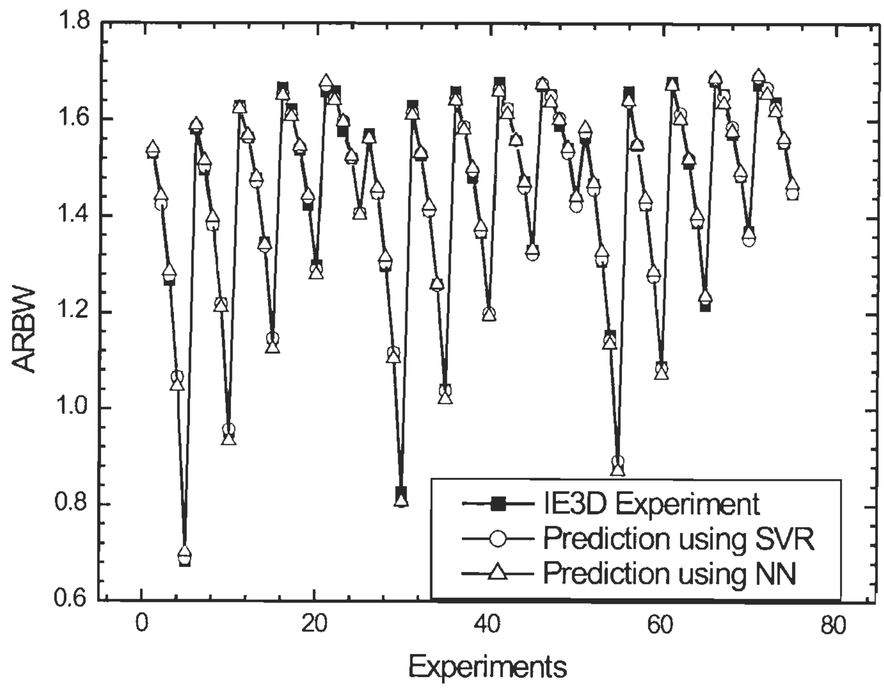

Figure 4.9: Predictions using SVR model and ANN model with IE3D experiment for Experiment 2

Table 4.4: Optimized parameters and ARBW using SVGA, and NNGA

Optimized Parameters	Experiment 1 (Dielectric const. = 7.2)		Experiment 2 (Dielectric const. = 2.33)	
	SVGA	NNGA	SVGA	NNGA
H.slit length (mm)	8.726	8.779	10.35	10.27
V.slit length (mm)	9.108	9.117	11.8	11.795
Patch length (mm)	24.47	24.41	31.996	31.985
Slot length (mm)	13.9	13.66	18.5	18.5
% ARBW	0.70	0.73	1.71	1.59
% ARBW(Using EM simulator)	0.75	0.65	1.68	1.68

from the axial ratio plot. The ARBW along with optimized design parameters are obtained using EM simulator and are shown in Table 4.4 for the purpose of comparison. The characteristic of AR vs. frequency for both methods are shown in Fig. 4.10 and 4.11 respectively for both the experiments. It is observed from the table that the ARBW obtained with SVGA approach is much closer to the value obtained from experiment with EM simulator compared to NNGA approache in both the experiments. The plots of VSWR vs. frequency are presented in Figure 4.12 and Figure 4.13 for both the experiments respectively. It is observed that the optimized results satisfy minimum VSWR criteria at desired 2.6 GHz frequency.

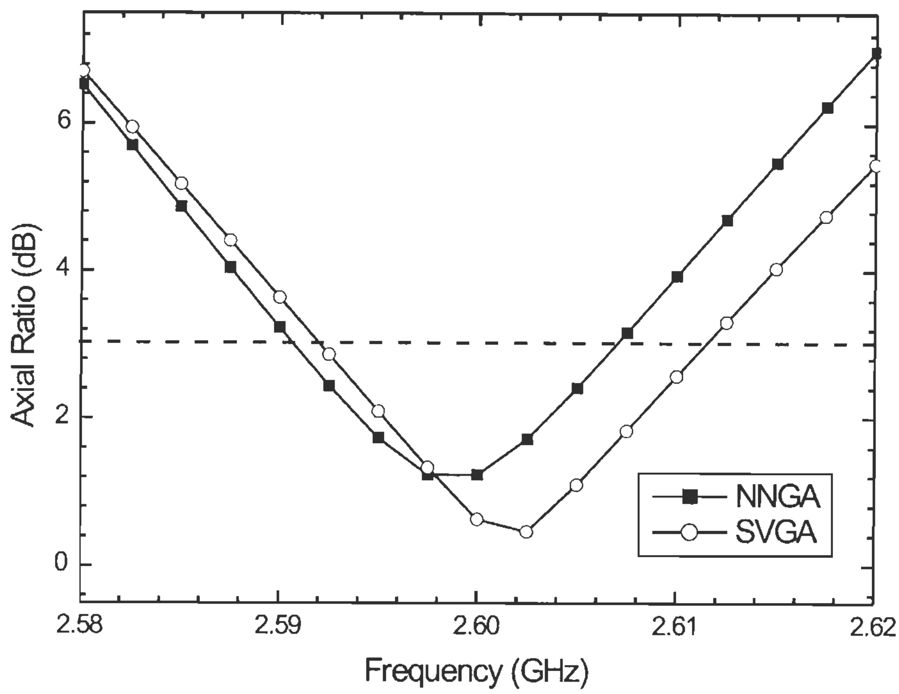

Figure 4.10: Plots of Axial Ratio vs. Frequency for Experiment 1

4.4.3 Design of aperture coupled microstrip antenna using Support Vector driven PSO algorithm

Problem description

The third structure we considered is a simple aperture coupled microstrip antenna [93, 110, 112, 117]. The geometry of the antenna structure considered for design is shown in Fig. 4.14. Here, two substrate layers are placed on each other without any air gap. The top substrate contains a rectangular patch, while bottom substrate contains slot on one side and feedline on other side. The variable design parameters for the chosen structure are the length of the slot, length and

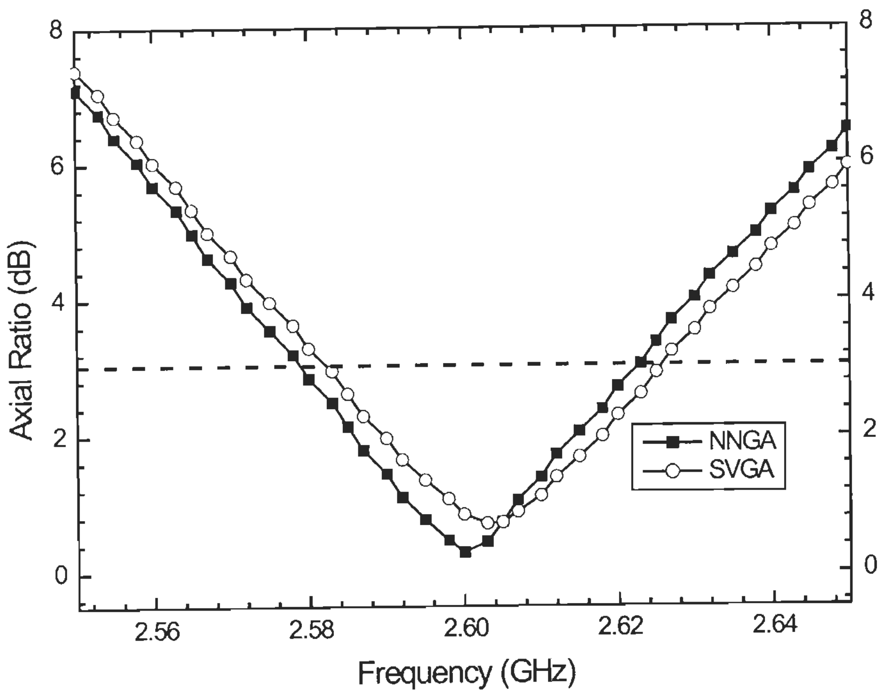

Figure 4.11: Plots of Axial Ratio vs. Frequency for Experiment 2

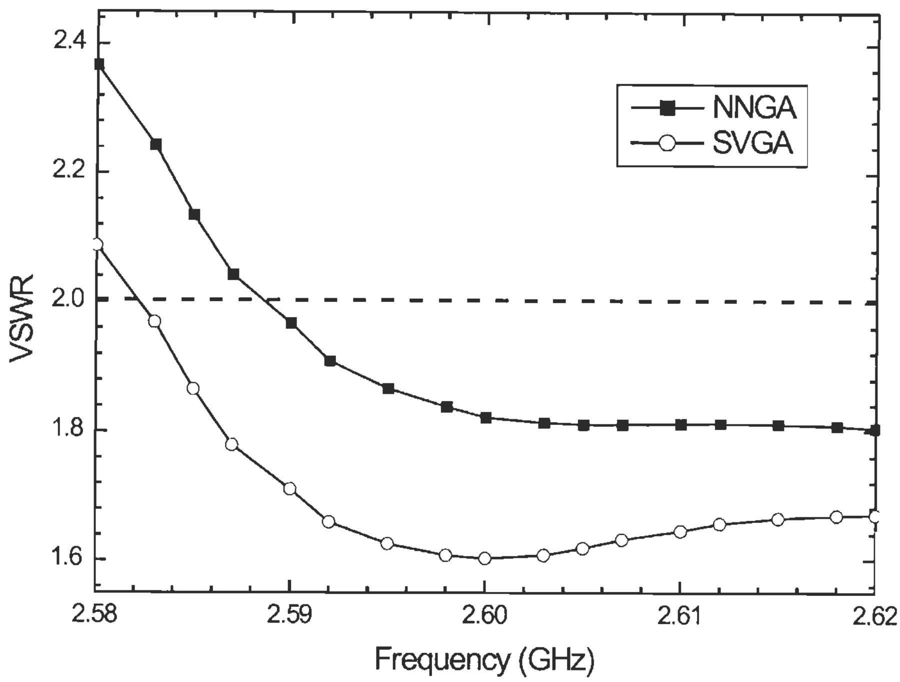

Figure 4.12: Plots of VSWR vs. Frequency for Experiment 1

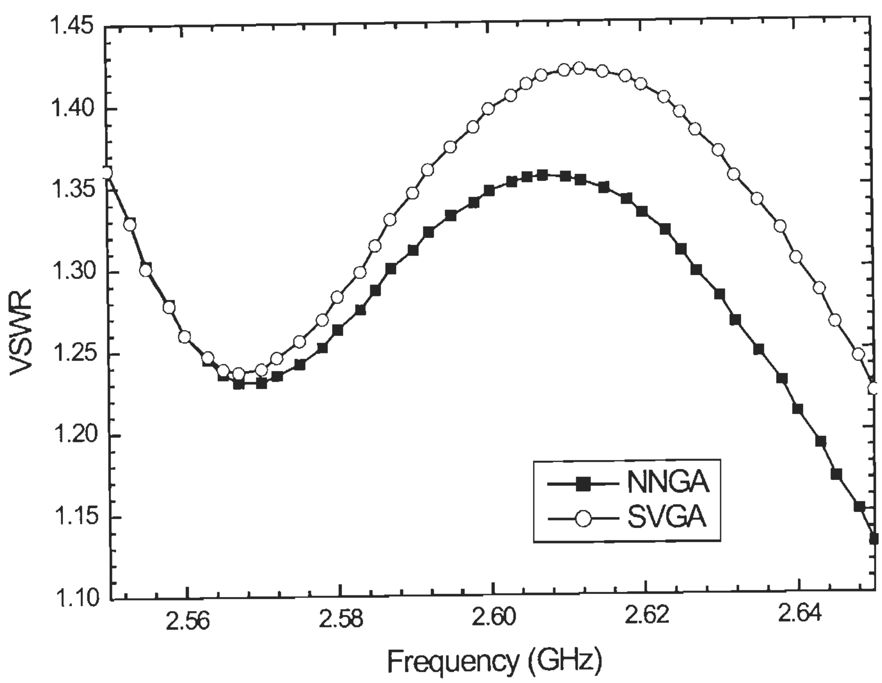

Figure 4.13: Plots of VSWR vs. Frequency for Experiment 2

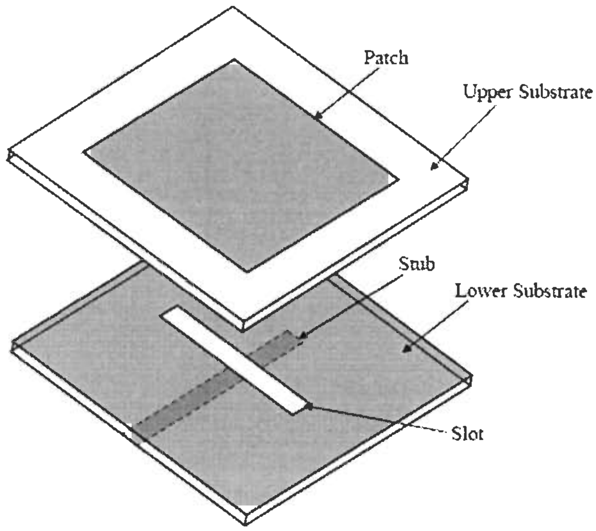

Figure 4.14: Geometry of the aperture coupled microstrip antenna

width of the patch, and the length of the open circuited stub. The other parameters such as dielectric materials and their heights were kept constant and they are listed as: $\varepsilon_{r1} = 2.17$, $\varepsilon_{r2} = 6.12$, loss tangent of substrate 1 = 0.0009, loss tangent of substrate 2 = 0.00022, $h_1 = 1.5748$ mm, $h_2 = 1.27$ mm.

The antenna is designed to operate at a frequency of 2.7 GHz. The range of frequencies around the operating frequency in which the antenna can operate depends on the frequencies at which the VSWR value is less than 2. The design objective is to maximize its VSWR BW and get the resonance at desired 2.7 GHz.

Experiment and results

In this example, we used PSO algorithm in order to obtain optimal design parameters of the microstrip antenna. The hybrid approach is named as Support Vector driven Particle Swarm Optimization (SVPSO). The fitness function used for optimization is:

Table 4.5: Accuracy of modeling for aperture coupled MSA

Models	MSE	ARE
Feedforward ANN	0.00309	0.018
SVM	2.025e-5	0.001663

$$f = \alpha(|f - CF|^{c1}) - \beta(BW^{c2}) \tag{4.16}$$

$$\alpha + \beta = 1 \tag{4.17}$$

where CF is the frequency at which resonance is obtained and BW is the VSWR bandwidth measured at level 2 from VSWR vs. frequency plot. The parameters $c1$, $c2$, α and β were chosen as per the requirement of whether a large bandwidth is desired or proper matching is desired. The variables $c1$ and $c2$ allow us to model a non-linear correspondence between $|f - CF|$ and BW. The function f attains the minimum value when frequency is matched, and the bandwidth is high. The design parameters corresponding to the minimum value of f would thus be the optimal design parameters.

The accuracy of SVM models of the microstrip antenna is compared with FF-ANN model generated using same dataset it is shown in Table 4.5. The optimization was carried out using presented SVPSO approach and the results are shown in 4.6. The optimized result is compared with the best result available in the training data set.

Table 4.6: Results of Optimization for aperture coupled MSA

	Bandwidth	VSWR	Operating Frequency
Without optimization*	0.03 GHz	1.20	2.6 GHz
After optimization	0.05 GHz	1.22	2.7 GHz

*Best Bandwidth, VSWR pair available in training set

4.5 Concluding remarks

An effective modeling of microwave components using SVM framework is discussed and used to model a one port microstrip via, an aperture coupled microstrip antenna, and a circular polarized microstrip antenna. The models obtained with SVM are compared with conventional ANN models and are found to be more accurate. In this experiment, grid regression was used to select parameters of SVM. However, EAs such as GA, PSO can also be used for obtaining best combination of these parameters.

In this chapter, we have presented a hybrid approach combining SVR model with evolutionary algorithms. The approach is demonstrated for the design of two microstrip antennas. The design of circular polarized microstrip antenna was carried out using SVGA approach, while the design of aperture coupled MSA was carried out using SVPSO approach. The advantage in applying this hybrid approach is that number of EM simulations required can be restricted to the number of experimental data required to generate SVR models. This number is very less compared to the number of simulations required, if EM simulator is invoked in the optimization loop of GA/PSO. The main requirement in performing this is to obtain desired accuracy of the model. As we observed, SVR gives better accuracy compared to ANN models.

Though we have considered the design of microstrip antennas as a case study in the present work, the hybrid method presented here can well be applied to the design of many other microwave components. It is highly advantageous when an approximate model with the desired accuracy can be obtained with less computational expense.

Chapter 5

Design and Optimization of a Nonlinear Taper using Swarm Intelligence based Algorithms

5.1 Introduction

Tapered transmission lines (tapers) are required to transform the output of a standard waveguide to oversized waveguide components. The taper should be designed in such a way that the characteristic impedances at both the ends are matched. Two basic types of cross-section tapers are straight taper and variable (nonlinear) taper. In the straight taper, the taper angle is fixed throughout the length and abrupt discontinuities occur at both the ends, while in variable taper the taper angle is smoothly varied along the length of the taper. The advantage of a nonlinear taper is that the conversion of power to unwanted (spurious) modes is very less compared to straight taper [19]. In this chapter, the design and optimization of a nonlinear taper for use in a specific high power gyrotron is presented.

Gyrotrons are capable of providing hundreds of kilowatts of power at microwave and millimetric wavelengths [19, 118]. The output power generated using a gyrotron is very high, ranging from long pulse to Continuous Wave (CW). High power gyrotrons are mainly used for plasma heating in thermonuclear fusion reactors, Tokamaks and stellarators. In addition, they are used in a variety of ISM applications ranging from spectroscopy, material processing to plasma diagnostics. The output system of gyrotron consists of an interaction cavity, output taper, a quasi-optical mode converter, and an RF window [19, 119]. In gyrotrons, the nonlinear taper is used to connect the interaction region with the output waveguide system. The main challenge in the design of a nonlinear taper for gyrotron is that it requires very high transmission (above 99%) with very less spurious mode generation. Due to high output power, even 1% of reflections cause severe damage to the entire system. For this reason, although it is a simple component, it has to be designed very carefully. This is a typical design application where the accuracy requirement is very high. It is necessary that a proper optimization tool be chosen so that it gives a global optimum from the complex and nonlinear design space.

Evolutionary Algorithms (EAs) such as GA, PSO, etc. have proved to be effective and promising tools for search and optimization in multidimensional feature space. In this chapter, we use two swarm intelligence based algorithms - a PSO and a modified bacterial foraging optimization for the design of a nonlinear taper as a case study application of high power microwave and millimeter wave devices. The applicability of PSO for gyrotron mode convertor application is illustrated in [120]. But the potential applications of more recent Bacterial Foraging Optimization (BFO) algorithm has yet to be investigated for the design applications in microwave domain. In this chapter, we also present a modified version of BFO algorithm and compare its performance with the standard PSO algorithm.

Related works:

Various nonlinear tapers used for matching purposes are triangular taper, exponential taper and Chebyshev taper [121, 122]. Few of tapers that are generally employed in microwave systems are those designed by Klopfenstein [123], and Hecken [124], etc. Flügel and Kühn developed programs for computer-aided analysis and design of Dolph-Chebyshev and modified Dolph-Chebyshev tapers [125] for use in gyrotrons. The theoretical evaluation of two nonlinear tapers of raised-cosine type was presented by Lawson in [126]. He showed that under some conditions, raised-cosine profile yields less mode conversion than modified Dolph-Chebyshev profile. In this work, we have considered the design and optimization of a raised-cosine taper for use in a specific gyrotron.

This chapter is organized as follows. Section 5.2 presents conceptual description of standard BFO algorithm, its modification for improved convergence, and its comparison with standard PSO algorithm using benchmark test functions. Section 5.3 presents the use of both the algorithms for the design and optimization of a specific nonlinear taper. Finally, section 5.4 presents concluding remarks on performance of the methods presented in the chapter.

5.2 Bacterial Foraging Optimization

Bacterial foraging algorithm is inspired by the pattern exhibited by foraging behavior of bacteria, more specifically *Escherichia coli* (E. coli) bacteria, which resides in our intestines. The algorithm proceeds by either selecting or eliminating bacteria based on their good or poor foraging strategies. Further, the algorithm may also refine poor foraging strategies into better ones.

5.2.1 Standard Bacterial Foraging Optimization

The foraging process in BFO algorithm involves four processes such as chemotaxis, swarming, reproduction, and elimination-dispersal. These four processes are described as follows:

Chemotaxis: The movement of E. coli bacteria towards the nutrient-rich areas is simulated by an activity called "chemotaxis". This process involves two sub-activities: tumbling and swimming. In tumbling, bacteria do not move noticeably, but positions themselves in some random directions in which later on swimming can occur. Swimming is performed in the specified direction with fixed swim length. The process of chemotaxis can be represented as,

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(i) \tag{5.1}$$

where $\theta^i(j,k,l)$ indicates the position of the i-th bacterium at the j-th chemotactic step, in the k-th reproductive loop, and at l-th elimination-dispersal event. $\phi(i)$ is a random unit vector, and $C(i)$ is the length of a unit walk in the direction specified by $\phi(i)$.

Swarming: It is a group behavior or cell-to-cell signaling exhibited by bacteria while moving towards rich-nutrient areas. In this, the healthy bacteria attract other bacteria towards them. Bacteria move into a group forming a pattern. Mathematically, swarming can be represented as,

$$\begin{aligned} J_{CC}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J_{CC}^i(\theta, \theta^i(j,k,l)) \\ &= \sum_{i=1}^{S}[-d_{attract}\exp(-w_{attract}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)] \\ &\quad + \sum_{i=1}^{S}[h_{repellent}\exp(-w_{repellent}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)] \end{aligned} \tag{5.2}$$

where $J_{CC}(\theta, P(j,k,l))$ is the cost function value added to the actual cost function which makes it time varying. Here, S indicates number of bacteria, p indicates number of design parameters, and $\theta = [\theta_1, \theta_2, ..., \theta_p]^T$ is a point in the p-th dimensional search space, while $d_{attract}$, $w_{attract}$, $h_{repellent}$, and $w_{repellent}$ are constants and should be chosen carefully.

Reproduction: In this process, healthy bacteria reproduce and split into two, while unhealthy bacteria die. For convenience, the total population is maintained constant by killing half the population with highest fitness values, and remaining half reproduces and is placed at same locations.

Elimination-dispersion: In this event, some bacteria are dispersed to random locations with some probability due to factors such as consumption of food, and other environmental effects. The bacteria with probability p_{ed} are dispersed to random locations in the optimization domain.

The flowchart of the standard BFO algorithm is shown in Fig. 5.1, while the detailed algorithm for further reference is given in Appendix-C.

5.2.2 Modified Bacterial Foraging Optimization

The above described algorithm when tested on multidimensional benchmark functions is observed to show a poor convergence compared to standard PSO [84]. One of the reasons may be that classical BFO ignores the effects of global swarming. Moreover, all the bacteria are assumed to have same swim length in their chemotaxis process. However, the use of variable swim length according to their relative distance from the bacterium with highest nutrient position may improve convergence.

In order to improve the convergence, a modified BFO (MBFO) algorithm is presented here by considering few changes in the standard BFO. The modifications applied to the standard BFO algorithm are as follows:

- In classical BFO, it is assumed that bacteria will move in a random direction

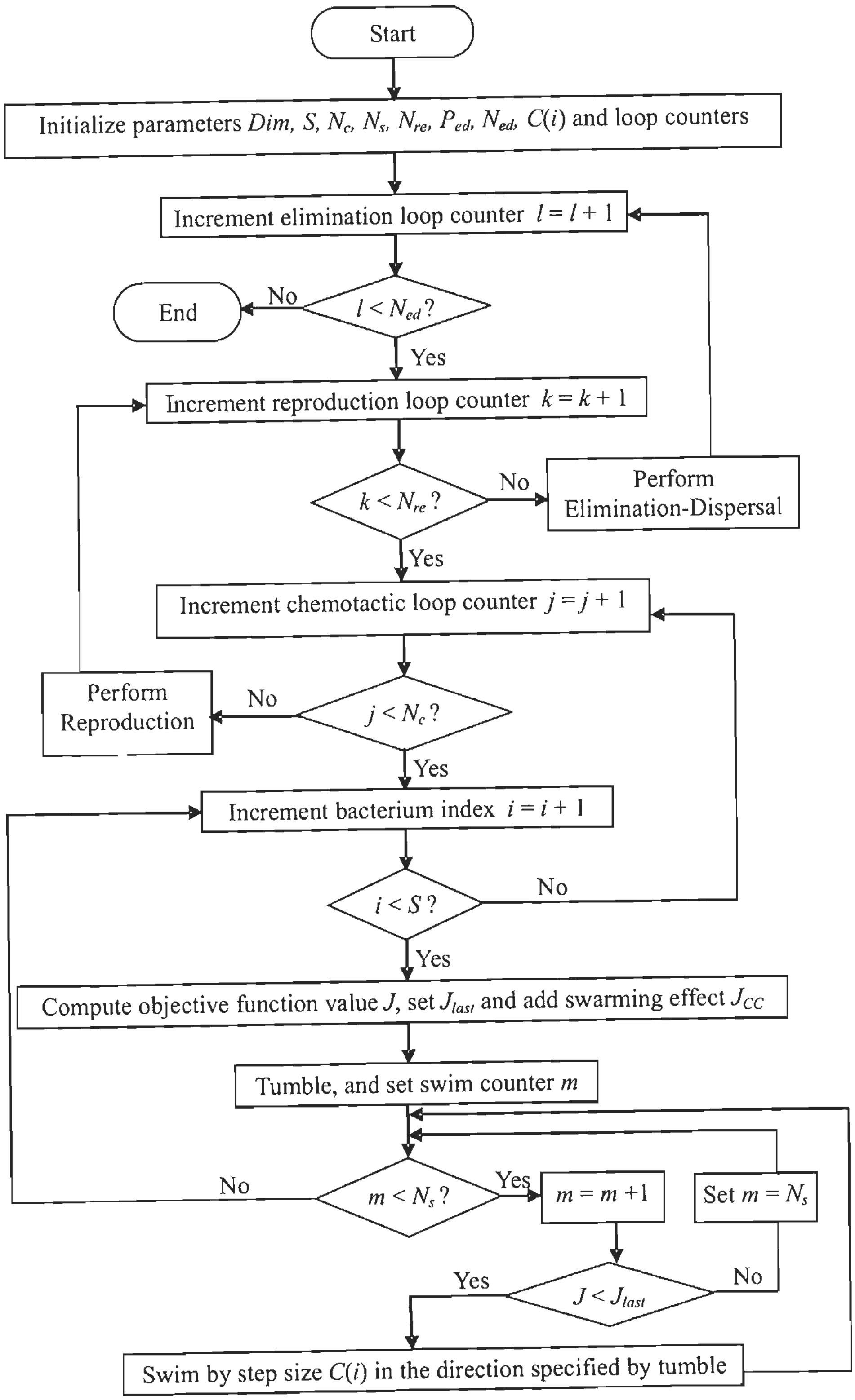

Figure 5.1: The flowchart of standard BFO algorithm.

in every chemotaxis loop. But, in nature, a bacterium can remember the nutrient concentration in its previous postion [8]. Based on this knowledge, a bacterium compares its current nutrient concentration with that of the previous concentration. This information is stored in a memory array which is a $S \times Dim$ dimensional vector. In the presented modification, each time a bacterium encounters a favorable environment, it remembers the direction in which it moved, so that in the next swim step it can move in the same direction as it is more probable to encounter a favorable environment. If at some point it reaches a toxic place (higher value of J_i) it moves back to its previous position and from this point it generates a random direction (i.e., it tumbles) and moves in a new direction. In this way the bacteria can reach highest nutrient concentration (minimum J_i) quickly.

- In the second modification to the standard BFO algorithm, after undergoing a chemotactic step, the position of bacteria is modified by applying PSO operator as suggested in [84]. In this phase, the bacterium is stochastically attracted towards the global best position found so far in the entire swarm. The 'social' component of PSO is only used, ignoring 'cognitive' component, as the local search in different regions of the search space is already taken care of by the chemotactic steps. The velocity and position update equations used in applying PSO operator are as follows:

$$V^i_{new} = wV^i_{old} + C_1 r_1 (x^{gbest} - \theta^i(j,k,l)) \tag{5.3}$$

$$\theta^i_{new}(j+1,k,l) = \theta^i_{old}(j+1,k,l) + V^{id}_{new} * Vary \tag{5.4}$$

where v_{id} is the velocity of ith bacterium in dth dimension, w, C_1, $Vary$ are constants, r_1 is a uniformly generated random number.

- The chemotactic step-size is varied in accordance with fitness [127] as:

Table 5.1: Values of user defined parameters of BFO

Name of parameter	Value of parameter
N_c	40
N_{re}	5
N_{ed}	5
P_{ed}	0.25
N_s	20
$C(i)$	variable
$Vary$	0.075 for range of search is small (say<100), 1 otherwise

$$A = \frac{K}{\mid Jbest - J(i, j+1, k) \mid} \tag{5.5}$$

$$C(i) = \frac{1}{1+A} \tag{5.6}$$

where K is constant. For bacteria far away from best, $C(i)$ should be near to 1, so it results in a large step size. For bacteria close to J_{best}, $C(i)$ should be near to 0, so that they can converge to global minima without much oscillations. In the process, K=400 was observed to give satisfactory results.

The detailed flowchart of the MBFO algorithm is shown in Fig. 5.2, whereas the detailed algorithm is given in Appendix-C.

Parameter Selection. The ability of BFO in exploring global optima is greatly dependent on the choice of parameters such as $C(i)$, N_c, N_{re}, N_{ed}, N_s. In classical BFO, Passino took $C(i) = 0.1, i = 1, .., S$. The values of parameters selected for the experiment on five benchmark functions are shown in Table 5.1

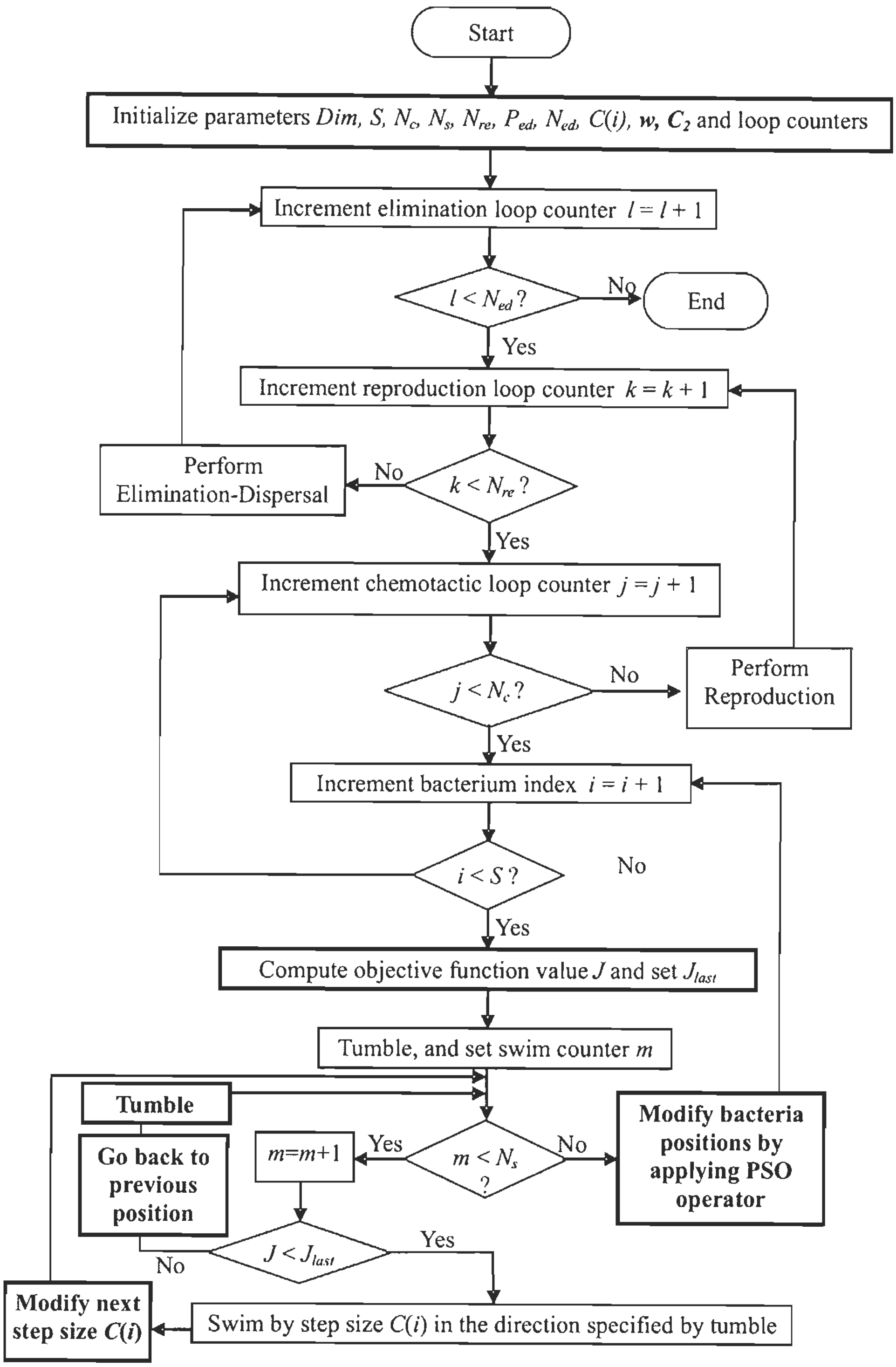

Figure 5.2: Flowchart of the Modified BFO algorithm

Table 5.2: Benchmark functions

Function name	Function
De Jongs's sphere function	$f_1 = \sum_{i=1}^{n} x_i^2$
Rosenbrock function	$f_2 = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
Generalized Rastrigrin function	$f_3 = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$
Generalized Griewank function	$f_4 = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$
Schaffer's f6 function	$f_5 = 0.5 + \frac{(\sin\sqrt{x_1^2 + x_2^2})^2 - 0.5}{(0.1 + 0.001(x_1^2 + x_2^2))^2}$

5.2.3 Experiment on benchmark functions

Experimental settings

The performance of the MBFO algorithm was evaluated on a test bed of same five benchmark functions that were used in Chapter 3 and are reproduced here in Table 5.2. The search range for these functions and the range of initializing bacteria positions are similarly reproduced and shown in Table 5.3 for convenience. Remember that asymmetric initializations are used for these functions in order to consider the practical situations. All these functions were tested with 10, 20 and 30 dimensions, except the last Schaffer f6 function which is two dimensional. For De Jong's Sphere function, the maximum number of iterations considered to stop the BFO algorithm were 1000, 2000 and 3000 for dimension 10, 20 and 30 respectively. While, they were considered to be 3000, 4000 and 5000 for 10, 20 and 30 dimensions respecively for Generalized Rastrigrin, Generalized Rosenbrock and Generalized Griewank functions. The maximum iterations considered for Schaffer f6 function was 1000. The maximum error tolerance considered for all functions was 0.01 except for Schaffer f6 function in which it was considered

Table 5.3: Initialization range, search range, and error tolerance

Test function	Range of search	Range of initializations	Error tolerance
f_1	$[-100, 100]^n$	$[50, 100]^n$	0.01
f_2	$[-100, 100]^n$	$[50, 100]^n$	0.01
f_3	$[-10, 10]^n$	$[2.56, 5.12]^n$	0.01
f_4	$[-600, 600]^n$	$[300, 600]^n$	0.01
f_5	$[-100, 100]^n$	$[15, 30]^n$	0.00001

to be 0.00001. The MBFO algorithm was stopped when either the error criterion or maximum iterations were reached.

Simulation results on benchmark functions

The results of testing MBFO on test functions are shown in Table 5.4. Due to probabilistic nature of evolutionary algorithms, the results shown here are an average of 50 runs of the algorithm for each test case. In order to compare the performance of MBFO algorithm, similar results were obtained using standard PSO algorithm. Here, three metrics are used for comparative study, (i) quality of solution (measured in terms of average achieved optimum value and its standard deviation), (ii) convergence speed (which is measured in terms of number of successful runs out of 50 runs), and (iii) average number of iterations for only successful runs.

The comparative results of MBFO and PSO on test functions show that MBFO outperformed PSO on Rosenbrock's function and Generalized Griewank function, while the standard PSO performed well on Generalized Rastrigrin and Schaffer f6 function. The total number of successes obtained with MBFO is higher than those obtained with standard PSO algorithm.

Table 5.4: Performance of MBFO on benchmark functions and its comparison with standard PSO algorithm

Fn.	Dim.	Average achieved optimum value (Standard deviation)		Number of successes (Average generation of success)	
		PSO	MBFO	PSO	MBFO
f_1	10	0.01(–)	0.14(1.28)	50(566)	38(374)
	20	0.01(–)	0.01(–)	50(1291)	50(1274)
	30	0.01(–)	0.015(0.00)	50(2081)	49(2338)
f_2	10	25.19(64.34)	0.14(1.28)	1(2365)	3(1955)
	20	131.94(269.92)	2.46(6.62)	0(–)	0(–)
	30	186.85(370.73)	3.88(2.41)	0(–)	0(–)
f_3	10	2.30(1.55)	59.35(41.44)	4(1904)	0(–)
	20	14.20(4.68)	58.37(24.73)	0(–)	0(–)
	30	31.44(7.15)	82.26(26.49)	0(–)	0(–)
f_4	10	0.075(0.035)	0.01(0.00)	0(–)	50(875)
	20	0.026(0.026)	0.01(0.00)	22(2339)	50(2349)
	30	0.02(0.015)	0.01(0.00)	27(3222)	50(3790)
f_5	2	0.00097(0.0029)	0.27(0.27)	45(532)	0(–)
Total successes (Total iterations)				249(14300)	290(12955)

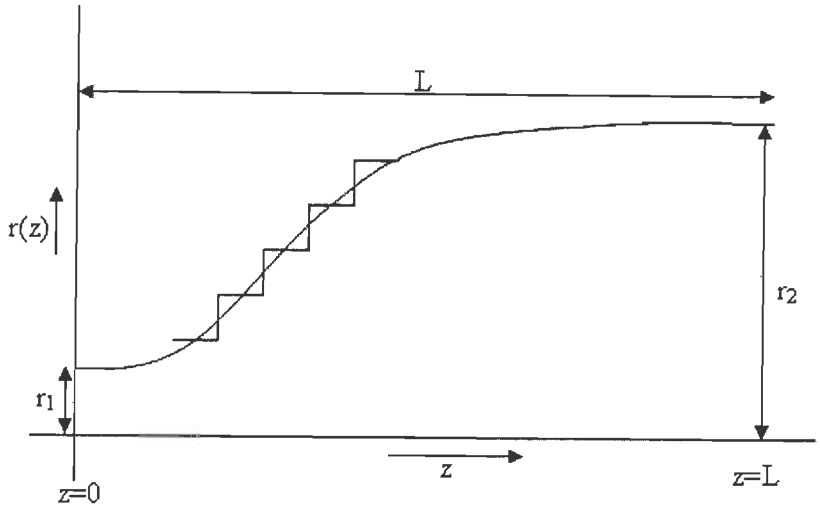

Figure 5.3: The raised-cosine taper profile.

5.3 Experiment

5.3.1 Design of a nonlinear taper for a high power gyrotron

In this work, the design of a nonlinear taper is carried out for a 42 GHz, 200 kW, CW gyrotron operating in the $TE_{0,3}$ mode with axial output collection. This work is carried out as a part of a specific gyrotron development project undertaken currently in India. A schematic diagram of a raised-cosine taper considered in this work is shown in Fig.5.3. The analysis of the taper was carried out using a dedicated scattering matrix code [18], as it was found to be fast and accurate for taper analysis. The tapered parts were divided like a flight of stairs (see Fig. 5.3). The scattering coefficient of each step was calculated by using a dedicated scattering matrix code. The synthesis of the raised-cosine taper profile was carried out using the following formulae [128]:

$$\alpha = -1.0 + 2.0 \left(\frac{i}{l}\right)^{\gamma} \tag{5.7}$$

$$r(z) = \frac{r_2 - r_1}{2} \cdot \left(\alpha + \frac{1}{\pi} sin(\pi\alpha)\right) + \frac{r_2 - r_1}{2} \tag{5.8}$$

$$r = r_1 + r(z) \tag{5.9}$$

The goal here is to find optimum shape for which maximum transmission occurs with minimum spurious mode contents. For a nonlinear taper to be used in gyrotron, its power reflection and spurious mode contents should be less than 1 %. The optimized performance of the taper was obtained using both standard PSO algorithm and MBFO algorithm as presented in section 5.2.2. In our design optimization task, we also identified that a geometrical parameter (γ), in Eq. (5.7), is very important for determining the shape of the raised-cosine taper. The effect of varying γ parameter on the transmission characteristics of the nonlinear taper is shown later in this section. In our optimization process, this parameter along with three other nominal parameters namely length of the taper (L), radius of the taper at output end (r_2), and the number of straight sub-sections (N) were considered as design parameters. In the experiment, the radius of the taper at input end (r_1) was kept constant at 13.991 mm. The range of design parameters considered are mentioned in Table 5.5. The goal during the optimization was to obtain maximum transmission coefficient (i.e., S_{21}-parameter), operating in $TE_{0,3}$ mode with minimized spurious mode content. The fitness function considered for minimization in this problem is as follows:

$$f_{obj} = -S_{21(TE_{0,3})} \tag{5.10}$$

where S_{21} is transmission coefficient for $TE_{0,3}$ mode. The minimization of spurious mode contents are also obtained by maximizing transmission coefficient, as the total power remains constant.

Table 5.5: Range of design parameters

Design Parameter	Range
Length (L)	200-350 mm
Radius at output end (r_2)	35-45 mm
Number of sections (N)	50-500 mm
Gamma (γ)	0.1-1.0

Table 5.6: Optimized values of taper parameters

Name of Design Parameter	Optimized Value	
	PSO	MBFO
Length (L)	349.99 mm	315.45
Radius at output end (r_2)	37.32 mm	35.0
Number of sections (N)	208	469
Gamma (γ)	0.504	0.517
Transmission	99.87 %	99.85 %

5.3.2 Results

The optimized design parameters and corresponding transmission coefficient using PSO and MBFO are shown in Table 5.6. It can be observed that excellent transmission of 99.87% and 99.85 % are obtained using both the algorithms respectively. The algorithm was executed with a swarm size of 10 particles and 20 bacteria respectively, for about 100 iterations using both algorithms. The iterations considered for the design were sufficient for the convergence of the swarm.

We have also observed the effects of varying gamma parameter (γ), radius

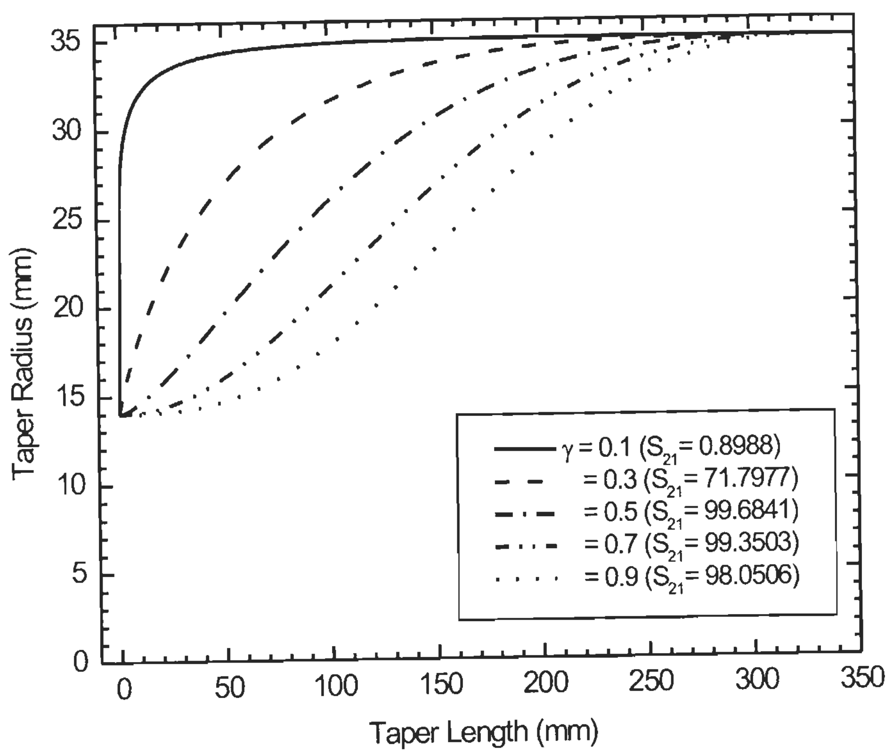

Figure 5.4: Contours of raised-cosine taper showing the effect of parameter gamma (γ)(L=350 mm, r_2 =35.0 mm , N=466)

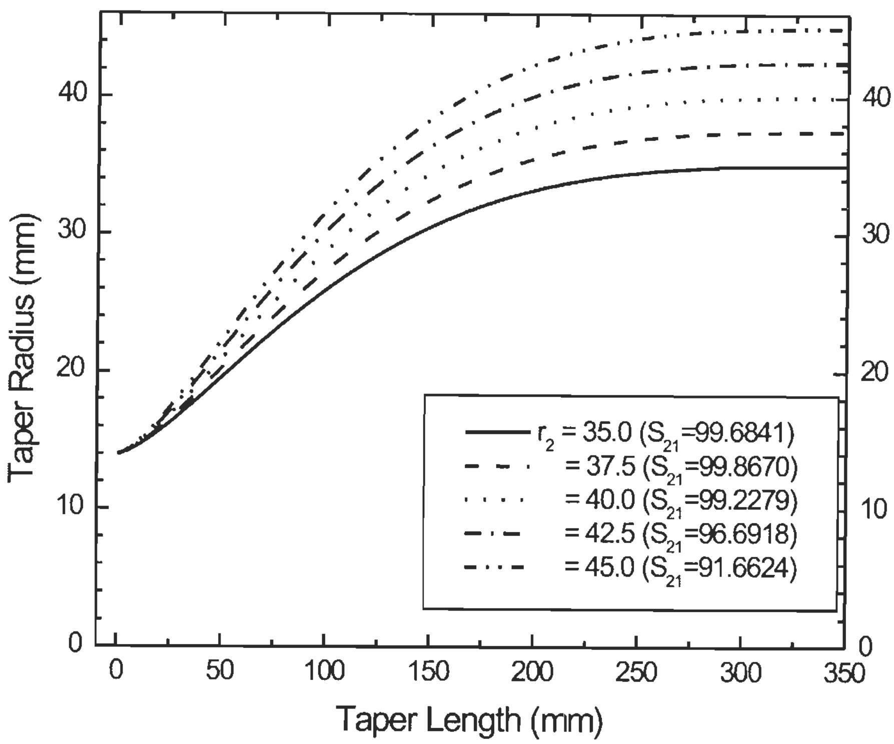

Figure 5.5: Contours of raised-cosine taper showing the effect of output radius (r_2) ($L = 350$ mm, $\gamma = 0.5$, $N = 466$)

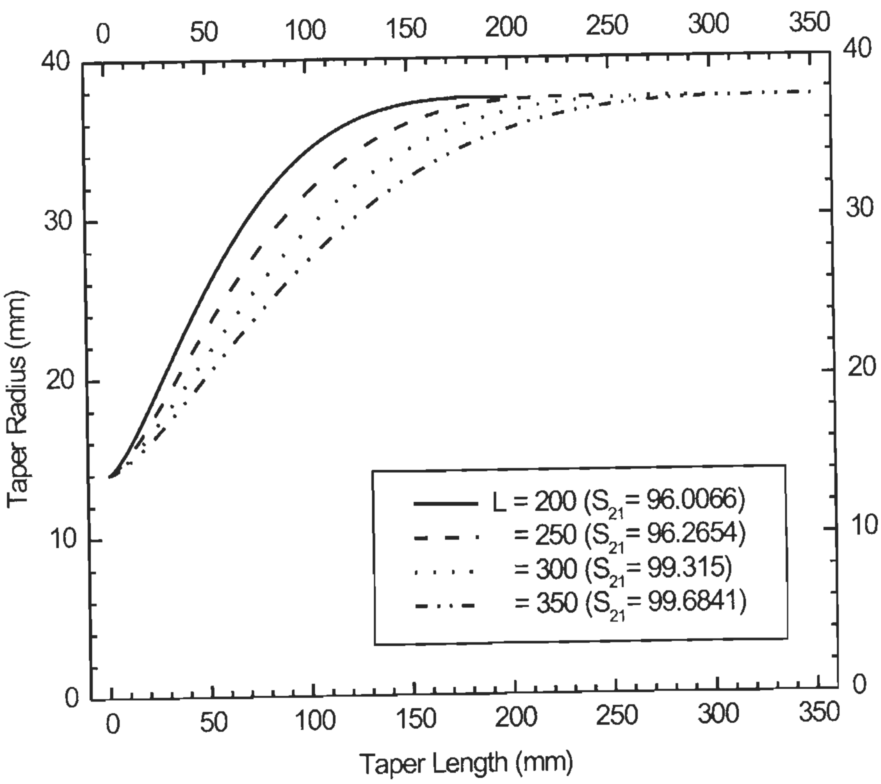

Figure 5.6: Contours of raised-cosine taper showing the effect of length (L) (r_2 = 35 mm, $\gamma = 0.5$, $N = 466$)

at the output end of the taper (r_2), and length of the taper (L) on the taper synthesis and the transmission coefficient. The effect of the gamma parameter is shown in Fig. 5.4, while the effect of radius at output end of the taper on the transmission coefficient is shown in Fig.5.5. It can be observed that the value of parameter gamma (γ) plays significant role on the transmission efficiency of the taper. Its value between 0.5 and 0.7 leads to transmission above 99%. It can also be observed that output radius of less than 40 mm leads to the desired transmission range and gives optimum transmission at 37.5 mm.

The percentage of transmission for various taper lengths within the desired range are shown in Fig. 5.6. It can be observed that as we increase the taper length, the transmission also increases. In addition, the percentage of transmission and reflection of the main mode $TE_{0,3}$ along with its azimuthal neighbours for an optimized run (with r_1=13.991, r_2=37.32, L=349.99, γ=0.504, N=208) are shown in Table 5.7.

5.4 Concluding remarks

The design and optimization of a raised-cosine type taper profile for a 42 GHz, 200 kW, CW gyrotron was carried out using two swarm intelligence based algorithms namely standard PSO algorithm and a modified version of BFO algorithm. A dedicated scattering matrix code [18] was used for the fast and accurate analysis of taper during design process. The selection of PSO, and MBFO parameters were carried out in accordance with previous experimental investigations.

The optimized results show excellent matching obtained for a raised-cosine taper which confirms effectiveness of the presented methods for the design of nonlinear tapers. The time required for the optimization was 20 and 40 minutes (approximately) respectively for PSO and MBFO algorithms on a latest workstation. It is concluded that both the algorithms can find global optimum from

Table 5.7: Percentage of transmitted and reflected power for various modes (Frequency: 42.0 GHz)

Mode	Reflection[%]	Transmission[%]
$TE_{0,1}$	0.00001	0.01673
$TE_{0,2}$	0.00001	0.00012
$TE_{0,3}$	0.00044	99.86609
$TE_{0,4}$	0.01239	0.00762
$TE_{0,5}$	0.00123	0.00028
$TE_{0,6}$	0.00036	0.00010
$TE_{0,7}$	0.00015	0.00019
$TE_{0,8}$	0.00007	0.00015
$TE_{0,9}$	0.00004	0.00005
$TE_{0,10}$	0.00002	0.00000

the nonlinear design space of a complex taper design problem, which requires perfect design with very high transmission (above 99%). Excellent transmission of 99.87% and 99.85% were obtained with both PSO and MBFO algorithms in very small number of iterations. This shows the power of swarm intelligence based algorithms in solving critical high power microwave design problems. Finally, a parametric analysis of the taper was carried out by varying individual design parameters in a discrete fashion while keeping other parameters constant.

Chapter 6

Design of RF Windows using Multi-Objective Particle Swarm Optimization

6.1 Introduction

High power microwave and millimeter-wave sources such as gyrotrons, klystrons, and other gyro-devices produce very large amount of output power at wavelengths from microwave to millimeter-wave range [19, 129]. RF-window is an important component of the output system of these devices. It serves as a barrier between the vacuum side of the device and the output transmission line. The most important task in the design of RF-window is the selection of suitable window material with required characteristics/features [130]. The material selected should have high power handling capability. It should withstand thermal and mechanical stresses, should avoid flashing/arching and puncturing/physical damage. So, care must be taken in selecting proper window material with low loss tangent, high thermal conductivity, suitable mechanical strength, and perfect design to minimize power reflections and absorption for better transmission

[19]. The other challenge is that a perfect design should be obtained that minimizes power reflections and exact matching at desired frequency. In this chapter we have presented the design of two types of windows - double disc window and pillbox-type window. Double disc windows are used in gyrotrons and their invariants [19, 20], while RF-windows of pillbox-type are usually employed in conventional microwave sources, such as, klystrons [131].

6.1.1 Related work

Few designs reported in the literature for the design and analysis of single disc, double disc, and pillbox-type RF-windows used in high power microwave sources are as follows. Thumm describes various types of high power windows and summarized the early development status of high-power millimeter-wave windows with emphasize on CVD diamond in [130]. Yang, *et al.* [20] have presented analysis of conventional single disc window, frequency tunable double disc window, and ultra-broadband Brewster window. They optimized geometrical parameters of the window units to obtain suitable transmission characteristics. Yang, *et al.* [132] also investigated the influence of some window parameters such as mechanical tolerance of the disc thickness, variation of distance between two discs, and frequency shift during gyrotron pulse on the transmission characteristics of millimeter waves. They show that power reflections are much more sensitive; and an accurate tuning is required for the design of double disc window to keep reflections below 1%. Jöstingmeier, *et al.* [131] present a systematic method for designing 75 MW S-band pillbox-type RF-window. They used an additional inductive iris to make use of ceramic disc of arbitrary thickness. In their work, the bandwidth is optimized by varying the thickness of the disc.

In this chapter, we demonstrate the use of Multi-Objective Particle Swarm Optimization (MOPSO) for optimizing design parameters of disc-type RF-windows. The MOPSO is selected to treat minimization of power reflection around resonant frequency (this also maximize BW around it) and matching at desired frequency as separate objectives. As this approach gives a set of solutions, which optimally balances the trade-off between objectives, it facilitates designer to fix a design from available set of solutions according to the requirement.

The organization of the chapter is as follows. Section 6.2 describes concept and earlier use of MOPSO in microwave design. Section 6.3 presents the design of three RF-windows for specific high power microwave sources using MOPSO methodology. Finally, section 6.4 presents the concluding remarks.

6.2 Multi-Objective Particle Swarm Optimization

6.2.1 Definition

It is observed that many real-time problems have more than one objective. In this case, it is desired to find a solution that optimally balances the trade-off between multiple objectives. The goal of the Multi-Objective Optimization (MOO) problems is to obtain a set of solutions, called *Pareto-optimal set*, which optimally balance the tradeoff between multiple objectives based on the concept of *Pareto dominance* [7, 133]. A solution X is called to dominate solution Y, if $f(X) \leq f(Y)$ for all individual objectives and $f(X) < f(Y)$ for at least one objective. A set of objective vectors in objective space corresponding to Pareto-optimal set is referred to as *Pareto front.* Similar to genetic algorithms, MOO is also implemented with particle swarm optimization by several researchers. A comprehensive summary of most MOPSO methods is given in [7].

6.2.2 MOPSO in microwave design

Electromagnetic researchers have used various MOPSO implementations for the design of various electromagnetic and antenna design problems. For instance, Gies and Rahmat-Samii used Vector-Evaluated PSO (VEPSO) for antenna array problem [134]. They applied VEPSO to optimize beam efficiency and Half Power Beam Width (HPBW) of a 16-element radiometer array antenna. The limitation with this algorithm is that handling of more than two objectives is not possible. Xu and Rahmat-Samii have also used adaptive MOPSO by applying it to two electromagnetic problems: synthesis of 16-element antenna array which is optimized for tradeoff between beam efficiency and HPBW, and optimization of shape reflector antenna for high gains of multiple feeds [56].

In this chapter, a specific implementation of MOPSO developed by Raquel and Naval [22] is used for the design of three different RF-windows. This implementation is based on a mechanism called *crowding distance*. Crowding distance is a metric which provides estimate of density of solutions surrounding a particular solution. This mechanism is incorporated in PSO algorithm for the selection of global best and for the deletion of solutions from external archive of non-dominated solutions. The method was found to be highly competitive in converging towards the Pareto-front and gave well distributed non-dominated solutions on optimization test problems. We use this method for finding optimum Pareto front for the design of double disc RF-windows and pillbox-type RF-window for use in high power microwave and millimeter wave devices such as gyrotrons and klystrons respectively. The algorithm is aimed to find optimum physical dimensions for both the types of RF-windows. Multi-objective optimizations using PSO have been used to achieve optimized trade-off between matching of desired resonant frequency and minimizing the power reflections which is obtained by maximizing the bandwidth around resonant frequency.

6.3 Experiment

Three design examples of disc-type RF-windows namely a double disc window for 42 GHz and 170 GHz gyrotrons, and a pillbox-type window for 2.856 GHz klystron have been considered. Out of the above mentioned windows, the design of a RF-window for a 42 GHz gyrotron is a part of the gyrotron development project currently undertaken in India. The details of the type of window, desired working frequency, window materials and their dielectric properties used for each type of window are shown in Table 6.1.

In all three experiments, an MOPSO with crowding distance [104] was used for getting optimum Pareto front. The algorithm was executed with a swarm size of 20 for 500 iterations in each case. The size of the archive for storing optimum Pareto sets during the execution was kept at 20 in each case. The values of c_1 and c_2 parameters of PSO were considered to be 2 in this implemetation. The value of inertia weight w was varied from an initial value of 0.9 to a final value of 0.4 during the iterations. The boundary constraints for the design parameters are handled by imposing boundary cutoff limits as described in Chapter 3.

6.3.1 Design of a double disc RF-window for a 42 GHz gyrotron

In this design example, a double disc RF-window is considered for a specific 42 GHz, 200 kW, CW gyrotron to work in the $TE_{0,3}$ mode. The schematic diagram of the double disc window considered is shown in Fig. 6.1. The design parameters considered for optimization are disc thickness ($D_1 = D_2$), distance between two discs (t_{dd}), and the disc radius (r_{dd}). The same disc thickness for both the discs are considered in the experiment. The range of parameters considered for the design optimization using MOPSO are shown in Table 6.2. In this design experiment, the initial guess for the value (and also to get the range)

Table 6.1: RF-windows considered for designs

Type of Window	Frequency [GHz]	Window Material	Dielectric Constant & Loss Tangent
Double disc	42.0	Sapphire	*ϵ_r=9.41, $tan\delta$=5.5e-05
		SiN	*ϵ_r=7.9, $tan\delta$=1.0e-04
Double disc	170.0	CVD-Diamond	*ϵ_r=5.67, $tan\delta$=4.0e-05
Pillbox	2.856	AL995	*ϵ_r=9.37, $tan\delta$=9.0e-05

* Note: Dielectric properties for Sapphire and SiN are given for T=300 K, f=42 GHz from Kartikeyan *et al.* [135] and for CVD-Diamond is given for T=300 K, f=170 GHz from Thumm [130], and for AL995 is given for T=300 K, f =2.856 GHz from Singh, *et al.* [136].

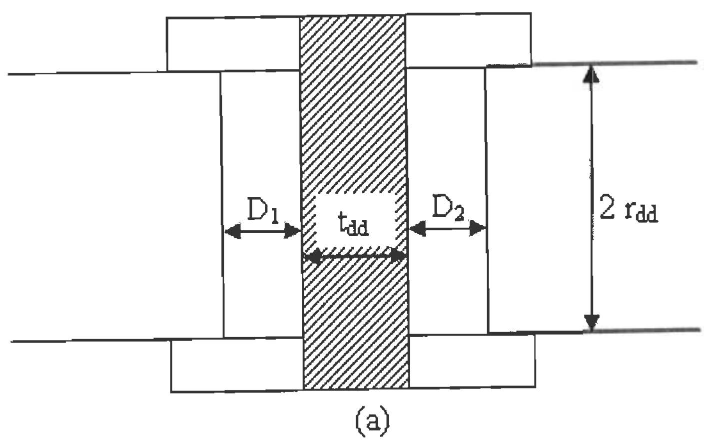

Figure 6.1: Schematic diagram of double disc RF-window.

Table 6.2: Range of design parameters of a double disc window for 42 GHz gyrotron

Design parameters	Range [mm]
Disc thickness (D_1=D_2)	2.0-3.0
Distance between two discs (t_{dd})	2.0-4.0
Radius (r_{dd})	35.0-45.0

of disc thickness for the TE modes is obtained from the following [20]:

$$D = \frac{\pi}{\sqrt{(\frac{2\pi f\sqrt{\epsilon_r}}{c})^2 - (\frac{\chi_{mn}}{R_{win}})^2}} \tag{6.1}$$

where f is desired resonant frequency, R_{win} specifies radius of the disc, and χ_{mn} is the Bessel root for the $TE_{m,n}$ mode.

The objective functions considered for the design using MOPSO are as follows:

$$f_1 = |f - f_{desired}| \tag{6.2}$$

$$f_2 = \frac{1.0}{BW + 1.0} \tag{6.3}$$

where f is the resonant frequency (in GHz) obtained in each execution, $f_{desired}$ is the desired resonant frequency for the window (in GHz) and BW specifies the bandwidth measured at -20 dB from the reflection response curve (S_{11}-parameter) around resonant frequency. Here, the function f_1 tries to match the frequency response at desired frequency, while the function f_2 minimizes the reflections around resonant frequency by maximizing the bandwidth.

In this design, two different experiments are carried out considering two different disc materials, namely, Sapphire and SiN. The dielectric constant and loss tangent for these materials are given in Table 6.1. During the design process, the analysis of the double disc window was carried out following a dedicated code [19, 137]. The code was invoked in the optimization loop of MOPSO algorithm for getting the analysis response each time.

The Pareto fronts showing the trade-off between two objectives for the double disc window using different materials (Sapphire and SiN) are shown in Fig. 6.2 and Fig. 6.3 respectively. Each symbol in the graph specifies a combination of design parameters with the value of objective functions. The transmission and reflection responses for the best designs obtained in each case (for Sapphire and SiN materials) are shown in Fig. 6.4 and Fig. 6.5 respectively. The responses using the same optimum design parameters were also obtained with a scattering matrix code Cascade 3.0 [138] for the purpose of comparison and they are presented in the same figures. The optimized values of design parameters in each case are specified along with their responses (see caption of Fig. 6.4 and Fig. 6.5). It can also be observed from the figures that both the tools (dedicated code [19, 137] and Cascade 3.0 scattering matrix code [138]) resulted in the similar responses for both the designs.

6.3.2 Design of a double disc RF-window for a 170 GHz gyrotron

In this subsection, the design of a double disc RF-window is presented for a 170 GHz, 1 MW, CW gyrotron (Gaussian mode) to be used in a Electron Cyclotron Resonance Heating (ECRH) applications [20, 132]. A CVD-diamond disc was considered as disc material in this design. The schematic diagram for this disc is same as Fig. 6.1. The design parameters considered in this example and their range are specified in Table 6.3. The disc thickness for Gaussian mode is given by [19, 20],

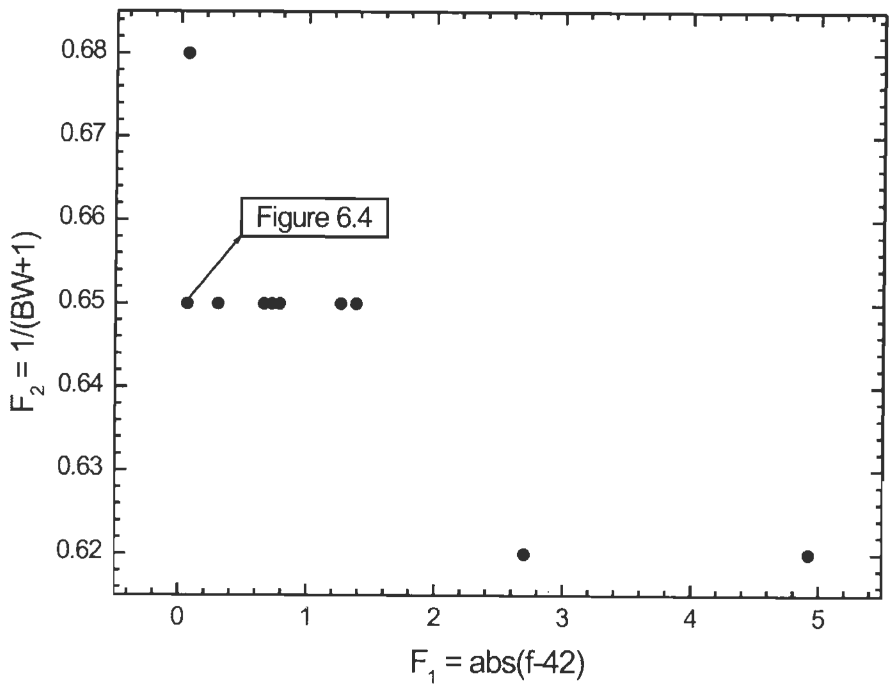

Figure 6.2: Pareto front of a double disc window with Sapphire disc material for a 42 GHz gyrotron

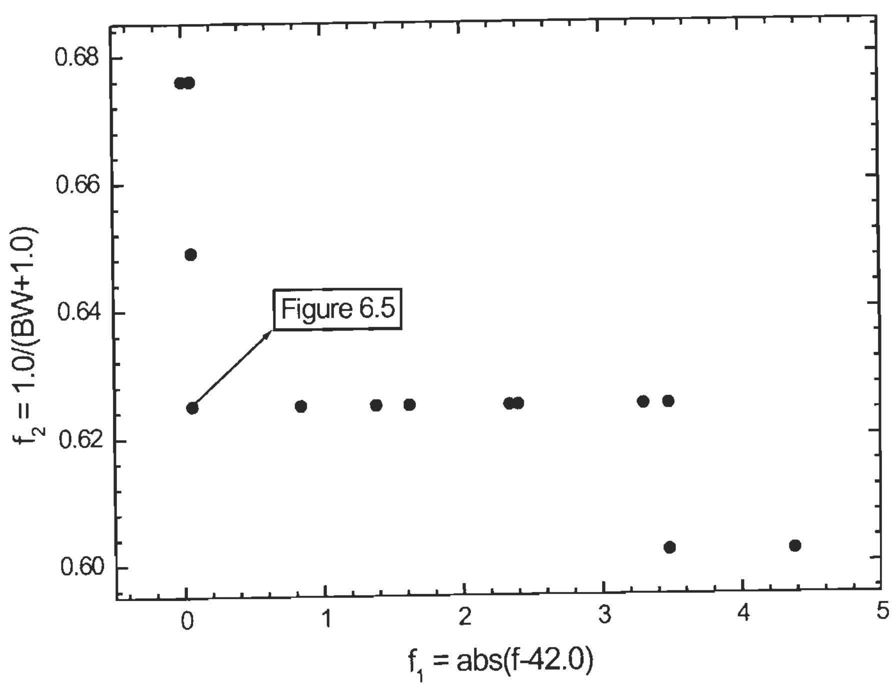

Figure 6.3: Pareto front of a double disc window with SiN disc material for a 42 GHz gyrotron.

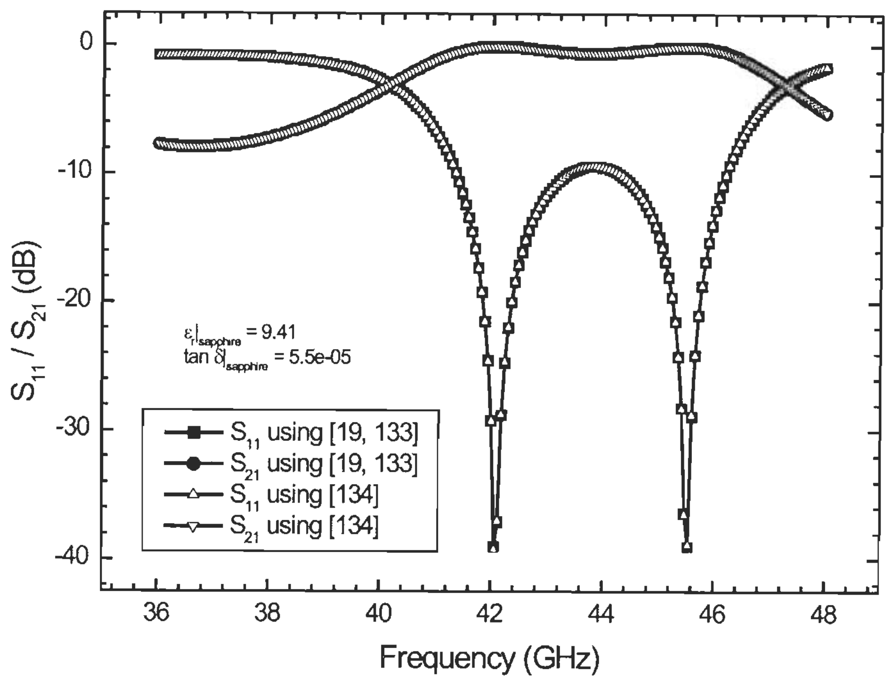

Figure 6.4: Optimized transmission and reflection characteristics of a double-disc window with Sapphire disc material for a 42 GHz gyrotron (D_1=D_2=2.28 mm, t_{dd}=3.6 mm r_{dd}=41.2 mm)

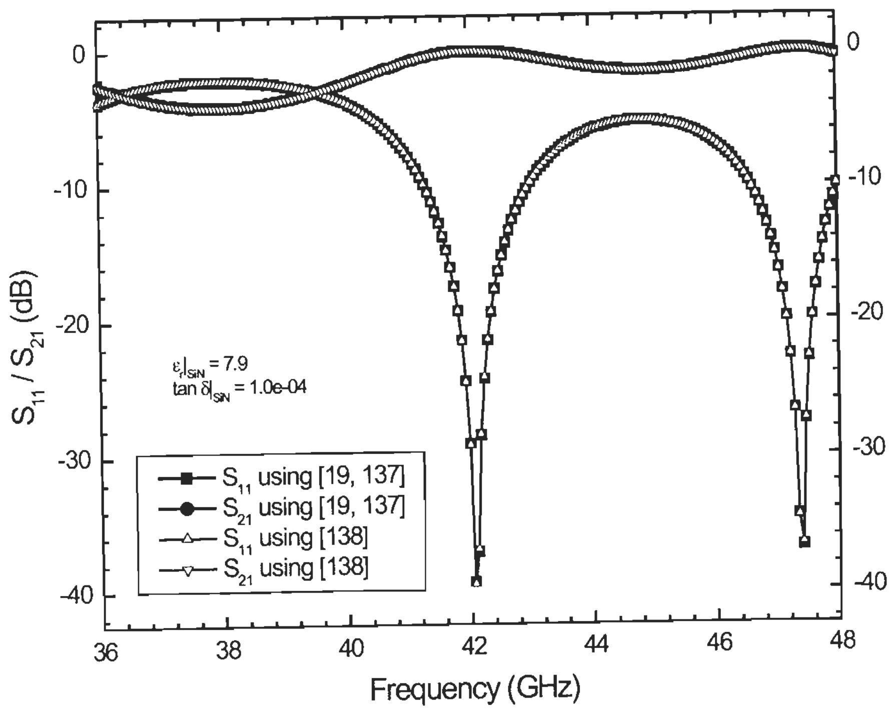

Figure 6.5: Optimized transmission and reflection characteristics of a double-disc window with SiN disc material for a 42 GHz gyrotron (D_1=D_2=2.53 mm, t_{dd}=3.02 mm r_{dd}=40.0 mm)

Table 6.3: Range of design parameters of a double disc window for 170 GHz gyrotron

Design Parameters	Range [mm]
Disc thickness (D_1=D_2)	1.0-2.0
Distance between two discs (t_{dd})	3.0-4.0
Radius (r_{dd})	45.0-55.0

$$D = N\frac{\lambda_n}{2} = N\frac{c}{2f\sqrt{\epsilon_r}} \tag{6.4}$$

where f is the desired resonant frequency and ϵ_r represents dielectric property of the disc material. The objective functions considered for this design are the same as those given in Eq.s (6.2) and (6.3). The analysis of the window during the iterative optimization process was carried out following the same dedicated code [19, 137] mentioned in the previous section.

The Pareto front for a double disc RF-window for 170 GHz gyrotron is shown in Fig. 6.6. One of the best optimized responses from the Pareto front is shown in Fig. 6.7. It can be observed that the best design from the Pareto front of double disc window (for 170 GHz) resulted in exact matching of desired frequency with a large bandwidth of 3.7 GHz measured at −30 dB level.

6.3.3 Design of a pillbox-type RF-window for a 2.856 GHz klystron

As a third example, the design of a pillbox-type RF-window for 2.856 GHz 5 MW, pulsed klystron is presented. The schematic diagram of a pillbox-type RF-window is shown in Fig. 6.8. Three design parameters namely length of the pillbox window (L_{pb}), the thickness of the disc (t_{pb}) and the diameter of the

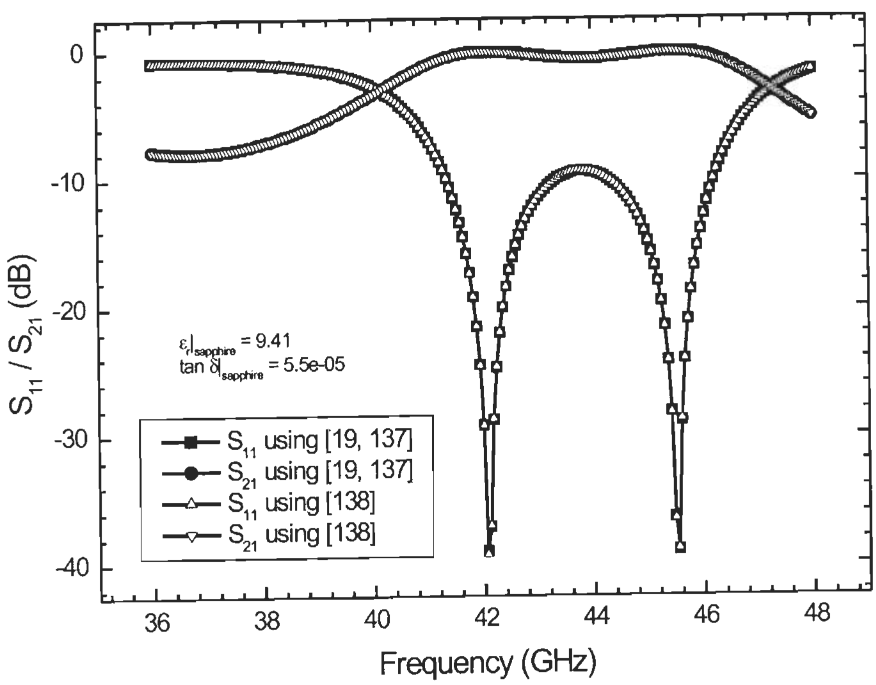

Figure 6.6: Pareto front of a double disc RF-window for a 170 GHz gyrotron

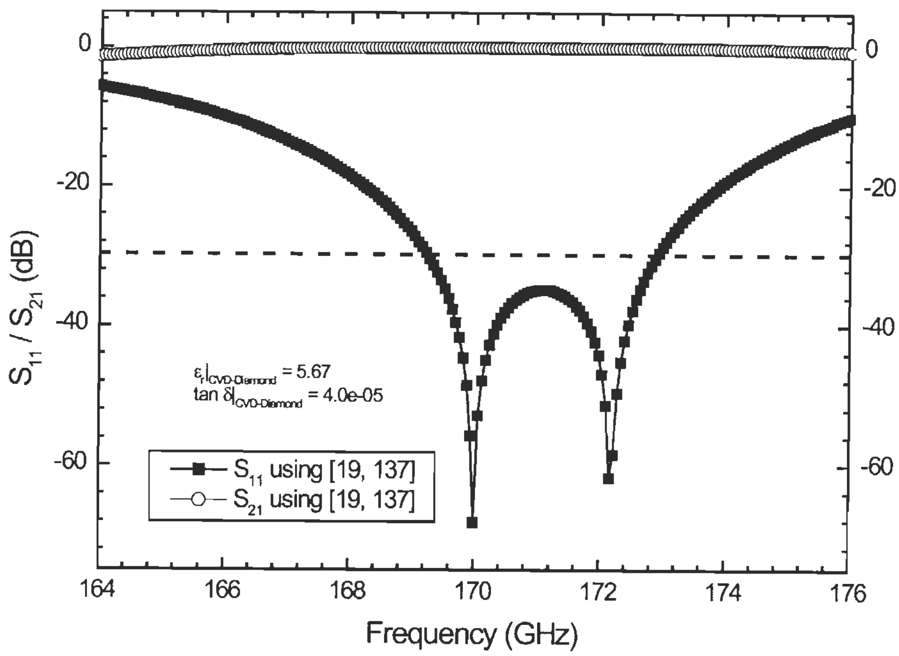

Figure 6.7: Optimized transmission and reflection characteristics of a double-disc RF-window for a 170 GHz gyrotron (D_1=D_2=1.111 mm, t_{dd}=3.0 mm r_{dd}=55.0 mm)

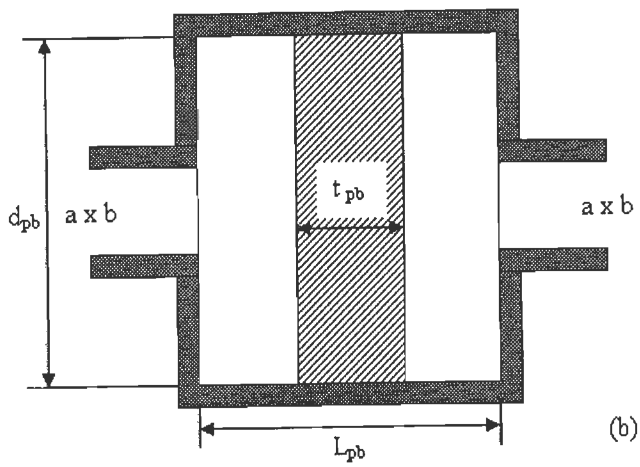

Figure 6.8: Schematic diagram of a pillbox-type RF-window (a=72.14 mm, and b= 34.04 mm [131]).

cylindrical disc (d_{pb}) are considered for optimizing the performance of the window. The range of these parameters considered for optimization is specified in Table 6.4. The range of the design parameters are determined from a specific design of pillbox-type window given in [131, 136]. The objective functions considered for getting the Pareto front are same as those used in double disc design experiments. The BW in objective function f_2 was measured at -30 dB from the S-Parameters curve in this experiment.

Table 6.4: Range of design parameters for a pillbox-type RF-window for a 2.856 GHz Klystron

Design Parameters	Range [mm]
Length (L_{pb})	35.0-40.0
Disc thickness (t_{pb})	2.0-4.0
Diameter (D_{pb})	87.0-92.0

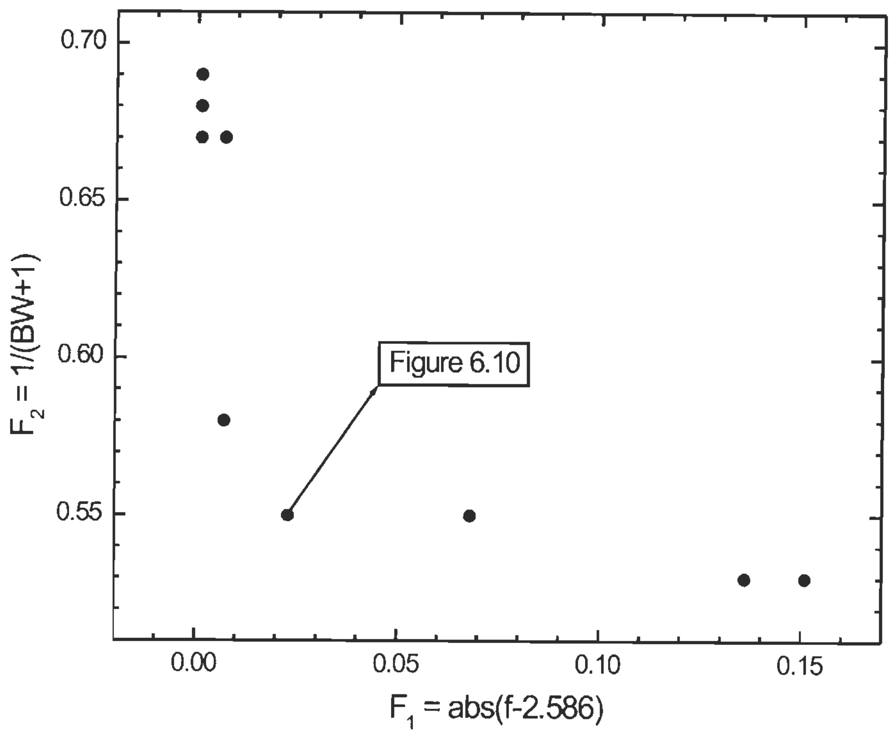

Figure 6.9: Pareto front of a pillbox-type RF-window for a 2.586 GHz klystron.

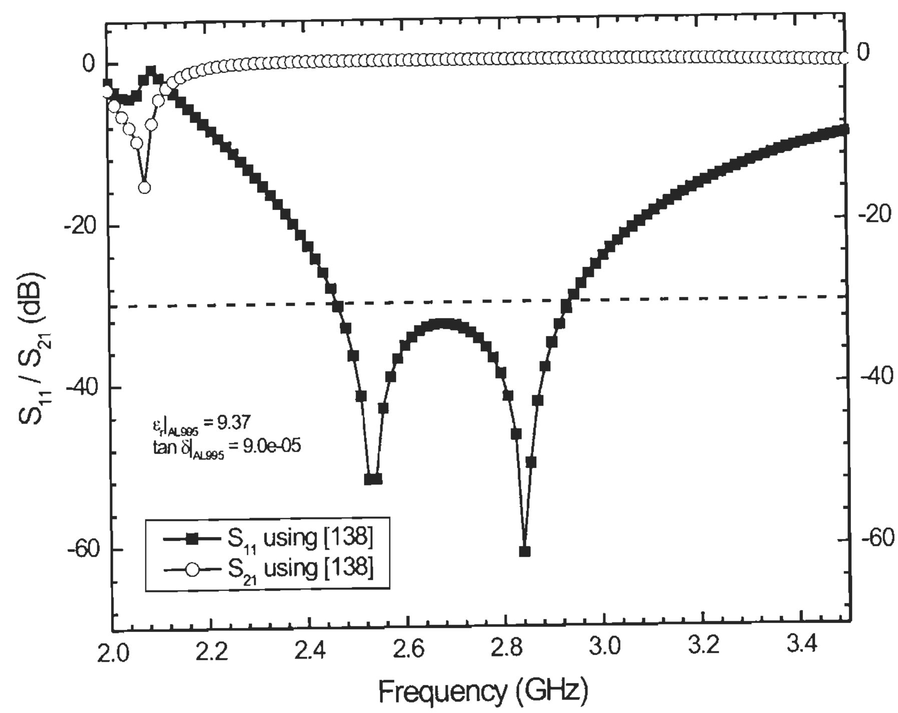

Figure 6.10: Optimized transmission and reflection characteristics of a pillbox-type RF-window for a 2.856 GHz klystron (L_{pb}=37.07 mm, t_{pb}=2.86 mm d_{pb}=88.1 mm)

The Pareto front of a pillbox-type RF-window is shown in Fig. 6.9. One of the best optimized responses from the Pareto front is shown in Fig. 6.10. It can be observed from the figure that the best design from the Pareto front of pillbox-type RF-window resulted in matching at desired frequency with a bandwidth of 475 MHz measured at -30 dB level around the resonant frequency.

6.4 Concluding remarks

A different method using multi-objective particle swarm optimizer is demonstrated for the design of disc-type RF-windows. The optimum trade-off between the objectives of matching with desired resonant frequency and minimizing the reflections around the resonant frequency (by maximizing BW around it) is achieved using the concept of MOPSO. The design and optimization of three RF-windows - a double disc window for 42 GHz gyrotron (with Sapphire and SiN as disc materials), a double disc window for 170 GHz gyrotron, and a pillbox-type window for 2.856 GHz klystron - are obtained as case studies of high power microwave and millimeter-wave components. In all experiments, the MOPSO algorithm converged with diversities in the solutions of Pareto optimal set.

The solution for the design of RF-window is also possible by formulating single objective. In this case, the matching at desired frequency should be treated as a constraint. For many microwave and millimeter-wave design problems, more specifically for the problems with high working frequencies (e.g. double disc windows at 42 GHz and 170 GHz gyrotrons used in presented experiments), fixing of the desired frequency along with other objectives is difficult. This is the reason why in this problem the matching of the desired frequency is treated as a separate objective rather than making it a constraint. Treating both as different objectives, MOO methods try to find optimum trade-off between them. Another advantage in designing components using MOO methods is that it gives a set of solutions instead of a single solution in case of single objective optimization. This gives the designer a choice for fixing (selecting) design parameters from a set of optimized solutions based on the compromise between the available objectives and the requirement.

However, in all our experiments the disc diameter (or radius) is considered as an important design parameter, it can also be fixed depending upon the material selection and availability. In all, it is concluded that the use of multi-objective particle swarm optimization is an efficient optimization tool for tuning design parameters and getting optimum response of a wide range of high power microwave devices/components and can be explored for other critical high power microwave and millimeter-wave design applications.

Chapter 7

Conclusions and Future Work

7.1 Contributions of the thesis

In this thesis various modified and hybrid soft computing methods are presented and used for diverse microwave design applications as case studies. The main object behind this exercise is to make the design as fast as possible while improving the quality/accuracy of the design. This is demonstrated using applications such as design of microwave filter, microstrip antenna, and modeling of one-port microstrip via. The thesis also deals with the design of critical applications where high precision with little tolerance is the prime requirement. Here, we considered the design of two important components, namely, a nonlinear taper and RF-windows for high power microwave sources.

The detailed contributions of the thesis are as follows:

- A novel modification to the Particle Swarm Optimization (PSO) algorithm is presented in the thesis and its applicability is demonstrated for the design of a specific microwave filter as a case study of microwave components. In the modified approach, a novel paradigm of multiple subswarms for searching parameter space with PSO algorithm is introduced. The particles in the swarm are divided to form multiple subswarms. The social component of PSO's velocity update equation is modified to include the effects of multiple subswarms. The presented approach, PSO with Multiple Subswarms (PSO-MS), is tested with a test-bed of five benchmark functions which are commonly used to compare the performance of different Evolutionary Algorithms (EAs) and their modifications. The concept is tested by applying it to two basic PSO variations, namely, PSO with Inertia Weight Method (IWM) and PSO with Constriction Factor Method (CFM). We have observed from the results obtained in Chapter 3, that if computational time is the prime requirement, we can fix the number of particles constant and achieve faster convergence, whereas if accuracy is the critical requirement the number of particles should also be increased in accordance with the number of subswarms. Finally, the presented PSO-MS algorithm is used for the design of coupled microstrip-line band pass filter. This is a computationally expensive problem when the design is conducted using EAs that invoke EM simulators in the optimization loop. The design results obtained with the PSO-MS algorithm are compared with those obtained using standard PSO. The comparison of results for the microstrip filter design problem proves the applicability of proposed approach in other microwave design problems where computational time is an important factor. Another advantage of this algorithm is that it can be parallelized easily as each subswarm's computation can be done on a separate processor. As a whole, the goal of obtaining faster design while improving quality of the design is fulfilled.

- An effective method for modeling microwave components using Support Vector Machine (SVM) is presented in the thesis. Modeling of three microwave components, namely, a one-port GaAs microstrip via, a circular polarized microstrip antenna and an aperture coupled microstrip antenna are carried out using the presented framework. The process of data generation, scaling, kernel selection, and parameter selection is described. The models developed using SVM are compared with those developed using existing ANN method. The results obtained indicate that the SVM model is better compared to that of ANN model due to its higher accuracy and generalization ability.

- A hybrid approach combining SVM with EAs is presented for microwave design applications. The aim behind the approach is to reduce the large computational expenses incurred by EM simulations when they are used in optimization loops of EAs. In this approach, an approximate model of the EM simulation based design process for the component to be designed is created using SVM. To obtain an optimum combination of design parameters, this approximate model (instead of EM simulators) is invoked in the optimization loop of EAs to get the output response. The hybrid approach is named as Support Vector driven Evolutionary Algorithms (SVEA). The exciting advantage obtained by the SVM model is that it responds quickly (approximately in milliseconds) compared to the parametric analysis of EM simulations which respond approximately in minutes depending upon the complexity of the component's structure. In this work, two different EAs - GA and PSO are used to optimize the model generated with SVM, making the approaches Support Vector driven Genetic Algorithms (SVGA) and Support Vector driven Particle Swarm Optimization (SVPSO). Both the hybrid approaches (SVGA and SVPSO) are used for the design of two microstrip antennas - a circular polarized microstrip antenna and an aperture coupled microstrip antenna respectively. The optimized design of circular polarized microstrip antenna obtained using the hybrid SVGA approach is also compared with the optimized design obtained using similar hybrid approach - a Neural Network driven Genetic Algorithms (NNGA), in which the approximate model is developed using well-known ANN method. The approach presented here is found to be highly effective in reducing computational expenses incurred by EM simulators.

- In this thesis, a Modified Bacterial Foraging Optimization (MBFO) algorithm is presented which includes three changes to the standard BFO technique. First, the bacteria are implemented with memory so that whenever bacteria encounters unfavorable environment, they return to their previous memorized position, tumble and swim again in the chemotaxis loop. Second, the PSO operator with only social component is applied after each chemotaxis step [84] to improve the convergence ability of the algorithm. Third, variable swim length is used to facilitate the bacterium to reach global optima faster. A comparison of presented MBFO algorithm is made with state-of-the-art version of standard PSO algorithm using five benchmark functions which proved the effectiveness of the presented algorithm.

- In this thesis, the design of a nonlinear taper for a 42 GHz, 200 kW, CW gyrotron is presented. This work is done as part of a project entitled "*Design and development of 42 GHz, 200 kW, CW, long pulse gyrotron*", which is presently undertaken in India. Our contribution in this work is to carry out the design optimization of a nonlinear taper to be used in the output system of the gyrotron. The power transmission requirement for this design is above 99%. This is a critical design application in which high precision and accuracy are required. The design optimization of a raised cosine type nonlinear taper is carried out using two swarm intelligence based algorithms, namely, PSO and MBFO. The parametric analysis of the taper is carried out for the selected design parameters and it is identified that the parameter gamma (γ) which is used in the synthesis of raised cosine taper profile plays critical role in obtaining desired response. The analysis of the taper was carried out using a dedicated Scattering Matrix

Code (SMC) [18]. The optimization parameters obtained using both the above mentioned algorithms resulted in an excellent transmission of 99.87% in the desired $TE_{0,3}$ mode with minimum spurious mode generation. It is concluded that a state-of-the-art version of PSO and MBFO can be used for the design of various other high power microwave and millimeter wave components.

- The concept of multi-objective optimizations using PSO algorithm is demonstrated considering by the design of disc-type RF-windows. The RF-window is also a critical output component in high power microwave and millimeter wave sources and needs careful design. The design and optimization of three RF-windows - a double disc RF-window for 42 GHz, 200 kW, CW gyroton (with sapphire and SiN disc materials), a double disc RF-window for a 170 GHz, 1 MW, CW gyrotron, and a pillbox-type RF-window for a 2.856 GHz, 5 MW, pulsed klystron - are presented. Due to sensitivity in matching with desired frequency while minimizing the reflections, a Multi-objective Particle Swarm Optimization (MOPSO) approach is chosen in this design. To carry out the design process, a specific implementation, MOPSO with crowding distance [22], is used. An optimum trade-off between the objectives of matching desired resonant frequency and minimizing the reflections around the resonant frequency (by maximizing BW) is achieved. It is demonstrated that a well distributed Pareto front is obtained in all the three experiments. It is concluded that MOPSO method can be useful for the design of high power microwave and millimeter wave sources when there are multiple objectives to be optimized.

7.2 Future work

There are a number of useful extensions that can be added to the the present research work. A few soft computing methods have been developed and used for solving challenging design problems in microwave domain. Yet the other design problems with the same or different challenges can also be picked up and solutions be found with the current or other emerging soft computing methods. The possible additions to the present work are stated below:

- It is possible to use soft computing methods presented in this thesis for the other microwave design applications with similar challenges. It is also possible to apply these methods for the design problems of other engineering disciplines.

- The implementation of EAs such as GA, PSO, BFO, and their modifications on multi-core environments is a promising research area. This can be helpful in performing faster design of microwave components. We are currently investigating the implementation of PSO on scalable multi-core environments.

- Parameter selection of SVM is also an open research issue. As the values of the critical hyperparameters affect the accuracy of the SVM model, an effective method may be developed for the optimum selection of these parameters.

- Due to continuous advancements in soft computing methods, it is possible to investigate other emerging methods such as artificial immune system, space mapping, differential evolution, ant colony optimization, etc., for microwave design problems. It may be useful to compare the performances of these methods.

- It is also possible to perform improvements and hybridizations to the present and emerging soft computing methods in order to remove the drawbacks and exploit the merits of these methods.

- As there are many user defined parameters of BFO algorithm, it is possible to carry out parametric analysis of BFO algorithm. It may also be possible to develop a method for the reduction of dependency on user defined parameter selection for BFO and also in other EAs.

Appendix A

Genetic Algorithms

Introduction

Genetic Algorithms (GA) [43, 4, 139] are evolutionary search and optimization algorithms based on the mechanics of natural selection and natural genetics. GA is different from most traditional optimization methods. The major difference between GA and other traditional search methods is that it starts with a set of solutions in contrast to the single solution approach used by traditional optimization methods. Each solution in GA is known as *chromosome* and the set of solutions (chromosomes) is known as *population*. In the evolution process of GA, solutions from one population are taken and used to form a new population with a hope that the new population will be better than the older one. Defining objective function (fitness function), representing chromosomes and applying genetic operators are three most important aspects of GA. The power of GA in effectively searching a multidimensional search space lies in its three basic operators: reproduction, crossover, and mutation.

Algorithm

The outline of the standard genetic algorithm is as follows:

ALGORITHM: *Genetic Algorithm*

1. *Initialization:* Generate random population of n solutions (encoded by chromosomes) to a given problem.

2. *Fitness evaluation:* Evaluate the fitness $f(x)$ of each chromosome x in the population.

3. *New population generation:* Generate a new population (offsprings) from old population by applying following steps,

   (a) *Reproduction:* Chromosomes are selected from parents, according to some selection strategy, to reproduce and generate offsprings. This selection is carried out in a probabilistic manner according to their fitness value. This follows Darwin's evolution theory of survival of fittest (the better fitness, the bigger chance to be selected). Reproduction makes clones of good chromosomes, but does not create new ones.

   (b) *Crossover:* Crossover proceeds in three steps: selection of a pair of chromosomes for mating based on some probability, selection of cross-site, and swapping the genetic material between two chromosomes based on their cross-site. The aim of crossover is to search parameter space.

   (c) *Mutation:* The mutation (changing bit from 0 to 1 or vice-versa) of the chromosomes is performed based on mutation probability. The mutation operator preserves the diversity among the population, prevent premature convergence, and restores lost information to the population. The probability of mutation is generally too low compared to probability of crossover.

(d) *Fitness evaluation:* Evaluate the fitness for newly generated population.

4. *Optimization loop.* Repeat steps 3 and 4 until some predefined error criteria or maximum number of iterations are attained.

Appendix B

Artificial Neural Network

Introduction

Artificial Neural Network (ANN) [9, 102, 139] is a simplified model of the biological neuron system. It can be considered as a parallel distributed processing system of highly interconnected computing elements. It acquires knowledge by learning from empirical data and makes it available for solving any given problem.

Neural network architecture:

One of the most popular neural network architectures is feedforward neural network. The architecture of a multilayer feedforward neural network is shown in Fig. B.1. It allows the signals to move only in forward direction from the input to the output layer through hidden layers without making feedback loops.

Learning methodology

There are three major learning methods that can be used for learning task. They are supervised learning, unsupervised learning and reinforcement learning.

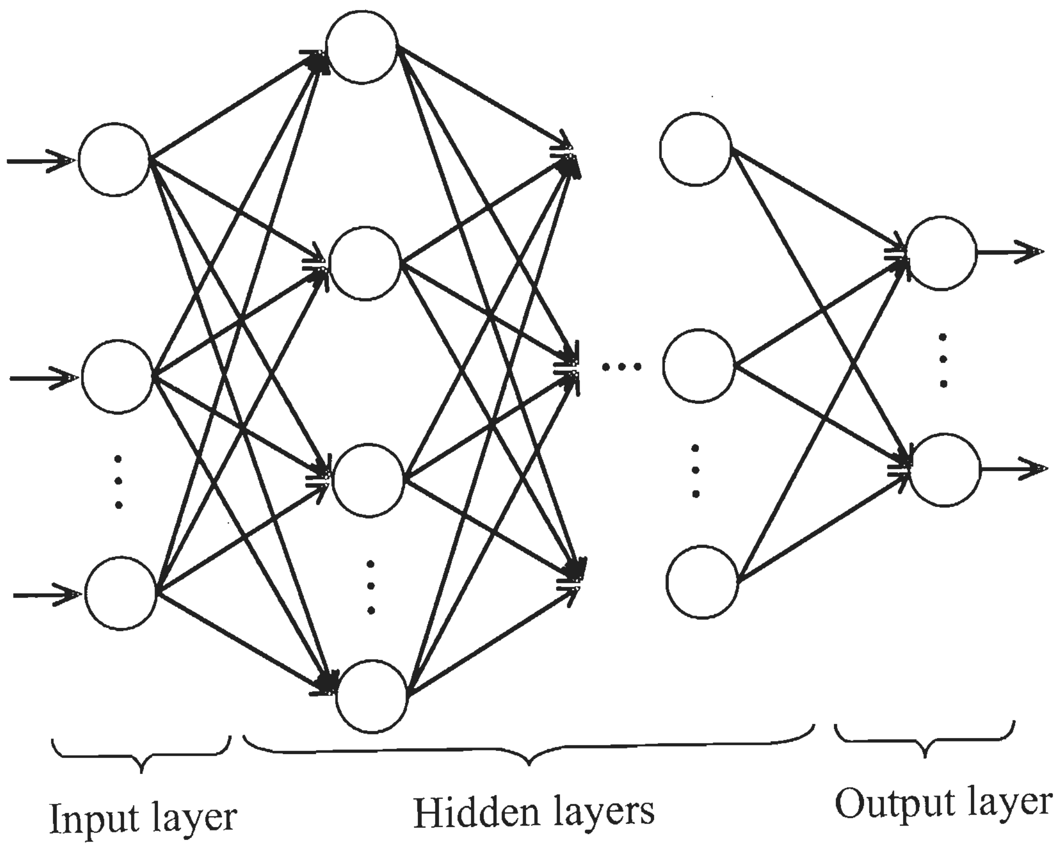

Figure B.1: An example of a multilayer feedforward neural network

Supervised learning: In this learning process, a training pattern from the training set is applied randomly to the network, error is calculated based on the desired response and the network synaptic weights are adjusted in order to minimize the error. Here, a teacher is assumed to be present behind the learning process.

Unsupervised learning: In this learning process, no output is presented to the network as if no teacher is available to present the desired response. Here, only some data and an objective function which is to be optimized are available during the learning.

Reinforcement learning: In this learning process, a teacher is present but do not specify the exact output, rather he gives reward for the correct answer and penalty for the wrong answer.

Backpropagation Learning Algorithm

Backpropagation learning is one of the most popular supervised learning methods for training multilayer feedforward neural network architecture. The steps followed by backpropagation learning algorithm are stated as follows:

ALGORITHM: *Backpropagation Learning Algorithm*

1. *Determine the structure of the neural network and other parameters:* This includes determining number of nodes in the input layer, number of nodes in the output layer, number of hidden layers, number of nodes in each hidden layer. There are also some other important parameters such as learning rate, momentum, number of training samples, etc., that are required to be determined carefully.

2. *Initialization of weights:* Initialize the network synaptic weights to small random values.

3. Repeat

   (a) For each training pattern

      i. *Forward pass:* The input patterns are applied to the input layer nodes which simply forward them to the input of the first hidden layer. The computation of input and output is performed at each hidden and output layer nodes.

      ii. *Calculate the error in the output layer:* Based on the output available at output layer node and the values of desired output, error is calculated at each output layer nodes.

      iii. *Error backpropagation and modification of weights:* In this step, the error at the output node is propagated back in the network and the synaptic weights of the network are updated based on the errors available at each of its posterior nodes.

   (b) end

4. Until the desired termination criteria is attained

Appendix C

Bacterial Foraging Optimization

Standard Bacterial Foraging Optimization algorithm

The standard Bacterial Foraging Optimization (BFO) Algorithm [8] is stated as below.

ALGORITHM: *The Bacterial Foraging Optimization Algorithm*

Initialization:

1. Initialize parameters Dim, S, N_c, N_s, N_{re}, P_{ed}, N_{ed}, $C(i)$ with $(i = 1, 2, ..., S)$, θ^i where,

   Dim: Dimension of the search space,

   S: Number of bacteria in the population,

   N_c: Number of chemotactic steps,

   N_{re}: Number of reproduction steps,

   N_s: Length of swimming,

   N_{ed}: Number of elimination-dispersal events,

   P_{ed}: Probability of elimination-dispersal events,

   $C(i)$: Size of the step taken in the random direction specified by the tumble,

$\theta^i(j,k,l)$: Position vector of the i-th bacterium, in j-th chemotactic step, k-th reproduction step and l-th elimination-dispersal event.

Iterative loops:

2. Elimination-dispersal loop: l=l+1

3. Reproduction loop: k=k+1

4. Chemotaxis loop: j=j+1

   (a) For $i = 1, 2, ..., S$, take a chemotactic step for bacterium i as follows:

   (b) Compute fitness function $J(i,j,k,l)$, and then let,
   $J(i,j,k,l) = J(i,j,k,l) + J_{CC}(\theta^i(j,k,l), P(j,k,l))$.

   (c) Let $J_{last} = J(i,j,k,l)$ to save this value since we may find a better cost via a run.

   (d) *Tumble:* Generate a random unit vector $\phi(i)$ with each element $m(i)$, m=1, 2,..., *Dim*, a random number on $[-1, 1]$.

   (e) *Move:* Following the Eq. (5.1).

   (f) Compute $J(i,j+1,k,l)$ as, $J(i,j+1,k,l) = J(i,j+1,k,l)+J_{CC}(\phi^i(j+1,k,l), P(j+1,k,l))$.

   (g) *Swim:* Consider only the i-th bacterium is swimming while the others are not moving, then,

      i. Let $m = 0$ (counter for swim length)

      ii. While $m < N_s$ (if have not climbed down too long)

         - Let m=m+1
         - If $J(i,j+1,k,l) < J_{last}$ (if doing better) then,
           $J_{last} = J(i,j+1,k,l)$ and $\theta^i(j+1,k,l) = \theta^i(j+1,k,l) +$

$C(i)\phi(i)$

and use this $\phi^i(j+1,k,l)$ to compute the new $J(i,j+1,k,l)$ as in (f).

- Else, if $m = Ns$ then end while loop.

(h) If $i \neq S$ then $i = i+1$ and go to (b) to process (i+1) bacterium.

5. If $j < N_c$ go to step 4 (i.e., continue chemotaxis as the life of the bacteria is not over).

6. *Reproduction:* Sort bacteria in ascending of their fitness value (J). Now, let $S_r = S/2$. The S_r bacteria with highest cost function (or fitness) values (J) die and the other half of bacteria population with the best values split (and the copies that are made are placed at the same location as their parent).

7. If $k < Nre$, go to step 3. We have not reached the specified number of reproduction steps. So we start the next generation of the chemotaxis loop.

8. *Elimination-dispersal:* For $i = 1, 2, ..., S$, eliminate and disperse each bacterium with probability P_{ed}. (If any bacterium is eliminated, then disperse other bacterium to random location in optimization domain in order to keep the number of bacteria in population constant.) If $l < N_{ed}$ then, go to step 2; otherwise end.

Modified Bacterial Foraging Optimization algorithm

The modified BFO Algorithm as presented and described in section 5.2.2 is stated as below.

ALGORITHM: *The Modified Bacterial Foraging Optimization Algorithm*

Initialization:

1. Initialize parameters Dim, S, N_c, N_s, N_{re}, P_{ed}, N_{ed}, $C(i)$ with $(i = 1, 2, ..., S)$, θ^i, w, and C_2 where,

   Dim: Dimension of the search space,

   S: Number of bacteria in the population,

   N_c: Number of chemotactic steps,

   N_{re}: Number of reproduction steps,

   N_s: Length of swimming,

   N_{ed}: Number of elimination-dispersal events,

   P_{ed}: Probability of elimination-dispersal events,

   $C(i)$: Size of the step taken in the random direction specified by the tumble,

   $\theta^i(j,k,l)$: Position vector of the i-th bacterium, in j-th chemotactic step, k-th reproduction step and l-th elimination-dispersal event,

   w : **Inertia weight,**

   C_2 : **Social coefficient of PSO algorithm.**

Iterative loops:

2. Elimination-dispersal loop: l=l+1.

3. Reproduction loop: k=k+1

4. Chemotaxis loop: j=j+1

   (a) For $i = 1, 2, ..., S$, take a chemotactic step for bacterium i as follows:

   (b) Compute fitness function $J(i,j,k,l)$, and then let,
   $J(i,j,k,l) = J(i,j,k,l) + J_{CC}(\theta^i(j,k,l), P(j,k,l))$.

   (c) Let $J_{last} = J(i,j,k,l)$ to save this value since we may find a better cost via a run.

(d) *Tumble:* Generate a random unit vector $\phi(i)$ with each element $m(i)$, m=1, 2,..., *Dim*, a random number on $[-1, 1]$.

(e) *Move:* Following the eq. (5.1).

(f) Compute $J(i, j{+}1, k, l)$ as, $J(i, j{+}1, k, l) = J(i, j{+}1, k, l) + J_{CC}(\phi^i(j+1, k, l), P(j+1, k, l))$.

(g) *Swim:* Consider only the i-th bacterium is swimming while the others are not moving, then,

i. Let m=0 (counter for swim length)

ii. While $m < N_s$ (if have not climbed down too long)

- Let $m = m + 1$
- If $J(i, j + 1, k, l) < J_{last}$ (if doing better) then, $J_{last} = J(i, j + 1, k, l)$ and $\theta^i(j + 1, k, l) = \theta^i(j + 1, k, l) + C(i)\phi(i)$

  and use this $\phi^i(j + 1, k, l)$ to compute the new $J(i, j + 1, k, l)$ as in (f).
- **Else (if position is not better)**

  Tumble to generate new unit random vector $\phi(i)$

  $J_{last} = J(i, j + 1, k, l)$ **and** $\phi^i(j + 1, k, l) = \phi^i(j, k, l) + C(i)\phi(i)$

  End if
- **Modify next step size $C(i)$ as,**

  $C(i) = 1/(1 + A)$, **where** $A = K/|J_{best} - J(i, j + 1, k, l)|$

iii. End while loop

(h) If $i \neq S$ then $i = i + 1$ and go to (b) to process (i+1) bacterium.

5. If $j < N_c$ go to step 4 (i.e., continue chemotaxis as the life of the bacteria is not over).

6. **Modify positions of bacteria by applying PSO operator as,**

(a) **For** $I = 1, 2, ..., S$

i. **Update** θ_{gbest} **and** $J_{best}(i, j, k, l)$

ii. **Update velocity and position of i-th bacterium as,**

$V_i^{new} = w \cdot V_i^{old} + C_2 r_1 (\theta_{gbest} - \theta^i(j, k, l))$

$\theta^i(j, k, l) = \theta^i(j, k, l) + V_i^{new}$

(b) **End for**

7. *Reproduction:* Sort bacteria in ascending of their fitness value (J). Now, let $S_r = S/2$. The S_r bacteria with highest cost function (or fitness) values (J) die and the other half of bacteria population with the best values split (and the copies that are made are placed at the same location as their parent).

8. If $k < N_{re}$, go to step 3. We have not reached the specified number of reproduction steps. So we start the next generation of the chemotaxis loop.

9. *Elimination-dispersal:* For $i = 1, 2, ..., S$, eliminate and disperse each bacterium with probability P_{ed}. (If any bacterium is eliminated, then disperse other bacterium to random location in optimization domain in order to keep the number of bacteria in population constant.) If $l < N_{ed}$ then, go to step 2; otherwise end.

Appendix D

Glossary

Antenna: It is a metallic structure used to transmit and/or receive radio waves.

Aperture coupled microstrip antenna: It is a microstrip antenna in which the power coupling between the patch and the feedline is done via the aperture (slot) on the ground plane.

Axial ratio: It an important antenna parameter that is defined as the ratio of major axis to minor axis of the field polarization.

Axial ratio bandwidth: It is the frequency range over which the antenna exhibits axial ratio parameter to be at a specified level (which is generally taken less than or equal to 3 dB for circular polarization).

Bandwidth: Bandwidth is the frequency range within which the component meets desired specification (say gain, impedance or VSWR).

Circular polarization: When a field vector at a given point in space rotates with a same magnitude and a phase shift of 90° is said to be circularly polarized.

Cross validation: It is a procedure to estimate the performance of a classifier/regressor. In a v-fold cross validation, training set is divided into

v-subsets of equal size. Repeatedly each subset is tested using the classifier/regressor which is trained on remaining v-1 subsets.

Crowding distance: It is a metric that determines density of solutions around a particular solution.

Evolutionary algorithm: It is a subset of evolutionary computation that is implemented as evolutionary process to form optimization algorithm.

Fitness: The fitness is a measure of how well a particular solution performs at solving the problem.

Fitness function: It is an objective function that determines fitness of a solution.

Foraging theory: It is a theory based on foraging behavior of biological population (animals) that search for nutrients to maximize their energy intake per unit time.

Gyrotron: It is an electronic device capable of generating high power at microwave and millimetric wavelengths.

Klystron: It is a widely used vacuum tube as a generator or as a microwave amplifier.

Microstrip antenna: It is a passive component that consists of a radiating element (patch) mounted over a grounded dielectric substrate.

Microwave filter: It is a two port network to control frequency response in microwave systems.

Microstrip via: It is a component used to interconnect micrstrip circuits.

Pareto front: The set of objective function vectors corresponding to Pareto-optimal set in the objective space is referred to as Pareto front.

Pareto-optimal set: A set of non-dominated solutions with respect to given objectives is referred to as Pareto-optimal set. A solution is non-dominated if its one objective can not be improved without loss of one or more objectives.

Polarization: Polarization is a property of an electromagnetic wave describing the time varying direction and relative magnitude of the field vector at a given point in space.

RF-window: It is a component used in the output system of high power microwave/millimeter-wave devices for power transition from the device to transmission line and vice versa.

Scattering matrix: It is a linear relationship between input and output that involves precisely measurable parameters which are known as S-parameters. S-parameters such as S_{11} (reflection coefficient) and S_{21} (transmission coefficient) are important for measuring transmission and reflection characteristics of a two port network.

Spurious modes: The modes other than the desired mode are spurious modes. The design should be carried out in such a way that the spurious mode contents are reduced.

Swarm intelligence: It is a problem solving behavior that emerge from a group (swarm) of agents which communicate among each other based on their local environment.

Tapered transmission line (Taper): It is a transmission line section which is used to connect transmission lines of different cross sectional areas.

Voltage Standing Wave Ratio (VSWR): It is a ratio of the maximum voltage to minimum voltage (i.e., V_{max}/V_{min}) due to mismatch of the load in the transmission line.

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1. **N. Chauhan**, Y. K. Roy, A. Kumar, M. V. Kartikeyan, and A. Mittal. SVM-PSO based modeling and optimization of microwave components. ***FREQUENZ - Journal of RF-Engineering and Telecommunications,*** 62:18-24, Jan/Feb 2008.

2. **N. Chauhan**, M. V. Kartikeyan, and A. Mittal. Support vector driven genetic algorithm for the design of circular polarized microstrip antenna. ***International Journal of Infrared Millimeter Waves (Springer),*** 29(6):558-569, June 2008.

3. **N. Chauhan**, A. Mittal, D. Wagner, M. V. Kartikeyan, and M. K. Thumm. Design and optimization of nonlinear tapers using particle swarm optimization. ***International Journal of Infrared Millimeter Waves (Springer),*** 29(8):792-798, August 2008.

4. **N. Chauhan**, M. V. Kartikeyan, and A. Mittal. A review on the use of soft computing methods for design applications of microwave domain. ***FREQUENZ - Journal of RF-Engineering and Telecommunications,*** (Article Id. #911, Accepted for publication in Issue - Jan/Feb 2009).

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1. **N. Chauhan**, M. V. Kartikeyan, and A. Mittal. CAD of RF windows using multi-objective particle swarm optimization. ***IEEE Transactions on Plasma Science,*** **(Under review – minor revision)**.

2. **N. Chauhan**, M. V. Kartikeyan, and A. Mittal. A modified particle swarm optimizer and its application to the design of microwave filters. ***International Journal of Infrared Millimeter Waves (Springer),*** **((Under review – minor revision)**.

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1. **N. Chauhan,** M. V. Kartikeyan, and A. Mittal. Design of RF window using multi-objective particle swarm optimization. In ***Proceedings of International Conference on Recent Advances in Microwave Theory and Applications (MICROWAVE-08),*** pages 34-37, University of Rajasthan, Jaipur, India, November 21-24, 2008.

2. **N. Chauhan**, B. R. Vasista, M. S. Reddy, M. V. Kartikeyan, and A. Mittal. Modified bacterial foraging optimization and its application for the design of a nonlinear taper. In ***Proceedings of International Conference on Advances in Computing Technologies (ICACT-2008),*** Pages 23-28, Hyderabad, India, December 26-27, 2008.

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1. **N. Chauhan**, S. Kamakshi, A. Kumar, D. Wagner, M. V. Kartikeyan, A. Mittal, and M. Thumm. Design and optimization of nonlinear tapers for high power gyrotrons. ***National Symposium on Plasma (PLASMA-2007)***, Institute of Plasma Research, Gandhinagar, India, December 2007. (A poster presentation)

2. **N. Chauhan**, M. V. Kartikeyan, and A. Mittal. Design of critical output components of high power gyrotrons using particle swarm optimization. In ***Proceedings of National Symposium on Vacuum Electronic Devices & Applications (VEDA-2009)***, pages Gyro3.1–Gyro3.3, Institute of Technology, Banaras Hindu University, Varanasi, India, January 8-10, 2009.

Papers under preparation

1. **N. Chauhan**, B. R. Vasista, M. S. Reddy, M. V. Kartikeyan, and A. Mittal. Modified bacterial foraging optimization for the design of high power microwave components.