FEDERAL UNIVERSITY OF ITAJUBA
GRADUATE PROGRAM IN
COMPUTER SCIENCE AND TECHNOLOGY

PSO Based Methodology for Optimization of Patch Antenna Design for ISM and 5G Bands Applications

Marcos Vinícius dos Santos Silva

June 2024
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Thesis work submitted to the Graduate Program in Computer Science and Technology as part of the requirements for obtaining the Master of Science degree in Computer Science.

Concentration area: Hardware and Basic Software.

Advisor: PhD. Rodrigo Aparecido da Silva Braga
Co-advisor: PhD. Fernanda Rodrigues Silva

June 2024
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Acknowledgements

I would like to express my deepest gratitude to my esteemed mentors, Dr. Rodrigo Aparecido da Silva Braga and Dr. Fernanda Rodrigues Silva, whose invaluable guidance, unwavering support, and insightful critiques have been instrumental in the completion of this thesis.

I am also deeply indebted to the Universidade Federal de Itajubá for providing the essential technical and theoretical foundation for this research. I extend my sincere appreciation to the dedicated laboratory technicians, knowledgeable professors, and supportive research assistants whose contributions have been invaluable.

Furthermore, I wish to acknowledge the support and encouragement of my family and friends, especially my parents and partner, whose love and belief in me have been a constant source of strength and motivation.

"The important thing is not to stop questioning. Curiosity has its own reason for existing."– Albert Einstein

Abstract

This thesis presents a novel methodology for optimizing patch antenna designs for both ISM (industrial, scientific, and medical) and 5G frequency bands, based on the particle swarm optimization (PSO) algorithm. Traditional design methods rely on equations to approximate antenna dimensions based on target frequencies, often requiring iterative adjustments to achieve desired performance specifications. This research demonstrates that by employing PSO to estimate geometric parameters, the time-consuming fine-tuning process can be significantly reduced. The proposed approach is validated through the design of patch antennas for both ISM and 5G bands. Results indicate substantial improvements in return loss and size reduction, achieving a 25% decrease in antenna size for ISM applications and a 12% reduction for 5G designs. This research contributes to the advancement of antenna design methodologies, showcasing the potential of PSO for efficient and effective optimization across different frequency bands.

Key-words: Antenna design, particle swarm optimization, patch antenna, ISM band, 5G band, optimization methodology.

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α	Weight coefficient for antenna dimensions in the cost function
β	Weight coefficient for return loss in the cost function
γ	Weight coefficient for resonance frequency error in the cost function
c	Speed of light in a vacuum
C_{func}	Cost function
dB	Decibel
Fi	Feed inset of the antenna
f_r	Resonance frequency
g	Global best position
GHz	Gigahertz
Gpw	Gap width of the antenna
h	Height of the dielectric substrate
L	Length of the microstrip antenna patch
L_{eff}	Effective length
ΔL	Extended Length
mm	Millimeter
p_i	Personal best of the i-th particle
r_1, r_2	Random numbers
S_{11}	Reflection coefficient
$\tan\delta$	Loss tangent of the substrate material
v_i	Velocity of the i-th particle
W	Width of the microstrip antenna patch
Wf	Feed width of the antenna

x_i	Position of the i-th particle
ε_r	Relative permittivity of the substrate material
ε_{eff}	Effective dielectric constant
λ	Wavelength
ϕ_1, ϕ_2	Acceleration coefficients
ω	Inertial weight

List of abbreviations and acronyms

5G	Fifth Generation (mobile network)
AI	Artificial Intelligence
ANN	Artificial Neural Network
BFO	Bacterial Foraging Optimization
CST	Computer Simulation Technology (software)
GPS	Global Positioning System
HFSS	High-Frequency Structure Simulator (software)
ISM	Industrial, Scientific, and Medical
ML	Machine Learning
MIMO	Multiple-Input Multiple-Output
N/A	Not Applicable
PCB	Printed Circuit Board
PSO	Particle Swarm Optimization
RFID	Radio Frequency Identification

Contents

1 Introduction

The introduction of wireless systems to the communication grid has marked a shift in the way information is transmitted and received. The core of these systems are antennas, the critical components that make transmission and reception of waves possible [1, 2]. Among many types of antennas, microstrip patch antennas have emerged as a common choice for different projects due to their compact size, performance, and fabrication cost [3]. Examples of these applications are mobile devices and satellite communication [4].

Despite their widespread use, microstrip patch antennas also have limitations, especially because the requirements from the design performance increase continuously as technology evolves. As the tech industry moves towards more compact and portable devices, the pressure to design smaller antennas without lost performance intensifies [5]. This miniaturization need has provided an incentive for the study and explorations of creative solutions, such as the use of fractals and hybrid combinations in the patch shape. However, the introduction of these techniques can increase design complexity. To address this problem, artificial intelligence (AI) has been pointed out as a potential solution [6].

Since the traditional design methodologies typically involve labor-intensive manual adjustments or mathematical optimizations, which are often time-consuming and may not always deliver optimal results, the use of AI becomes attractive for this particular application [7]. The integration of techniques such as machine learning (ML) and artificial neural networks (ANNs) offers promising opportunities for improving the design, simulation, and optimization of antennas [8].

This thesis specifically explores the application of Particle Swarm Optimization (PSO) in the optimization of microstrip patch antennas. PSO follows the logic of social behavior patterns of swarms in nature to continuously refine design parameters, enabling the efficient convergence on optimal solutions. By incorporating PSO into the antenna design process, this work aims to overcome the limitations of conventional design methods while providing broader options that could be used in different application scenarios.

1.1 Justification

Antenna size plays a critical role in the performance of wireless communication systems. As antenna size decreases, the antenna bandwidth also decreases, which poses a challenge for compact antenna design [9]. The performance of reduced-size antennas must be comparable to that of their larger counterparts, as smaller antennas are increasingly preferred in modern wireless systems for their portability and aesthetic appeal [10].

Consequently, researchers and engineers must develop innovative design techniques and materials to overcome the limitations imposed by smaller antennas while maintaining the desired performance characteristics.

Designing an antenna at a required operating frequency is fundamentally an optimization problem since the patch geometric parameters need to be adjusted to reduce the error between the performance of the antenna designed according to the simplified equations and the actual antenna [9].

Traditionally, the design of antennas is a complex and iterative process that involves manual trial and error methods, or mathematical optimization techniques [11]. Through a set of equations, it is possible to design a base antenna according to the required frequency resonance, which can be further improved manually by making small modifications to the antenna dimensions. Likewise, other requirements such as impedance matching, radiation pattern, gain, bandwidth, and radiation efficiency can be adjusted through the fine-tuning of input impedance, ground plane height, and substrate width [11].

However, in recent years, there has been a growing trend toward using artificial intelligence techniques to improve the efficiency and accuracy of antenna design. The AI techniques, such as ML and Artificial Neural Networks (ANNs), have been used to model and predict the behavior of antennas, allowing for more efficient optimization [6].

In addition to improving the optimization process, AI techniques have also been used to enhance the accuracy of antenna design simulations. ANNs, for example, have been used to model the behavior of antennas in complex environments, such as in the presence of obstacles or in multi-path fading scenarios [12].

Many researchers have explored machine learning algorithms as a solution for the design of antennas. These solutions can be broadly categorized into two distinct yet interconnected areas [8]. The first covers optimization through data training, where algorithms like ANNs play a crucial role. These algorithms use historical simulation data to leverage past designs and optimize the parameters of new antenna models. This approach not only streamlines the design process but also improves accuracy and reliability in the performance of the antennas [8].

The second area is the enhancement of evolutionary computation algorithms. Where, machine learning is applied to evolutionary algorithms like PSO, creating a synergistic relationship that improves the capabilities of these computational methods. By embedding ML into the framework of evolutionary algorithms, the antenna design process becomes more efficient and effective. The algorithms are able to rapidly converge on optimal solutions, significantly reducing the time and computational resources required for design and testing. The integration accelerates the design step and supports a more innovative exploration of antenna capabilities, enabling designers to achieve desired levels of performance and efficiency [8].

Usually, the ML algorithms are mainly applied in a specific step of the design process. Since the design goes through several steps, such as estimation of base parameters, feedline, gaps, and further tuning based on tests, the PSO algorithm, which converges to an optimal solution in a complex space of possibilities, may offer a better and less costly solution when applied to the complete design process [7].

While PSO represents a more direct method of optimization, seamlessly integrating into the antenna design process, it operates by iteratively refining the antenna parameters, leveraging a swarm intelligence algorithm that mimics social behavior patterns observed in nature [13]. This method allows for direct, real-time adjustments to the antenna design, converging towards an optimal solution through a dynamic exploration of the design space. The integration of PSO within the design process enables it to respond smoothly to changes in design parameters, making it an ideal choice for scenarios where rapid optimization is required [14].

On the other hand, ANNs and similar machine learning techniques rely heavily on pre-existing databases, following a three-step approach: simulating electromagnetic characteristics, storing these simulations in a database, and then using this accumulated data to train the ANN [8]. This training enables the ANN to recognize complex patterns and relationships within the data, subsequently applying this learned knowledge to predict antenna designs. While this approach offers the advantage of learning from an array of past simulations and uncovering insights that would otherwise be overlooked in direct methods, it inherently depends on the quality and comprehensiveness of the database. Additionally, the process of training the ANN can have more computational costs, especially with large databases [8].

Comparatively, the direct optimization approach is faster and more adaptable to specific designs. However, it may fail to capture insights that a well-trained ANN could provide, especially in cases where past data presents a wide variety of scenarios and parameters. In contrast, ANNs excel in scenarios where historical data is rich, allowing the algorithm to extract interactions within the data, which can lead to more innovative and refined designs. That being said, some researchers propose a combined approach, aiming for the benefits of both methods [12, 15, 16].

Table 1 presents a selection of these works to provide a comprehensive understanding of the research being conducted in PSO-based microstrip antenna design. Table 1 highlights each study's key features and achievements, such as the antenna shape, specific AI techniques used, the resonance frequency, the achieved patch area reduction, dimensions, and simulation software used.

Table 1 – Study of Existing PSO-based Microstrip Antenna Design Methods

Ref	Shape	AI Technique	Frequency	Results	Dimensions	Software
[9]	Hemicircle hybrid	PSO	2.45 and 7.0 GHz	N/A	32x28mm	HFSS
[12]	Tree hybrid fractal	ANN-PSO	2.45 GHz	N/A	Lg = 17.70 mm	HFSS
[17]	Pinwheel fractal	PSO	0.98,1.59, 2.22, 2.45, and 3.6 GHz	50% reduction	12.5x11.5 mm	HFSS
[15]	Circular fractal	PSO-ANN	2.45 GHz	35.5% reduction	R = 13.50 mm	CST
[18]	Square (Ground fractal)	PSO	2.4 and 4.9 GHz	69.08% reduction	10x10mm SF=1/6	HFSS
[16]	Tree hybrid fractal	BFO-PSO	5.2 and 10.6 GHz	43.1% reduction	22.9x21.9mm 75.09 ∘	HFSS

Article [9] employed a PSO-based optimization technique to design a hemicircle hybrid antenna operating at 2.45 and 7.0 GHz, though specific performance improvements were not detailed. This early work demonstrates the versatility of PSO in handling complex hybrid structures, establishing a foundation for further research in multi-band antennas.

In contrast, [12] and [15] advanced the field by integrating Artificial Neural Networks (ANN) with PSO to optimize fractal-based antenna designs, specifically at the 2.45 GHz band. The inclusion of ANN allowed for enhanced predictive capabilities in the optimization process, leading to a notable size reduction of 35.5% in [15]. The use of fractal geometries in these studies highlights the effectiveness of combining AI techniques for compact antenna design, particularly in frequency bands that are critical for wireless communication.

Further emphasizing the capability of PSO in achieving compact designs, articles [17] and [18] focused exclusively on size reduction through PSO optimization applied to fractal antenna shapes. [17] achieved a 50% reduction across multiple frequency bands, including 2.45 GHz, showcasing the flexibility of PSO in handling multi-band requirements. Meanwhile, [18] achieved a reduction of 69.08% at 2.4 and 4.9 GHz, demonstrating the significant impact of fractal geometries when combined with PSO for area reduction.

Lastly, [16] explored a hybrid approach by combining Bacterial Foraging Optimization (BFO) with PSO, targeting fractal-shaped antennas operating at higher frequency bands (5.2 and 10.6 GHz). This study demonstrated a substantial size reduction of 43.1%, further validating the potential of hybrid optimization techniques in addressing the challenges of modern antenna design, particularly in higher-frequency applications.

The traditional optimization methods used in antenna design often focus on a single design parameter or optimization target, resulting in sub-optimal solutions that may not meet all performance requirements. By automating the design of the antenna, with options to adjust the requirements, the method proposed in this article takes into account multiple design parameters and optimization targets, resulting in a more focused and well-rounded solution for different problems.

Therefore, the contribution of this paper to the field of antenna design optimization is the development of an automated optimization process that considers multiple design parameters and optimization targets.

1.2 Objective

The main objective of this thesis is to propose an optimization methodology for microstrip patch antenna design based on a particle swarm optimization technique. This exploration is driven by the need for compact, high-performance antennas in the rapidly evolving field of wireless communication. To achieve the proposed general objective, this work delineates three specific objectives:

- Develop a generalized PSO-based method for microstrip antenna design that considers multiple objectives, optimizing key performance indicators such as size, resonance frequency, bandwidth, and return loss. The intent is to create a flexible design tool that can accommodate a wide range of design specifications;
- Validate the effectiveness of the developed PSO-based design methodology by applying it to the design of antennas for common applications, such as the ISM band and 5G band. This will involve designing, simulating, and comparing the results to assess improvements in performance.

1.3 Structure of the Work

This thesis is structured into five main sections to provide a comprehensive understanding of the process and outcomes of the proposed design. Section I sets the stage by presenting the study's general considerations, motivations, and objectives. Section II discusses the literary background used in this work. Specifically, the design and operation of microstrip antennas. Section III details the steps involved in the design process. Section IV presents the outcomes of the study, including the optimized antenna designs, their performance characteristics, and a comparison with benchmarks from the literature and the base antenna. Section V summarizes the main findings, highlights the contributions of the research, and suggests opportunities for future work in the area of microstrip antenna design using artificial intelligence techniques.

2 Patch Antennas for ISM and 5G band applications

Microstrip antennas, or patch antennas, consist of a conducting patch on one side of a dielectric substrate and a ground plane on the other [19]. The versatile features of microstrip antennas, such as their low profile, lightweight construction, and compatibility with printed circuit board (PCB) technology, have paved the way for their widespread adoption across various applications. These antennas are extensively used in wireless communication systems, both as transmitting and receiving elements in mobile phones, wireless routers, and other communication equipment. The compact size and flexibility in shape of microstrip antennas make them suitable for integration into the limited spaces of portable electronic devices [3].

In satellite communications, microstrip antennas are used due to their low mass and small size, which are important in space applications where payload weight is a major consideration. An example is the arrays of microstrip antennas used in beam-steering systems, vital for maintaining communication with moving satellites [20]. Moreover, the inherent reliability and durability of these antennas under harsh environmental conditions make them ideal for space and air applications.

Radio Frequency Identification (RFID) systems also benefit from the use of microstrip antennas. Considering that these systems focus on tracking and identification for logistics, they require compact and efficient antennas with specific radiation patterns. Microstrip antennas can be easily designed to meet these specific requirements [21].

Likewise, the advancement in microstrip antenna technology has contributed to new fields such as wearable electronics, where antennas must be printed on non-traditional surfaces and operate efficiently close to the human body. The adaptability of microstrip antennas in terms of shape and size, combined with their ability to operate across a wide range of frequencies, makes them a good choice for integration into wearable devices for health monitoring, personal communication, and location tracking [22].

ISM (Industrial, Scientific, and Medical) and 5G band patch antennas are essential components of modern wireless communication systems. The ISM band, particularly the 2.45 GHz frequency, is widely used for applications such as Wi-Fi, Bluetooth, and microwave ovens due to its unlicensed spectrum availability and robust performance in diverse environments [23]. On the other hand, 5G technology, operating in the 3.3 to 3.8 GHz range, represents the next generation of mobile networks, promising significantly enhanced data rates, reduced latency, and improved connectivity for several applications, from autonomous vehicles to smart cities [24]. The widespread use of 2.45 GHz antennas facilitates the availability of extensive references, enabling comprehensive comparisons and validation of research findings. Additionally, the inclusion of the 5G band due to its innovative potential highlights the relevance and forward-thinking nature of this research.

Overall, microstrip antennas offer a range of benefits and are extensively used in wireless systems. Understanding the radiation pattern, performance parameters, and design considerations is essential for optimizing the performance of these antennas. By shaping the radiation pattern, considering parameters such as patch dimensions and substrate properties, and addressing design factors such as feed line placement and impedance matching, microstrip antennas can be designed to meet specific application requirements [20].

2.1 Design Considerations

Microstrip antennas are chosen for several applications due to their compactness and cost-effectiveness. However, other performance parameters must be considered when designing an antenna. These parameters include gain, resonance frequency, and return loss [25]. Optimizing these parameters ensures the microstrip antenna meets the desired specifications and performs effectively within its intended application.

Fig. 1 illustrates a standard rectangular patch microstrip antenna. The patch, with length (L) and width (W), is located on the top side of the dielectric substrate. The substrate of height (h) is positioned between the patch and the ground plane. Below the substrate lies the ground plane, which serves as a reference point for the antenna. Connected to the rectangular patch, the feedline is responsible for delivering the input signal. The precise dimensions and the arrangement of these elements are essential for determining the antenna's performance [26].

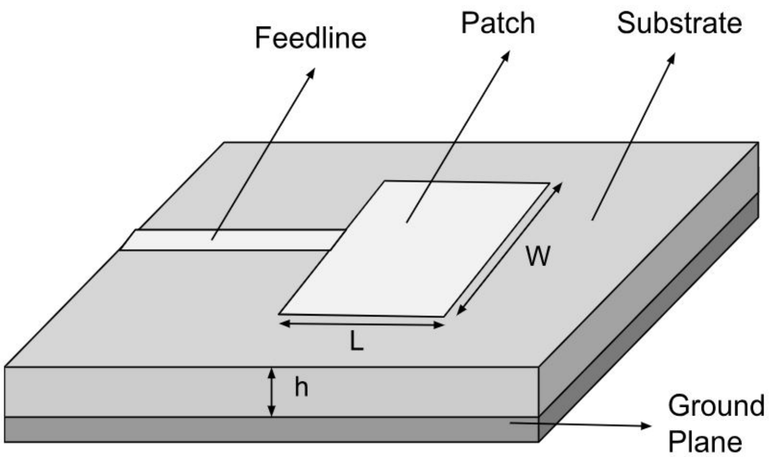


Figure 1 – Microstrip Patch Antenna.

2.1.1 Antenna Gain

Gain is a measure of an antenna's ability to direct or concentrate radio frequency energy in a particular direction when compared to a hypothetical isotropic radiator that emits equally in all directions [26]. The gain of a microstrip antenna is influenced by its physical dimensions and the electrical properties of the substrate. Larger patches and substrates with higher dielectric constants can increase the gain but may also affect the antenna's bandwidth and efficiency [27].

Antennas achieve gain by concentrating the radiated energy in a specific direction while sacrificing gain in other directions [1]. For mobile applications, minimizing upward and downward radiation while concentrating the signal in the forward direction is advantageous. This can be achieved by shaping the radiation pattern of microstrip antennas, improving their performance, and providing directional coverage tailored to specific requirements [28].

2.1.2 Resonance Frequency

The resonance frequency (f_r) is usually the starting point of the antenna design process. It defines the frequency range within which the antenna is expected to operate efficiently. The choice of f_r is dictated by the application for which the antenna is being designed, such as a specific communication band (Wi-Fi, Bluetooth, GPS). The frequency directly influences the dimensions of the radiating patch, as these dimensions are typically a fraction of the wavelength (λ) at the desired f_r [26].

The simplified resonance frequency f_r can be calculated using the following equation:

$$f_r = \frac{c}{2L\sqrt{\varepsilon_r}} \tag{2.1}$$

Where,

- f_r is the resonant frequency;
- c is the speed of light in a vacuum (3×10^8 meters per second);
- L is the length of the microstrip antenna;
- ε_r is the relative permittivity of the substrate material.

2.1.3 Radiation Pattern

The radiation pattern of an antenna describes the spatial distribution of the radiated power and is an important characteristic of microstrip antennas. It can be represented mathematically or graphically, showcasing properties such as power flux density, radiation intensity, field strength, and polarization. In the far-field region, the radiation pattern is determined with respect to space or directional coordinates [29].

For microstrip antennas, the radiation pattern is predominantly determined by the shape and size of the radiating patch, as well as the dielectric properties of the substrate [30]. The pattern can be broadly categorized into two main types, omni-directional and directional. Omni-directional patterns radiate power uniformly in all directions in a single plane, making them ideal for applications requiring broad coverage. In contrast, directional patterns focus the radiated power in specific directions, offering higher gains but limited coverage areas [31].

2.1.4 Return Loss

Return loss is a critical performance parameter in antenna design for several reasons. High return loss ensures that more power is effectively radiated into space, contributing to better signal transmission and reception. While, low return loss leads to increased power losses within the system, reducing its effectiveness [32]. Moreover, return loss also affects the bandwidth and frequency response of the antenna. A wider bandwidth typically corresponds to a higher return loss, indicating that the antenna can operate efficiently over a broader range of frequencies without significant losses [33].

The selection of resonance frequency, substrate material, and substrate thickness are critical steps in the microstrip antenna design process, setting the stage for subsequent design decisions such as the determination of the patch dimensions, feed type, and impedance matching techniques.

2.1.5 Substrate

The substrate material of microstrip antenna project is chosen based on its dielectric constant (ε_r), loss tangent ($\tan\delta$), and mechanical properties [26]. A higher ε_r results in a smaller antenna size for a given frequency but can also reduce the bandwidth and increase the losses. The loss tangent indicates the amount of electromagnetic energy absorbed by the substrate material, affecting the antenna's efficiency. Mechanical properties, including the substrate's rigidity and thermal stability, are also important considerations, especially in environments subject to physical stress or temperature variations [3].

The thickness of the substrate (h) impacts the antenna's bandwidth and radiation pattern. A thicker substrate can offer a wider bandwidth due to increased space for the electromagnetic fields to propagate, but it may also lead to a more significant fringing effect and a higher radiation angle away from the surface plane [26]. The choice of h involves balancing the need for bandwidth with the desire for a compact design and specific radiation characteristics.

These initial design parameters are correlated, and their selection must consider the trade-offs involved to meet the antenna's performance requirements. For example, while a high dielectric constant substrate can reduce the antenna's size, it might necessitate compromises in terms of bandwidth and efficiency. Similarly, optimizing the substrate thickness for a wider bandwidth might require adjustments in the patch dimensions or the selection of a substrate material with a suitable dielectric constant.

2.1.6 Feedline

Each feeding technique impacts the antenna's performance, bandwidth, and ease of integration with other components. The choice of feed method depends on the specific requirements of the application, including impedance matching, bandwidth, size constraints, and fabrication considerations [34].

2.1.6.1 Coaxial Feed

The coaxial or probe feed technique involves inserting a coaxial cable through the substrate to make direct contact with the radiating patch. This method allows for precise control over the feed point's location, enabling the designer to adjust the impedance matching by moving the feed point towards or away from the patch center. The closer the feed point is to the edge of the patch, the higher the impedance, which can be beneficial for matching purposes. However, the coaxial feed can introduce unwanted inductance and may disrupt the radiation pattern if not properly designed [35]

2.1.6.2 Aperture Coupling

Aperture coupling involves feeding the radiating patch indirectly through an aperture or slot in the ground plane, separating the feed line from the patch with a dielectric layer. This technique minimizes perturbations to the radiating element, potentially offering better bandwidth and radiation pattern control [36]. The aperture coupled feed allows for dual-polarization and frequency operation, making it versatile for complex antenna systems. However, it is more complex to design and manufacture due to the multi-layer structure [35].

2.1.6.3 Microstrip Feed

The microstrip line feed involves a conducting strip directly connected to the edge of the radiating patch, acting as both the feed line and the matching element. This technique facilitates easier integration with printed circuit boards and can provide a cleaner radiation pattern compared to the coaxial feed [35]. The main challenge with the microstrip line feed is achieving a wide bandwidth, as the feed line and the patch must be carefully designed to ensure effective impedance matching over the desired frequency range [37].

2.2 Traditional Patch Antenna Design

Design considerations for microstrip antennas are driven by system requirements for low-profile design, lightweight construction, cost-effectiveness, and easy integration with microwave-integrated circuits, as emphasized by [29]. These considerations make microstrip antennas suitable for applications where space constraints and performance optimization are crucial factors.

When designing microstrip antennas, several factors must be carefully considered. The physical and electrical properties of the substrate material play an important role in the antenna's performance. Specifically, the dielectric constant (ε_r) of the substrate influences the antenna's size and resonance frequency. A higher ε_r typically results in a smaller antenna size but may reduce the bandwidth and increase the loss [26].

The dimensions of the patch, length (L) and width (W), will influence the resonant frequency (f_r) of the antenna. The length of the patch is approximately half the wavelength ($\lambda/2$) of the desired resonant frequency in the substrate medium, making the effective length (L_{eff}) important for accurate design calculations. While the width of the patch affects the radiation pattern and impedance bandwidth, wider patches generally offer wider bandwidths [26].

Achieving optimal impedance matching between the microstrip line and the patch is important for maximizing power transfer and minimizing reflections at the feed point. This can be accomplished through the selection of the feed line's position and characteristics, ensuring that the antenna's input impedance matches the characteristic impedance of the feed line. Techniques such as quarter-wave impedance transformers, inset feed, and probe feeding are commonly employed to achieve desired impedance levels [20].

The placement of the microstrip feed line and achieving impedance matching are also essential for optimizing the antenna's performance [20].

2.2.1 Width (W)

The width of the patch is mostly determined to control the radiation pattern and to achieve a desired impedance, typically 50 Ω for most applications [38]. The width can be calculated using the following equation:

$$W = \frac{c}{2f_r\sqrt{\frac{\varepsilon_r+1}{2}}} \tag{2.2}$$

Where,

- W is the width of the microstrip patch;
- c is the speed of light in a vacuum (3×10^8 meters per second);
- f_r is the resonance frequency;
- ε_r is the relative permittivity of the substrate material.

This equation provides a starting point for the patch width, ensuring that the antenna's resonates at the desired frequency with a controlled impedance level.

2.2.2 Dielectric Constant (ε_{eff})

The effective dielectric constant (ε_{eff}) is a parameter that accounts for the mixed dielectric medium (substrate and air) around the patch due to the fringing fields. It is a weighted average of the dielectric constant of the substrate (ε_r) and the air (approximately 1). The fringing fields increase the effective electrical path length, which in turn affects the velocity of propagation of the waves on the patch surface and thereby the resonant frequency [39]. The effective dielectric constant can be calculated using the equation:

$$\varepsilon_{eff} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left(\frac{1}{\sqrt{1+12\frac{h}{W}}}\right) \tag{2.3}$$

This equation reflects how ε_{eff} is influenced by the height (h) of the substrate and the width (W) of the patch. The fringing effect becomes more evident with thicker substrates and narrower patches, leading to a higher ε_{eff} and thus a lower resonant frequency than would be predicted by considering the substrate's dielectric constant alone.

2.2.3 Effective Length (L_{eff})

The effective length of the patch contains the physical length of the patch and an additional length due to the fringing fields around the patch edges. The fringing effect extends the electrical length of the patch, lowering the resonant frequency [40]. To estimate L_{eff}, the subsequent steps are followed:

1. Determine the Extended Length (ΔL):

$$\Delta L = 0.412h \left(\frac{\varepsilon_{eff} + 0.3}{\varepsilon_{eff} - 0.258} \right) \left(\frac{W + 0.264}{W + 0.8} \right) \tag{2.4}$$

Where,

- h is the substrate thickness;
- ε_{eff} is the effective dielectric constant, calculated as previously described.

2. Calculate the actual Length (L): With ΔL determined, the actual length of the patch can be calculated by considering the desired resonant frequency and the effective dielectric constant:

$$L = \frac{c}{2f_r\sqrt{\varepsilon_{eff}}} - 2\Delta L \tag{2.5}$$

This step ensures that the patch resonates at f_r by compensating for the fringing effect, which effectively increases the electrical size of the patch.

The effective length (L_{eff}) is then $L + 2\Delta L$, providing a more accurate representation of the patch's resonant behavior.

3 Optimization Problem Definition

This section details the methodology followed in designing a rectangular microstrip antenna using the Particle Swarm Optimization (PSO) algorithm, implemented through a combination of MATLAB and CST software. The main goal of the design is to reduce the physical area of the antenna while optimizing the return loss and considering the resonance frequency and minimum bandwidth requirements.

The research methodology was structured to ensure a comprehensive and systematic approach to optimizing microstrip antenna design using PSO. The process began with a literature review to gain a deep understanding of the strategies employed in antenna design through artificial intelligence techniques, with a particular focus on PSO and similar algorithms. This review informed the development of a new strategy that accounts for multiple evaluation parameters during the optimization process, ensuring a holistic approach to antenna design.

Following the literature review, the key design parameters were defined, including antenna size, resonance frequency, and minimum bandwidth. A cost function was carefully formulated to evaluate the trade-offs among these parameters, striking a balance between the physical size and the performance of the antenna. The design process was further refined by imposing constraints, specifically limiting the antenna to a rectangular shape with inlets in the feed connection. These constraints were incorporated to ensure that the final designs adhered to specified requirements. Additionally, a base antenna resonating at the proposed frequency was designed according to equations (2.2) and (2.5) to set reasonable parameter limitations and serve as a benchmark for later comparisons.

The PSO algorithm was then meticulously designed to search for optimal solutions within the defined design space, guided by the cost function and design constraints. This algorithm was implemented in MATLAB and iteratively applied to optimize the antenna design. The integration of MATLAB with CST simulation software was achieved through the development of a custom connection module based on an open-source code. This integration allowed the PSO algorithm to seamlessly send antenna design parameters to CST for simulation and performance evaluation at each iteration. The simulation results were then used to update the particle swarm, guiding the search process toward optimal design solutions.

The experimentation phase involved testing and iterative modification of the algorithm to enhance its performance in achieving the design objectives. The search process was fine-tuned, and convergence properties were carefully assessed to ensure that the algorithm reliably produced optimal results. Finally, the performance of the optimized antenna designs was thoroughly analyzed by comparing them with relevant benchmarks from the literature. This comparative analysis served to validate the effectiveness of the PSO-based design strategy, demonstrating its relevance compared to other AI-based methodologies in optimizing the size and performance of rectangular microstrip antennas.

3.1 Cost Function

Following the main objective of reducing the base dimensions of the patch antenna while maintaining or improving its efficiency, the cost function or fitness function needs to consider the size of the antenna, the resonance frequency, and the return loss inside the required bandwidth.

$$C_{func} = (L \times W) \times \alpha + (\sqrt{(f_r - f)^2}) \times \beta + \left(45 + \frac{\sum_{k}^{n} S_{11}(k)}{n} \right) \times \gamma \tag{3.1}$$

Where, L is the length of the patch, W the width of the patch, f_r the expected resonance frequency, f the actual resonance frequency, S_{11} the return loss in dB, k and n are the index and upper limits of the summation, which assume values within the array of sampled frequencies of the antenna bandwidth.

To offset the negative amplitude of S_{11} at the resonance frequency, the value 45 was added to the last term of the equation. This number was estimated according to the maximum amplitude present in other works.

Because the three parts of the cost function (patch size, frequency error, and return loss) will influence the optimized solution differently, they need to be balanced. Not only to prevent one part from adding excessive cost to a potential solution but also to establish what compromises are more acceptable in the design. For instance, while a larger antenna might be undesirable for a certain application, a high deviation in the resonance frequency would be unacceptable.

Therefore, the coefficients α, β, and γ are used to balance the weight of the antenna size, resonance frequency, and return loss, respectively, in the desired solution. The values are calculated by trial starting from an initial value that sets the three parts of the function on the same scale.

3.2 Metaheuristic Optimization

Many real-world problems are inherently complex and involve multi-objective targets, multiple variables, and big datasets. These large-scale problems have many correlated elements and wide search spaces, commonly found in applications in industrial control, aerospace, telecommunications, and logistics [41].

In computer science, metaheuristics are a class of optimization techniques that use a probabilistic approach to find near-optimal solutions to complex problems [42]. These algorithms are valuable for targeting large-scale challenges that were previously considered problematic due to their computational complexity [43]. The development of various optimization and metaheuristic algorithms has led to ongoing research focused on identifying the most suitable approach for specific problems [44].

Solving large-scale problems using metaheuristics often requires a higher computational cost compared to simpler problems. Processing times can range from hours to days, requiring more powerful computing resources to achieve optimal results [45]. In fact, metaheuristics belong to the broader category of stochastic optimization, which involves searching for the best element within a set using a defined objective function that incorporates random variables [46]. This technique is particularly useful for problems where constraints and parameters are highly random.

In this context, metaheuristics are defined as a collection of algorithms, techniques, and methods that use some randomness to achieve optimal or near-optimal solutions for complex problems [47]. Since the true optimal solution may not be obvious, metaheuristics rely on iterative testing to discover the best possible outcome. Even though the most optimal solution is not guaranteed.

3.2.1 Artificial Intelligence, Machine Learning, and Particle Swarm Optimization

Artificial Intelligence (AI) involves the development of computational systems that display intelligent behaviors typically associated with humans. These behaviors include learning, reasoning, problem-solving, and adaptation [48]. Therefore, AI research aims to create machines capable of handling complex tasks traditionally requiring human expertise.

Similarly, Machine Learning (ML) is a subfield of AI that focuses on algorithms that enable machines to learn and improve from data without being explicitly programmed [49]. ML algorithms use different techniques like supervised, unsupervised, and reinforcement learning to extract patterns, make predictions, and guide decision-making [50].

Meanwhile, optimization plays a critical role in artificial intelligence and machine learning. Optimization algorithms refine algorithms to achieve the best possible performance, with either training models, improving accuracy, or boosting efficiency. These algorithms search for optimal parameter configurations or model structures that minimize or maximize a defined objective function [51].

The PSO algorithm is a simplified model of social swarming theory well adapted for the optimization of nonlinear functions in multidimensional space [52]. This technique attempts to reproduce generic social behavior and has been tested against many real-world problems with good performance [53].

AI is the broadest field, encompassing all technologies and methods that enable machines to mimic human intelligence. Within AI, Machine Learning represents a subset focused on algorithms that allow systems to learn and improve from experience without being explicitly programmed. PSO is a specific optimization technique, often used for solving problems by iteratively improving a candidate solution with respect to a given measure of quality [54].

Compared to other genetic algorithms, the PSO has shown an advantage due to its simplicity and robustness [46]. Besides, it has been applied and tested in many electromagnetic applications [55]. Another worthy point is the capacity of accommodating multi-objective optimizations by adding multiple fitness functions [52].

In the algorithm, each individual is called a particle while the population is the swarm. A fitness value is assigned to each particle before being evaluated against the fitness function. Initially, the population assumes random solutions in the space of possibilities. Then, each particle moves with a set velocity towards a combination of its local best and the global best solution [53].

After each iteration, the particles should move closer to a global best solution. The algorithm either stops after achieving a preset number of iterations or when the successive local best solutions have a distance shorter than an acceptable tolerance. The latter indicates that the local best solution is close enough to the optimal solution and the distance of the new local best should be negligible [56].

Particle Swarm Optimization benefits lie in its simplicity, efficiency, and adaptability, offering advantages in certain AI and ML optimization scenarios [53]. In PSO, particles navigate a search space, guided by their own best positions and the collective best position of the swarm. This mechanism avoids complex calculations, making PSO suitable for various optimization problems [57]. While parameter tuning is required for PSO, its stochastic nature can help maintain exploration, potentially preventing stagnation in local minima. This makes it adaptable to various optimization landscapes. Since particle updates can be calculated independently, PSO scales well for large datasets and distributed computing environments, making it a good option for large parallel tasks [58]. Due to this versatility, PSO has been successfully employed in many areas, such as engineering, finance, healthcare, and many other fields, demonstrating its potential for addressing diverse optimization challenges, which encourages research and new application techniques [59].

3.2.2 PSO Algorithm

On a PSO algorithm, a swarm of particles is randomly initialized. Each particle having a position (x_i), a velocity (v_i), and a personal best (p_i). In this context, position is defined as a candidate solution within the search space, represented by a vector of real numbers. The dimensionality of this vector depends on the number of variables involved in the problem [60].

Likewise, the velocity is the representation of the particle's movement vector, which is a real-valued vector with the same dimensionality as the position. Initially, velocities are randomly assigned. While the personal best marks the best solution encountered by the particle so far, which is set initially to the particle's initial position [52].

During the execution of the algorithm, each particle's position is evaluated using the objective or fitness function specific to the optimization problem. This function quantifies the potential solution, allowing the algorithm to differentiate between better and worse solutions [61]. To determine a general solution to the problem, the algorithm needs to identify the global best position (g) from the position of the particle with the best fitness value encountered so far across the entire swarm. Following this logic, with every iteration, the algorithm updates each particle's velocity based on equation (3.2):

$$v_i^{k+1} = \omega v_i^k + \phi_1 \cdot r_1 \cdot (p_i^k - x_i^k) + \phi_2 \cdot r_2 \cdot (g^k - x_i^k) \tag{3.2}$$

Where,

- ω is the inertial weight, which controls the momentum from the particle's previous velocity. A higher ω encourages exploration, while a lower ω promotes exploitation. Common strategies involve dynamically decreasing ω over iterations to improve convergence.
- ϕ_1 and ϕ_2 are acceleration coefficients. These coefficients influence the attraction towards the particle's personal best (p_i^k) and the swarm's global best (g^k), respectively.
- r_1 and r_2 are random numbers (uniformly distributed between 0 and 1) to introduce randomness and prevent premature convergence.

The position update is carried out based on the updated velocity, according to the following equation:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{3.3}$$

Where,

- x_i^{k+1} is the updated position of the i-th particle at iteration $k+1$.
- x_i^k is the current position of the i-th particle at iteration k.
- v_i^{k+1} is the updated velocity of the i-th particle at iteration $k+1$.

Following that, the personal best is set if a particle's new position (x_i^{k+1}) has a better fitness value than its current personal best (p_i^k).

Moving forward, the iteration process is repeated for a predefined number of iterations (k) or until a convergence criterion is met. Ideally, the swarm converges towards optimal or near-optimal solutions within the search space.

Therefore, the algorithm terminates either when the maximum number of iterations is reached or the improvement in the global best position falls below a specified tolerance, indicating negligible benefit from further optimization.

Considering the PSO specifics discussed above, an algorithm can be optimized for a particular problem by tuning parameters or changing the smarm size. The performance of PSO is highly sensitive to the chosen values for (ω), (ϕ_1), and (ϕ_2). These parameters can significantly affect the balance of objectives and convergence behavior. Strategies like linearly decreasing (ω) and carefully selecting (ϕ_1) and (ϕ_2) are important for optimal performance. Similarly, the size of the swarm (number of particles) can influence the algorithm's efficiency and convergence. While a larger swarm may improve exploration, it also increases computational cost.

That being said, analyzing and understanding the convergence behavior of the algorithm for a specific problem will be essential to adjusting those parameters. After all, the PSO is designed to operate in a balance between exploration (searching new areas of the search space) and exploitation (refining known promising solutions) [60].

Mathematical analysis has demonstrated that carefully selected ranges for these parameters promote convergence, preventing particles from straying too far into unproductive regions of the search space [61].

In the process of antenna design optimization, it is crucial to consider the challenges posed by the significant non-linearity behavior of the antenna. Traditional optimization methods may struggle to address these complexities effectively. Recent studies have suggested the use of stochastic global optimizers to tackle these issues, with PSO being a particularly promising candidate. According to [62], "As a stochastic global optimizer, PSO is a good candidate to address the significant nonlinearity and multimodal effect induced by the full-wave analysis."This highlights the potential of PSO in navigating the complex design landscape and finding optimal solutions for antenna design.

3.2.3 MATLAB-CST Interface

The minimum requirement for an improved miniaturized antenna is to maintain its efficiency to a certain level while reducing its total area, thus reducing its production cost [63]. Therefore, the experiments require a practical method to simulate the antenna's performance at several settings, as needed for any machine learning technique. Since relatively accurate and largely accepted simulators already exist, this work chose to use the CST Studio Suite [64], which is a software for designing, analyzing, and improving electromagnetic components.

Besides performing many simulations, the PSO technique also requires real-time modifications in the parameters of the antenna. Additionally, based on similar research, it is estimated more than a hundred iterations before the algorithm delivers a solution. On that account, manually setting each antenna parameter for every simulation becomes impractical. Fortunately, the literature already records examples of using task automation in the CST with the help of programmable software like MATLAB [65].

Since this research focuses on the PSO algorithm and the miniaturization techniques, it is best to use a finished and tested application to interface between the software. The chosen interface is available open-source in a GitHub repository [66]. Due to its simple and functional interface, which uses VBS code to invoke tools inside the CST software, it is possible to modify the code to access any designing functions in the simulator. Moreover, this interface uses Matlab, which can readily implement the PSO algorithm and provide all the graphical analysis tools for the later discussion of results.

Fig. 2 represents the algorithm flow used in this thesis. The proposed PSO algorithm commences by randomly initializing particle positions (W and L dimensions) within the search space. A known optimal solution is incorporated by designating a particle with the base antenna dimensions as an initial target. Subsequently, antenna performance results are simulated for each particle's dimensions. A cost function evaluates these results, and particles update their velocities and positions based on their individual best (personal best) and the swarm's global best positions. This iterative process continues until predefined termination criteria are satisfied, culminating in optimized antenna dimensions.

Fig. 3 demonstrates the Data Diagram of the complete integration. The proposed workflow commences with user-defined antenna target parameters, which subsequently inform PSO algorithm configurations. Particle positions, initialized randomly with a portion of particles set to base antenna dimensions, are iteratively updated based on personal best and swarm intelligence. These dimensions are then translated into antenna drawing commands via a MATLAB-CST interface. The CST software simulates the generated antenna structures, exporting performance data back to the interface for processing. A cost function evaluates these results against target parameters, determining whether to update

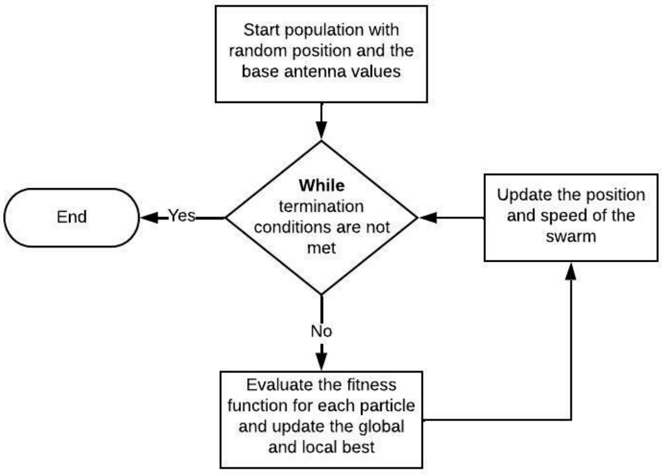


Figure 2 – PSO Algorithm Flow.

particle positions or terminate the optimization process based on predefined convergence criteria.

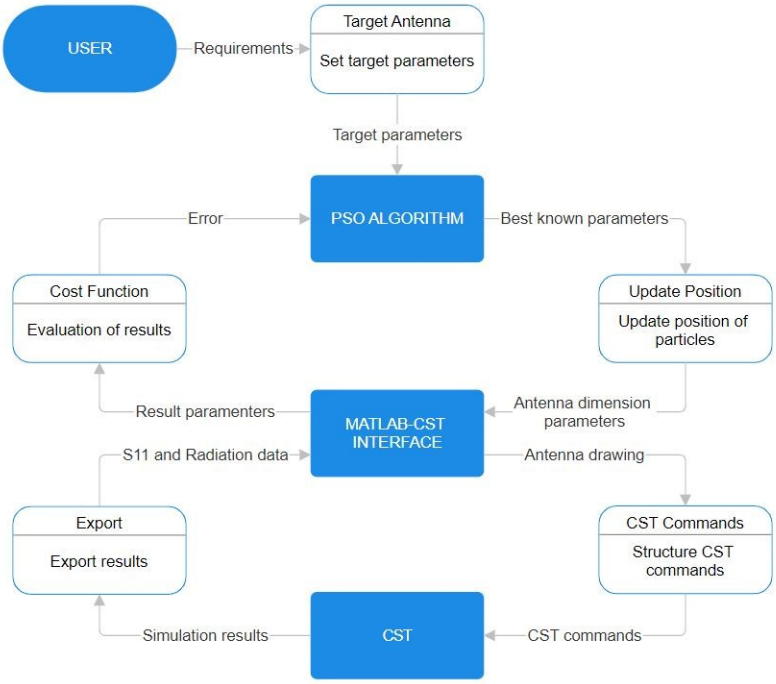


Figure 3 – Data Diagram.

4 Results and Discussion

In this section, the results of the study on designing the proposed antennas are presented. For the simulation of all the antennas, standard values of the dielectric constant ε_r (3.6) and substrate thickness (1.6 mm) were used. Furthermore, the microstrip line feed was used as the feedline method of the simulated antennas. The dimensions of the base antennas used for comparison were obtained by using the equations (2.2) and (2.5) for the 2.45 and 3.5 GHz frequencies.

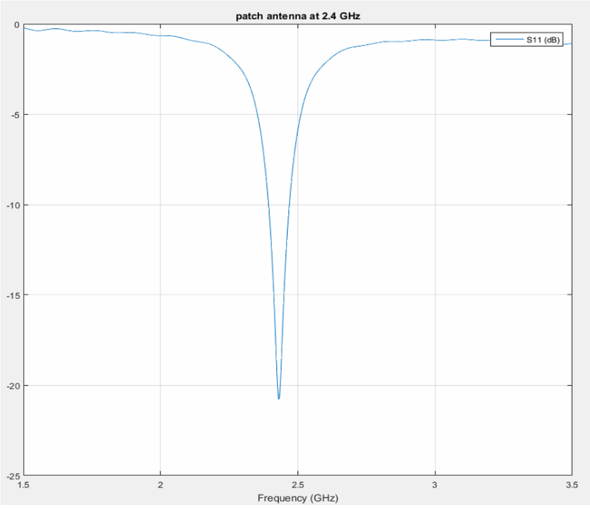
First, experiments were carried out to determine the appropriate coefficients (α, β, γ) of the cost function that would better suit the proposed objectives. These tests involved the use of the PSO algorithm to obtain the most suitable dimensions for the antenna according to the targets (resonance frequency, return loss, and area) of the cost function.

The weights of the coefficients were adjusted from 0 to 10, adopting values of either 0, 5, or 10. Since the most basic requirement of an antenna is to operate at a certain frequency or band, the β value, which represents the weight of the resonance frequency, only assumed the values of 5 and 10. Figure 4 presents the estimated dimensions and reflection pattern of the antenna for different values of the constants.

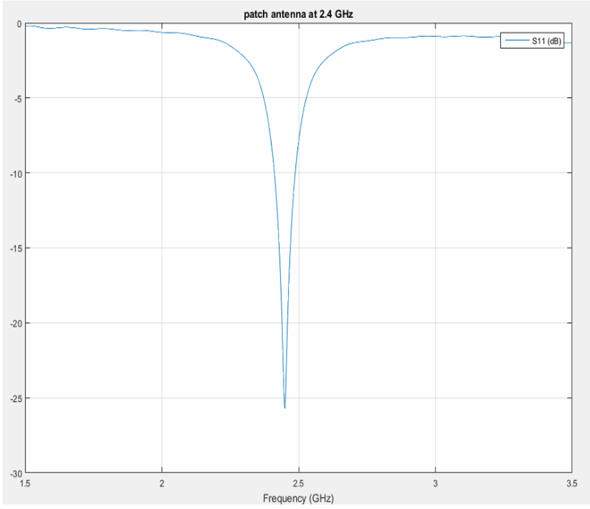
The first test, presented in Fig. 4a, which set α and γ to 0, keeping only the resonance frequency error in the cost function, achieved perfect resonance at the 2.45 GHz frequency. This result proves the ability of the proposed algorithm to converge to a solution. However, the estimated dimensions did not have any relevant improvements compared to the base antenna, while the return loss was worsened. By adding value to γ, as shown in Fig. 4b thus including the return loss in the cost function, with the same weight as the resonance frequency error, the width of the antenna increased but the return loss improved.

When altering β to 5, reducing the weight of resonance frequency in relation to the return loss, the simulated antenna reached the lowest return loss, improving its performance considerably while only experiencing a small shift in the resonance frequency as demonstrated in Fig. 4c. However, the dimensions of the antenna further increased.

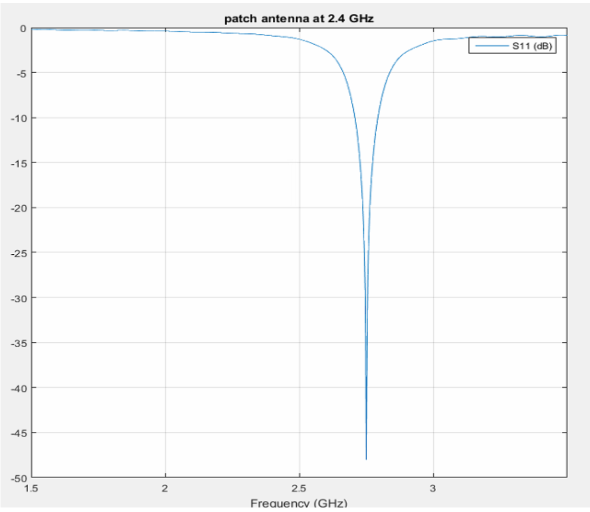
The final tests presented in Fig. 4d and Fig. 4e included α, and consequently, the antenna area in the cost function. With lower coefficients for the return loss and area, the simulated antenna experienced a size reduction and return loss improvement. Meanwhile, balancing the three coefficients reached better performance in antenna area and return loss, but with a bigger shift in the resonance frequency, which was still within acceptable limits of ISM band applications.



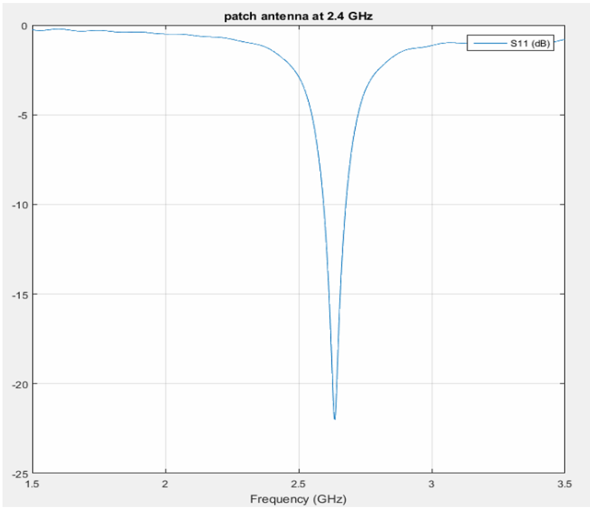
(a) Patch Dimensions (W=35mm, L=29mm) and Coefficients (α=0, β=10, γ=0)



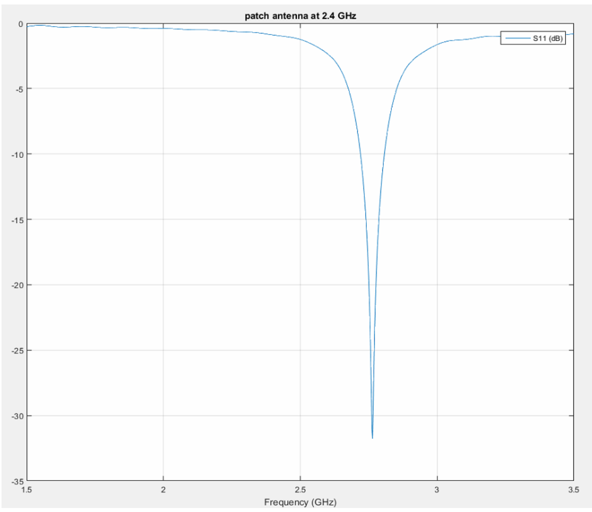
(b) Patch Dimensions (W=37mm, L=29mm) and Coefficients (α=0, β=10, γ=10)



(c) Patch Dimensions (W=34mm, L=30mm) and Coefficients (α=0, β=5, γ=10)



(d) Patch Dimensions (W=32mm, L=26.5mm) and Coefficients (α=5, β=10, γ=5)



(e) Patch Dimensions (W=31 mm, L=25mm) and Coefficients (α=10, β=10, γ=10)

Figure 4 – S11 - Cost Function Coefficients for the Patch Antenna at 2.45 GHz

Considering the previous tests, the values of α, β, and γ, were set to 8, 10, and 10, respectively. This arrangement kept the frequency error with a higher weight to avoid a relevant error in the resonance frequency, while also balancing the return loss and patch area, which are important targets of the proposed antenna.

4.1 Case Study 1: ISM band at the 2.45 GHz frequency

The design requirements are set according to a commercial ISM Band antenna operating at the 2.45 GHz frequency, with an acceptable frequency error of ±5% (range of 2.32 GHz to 2.57 GHz) and bandwidth of at least 80 MHz. Figure 5, which illustrates the proposed antenna design, and Table 2, which provides the design dimensions, demonstrate the results of the proposed approach for the ISM band antenna. The representative drawing of the antenna design was created using CST software, following the dimensions obtained through the optimization algorithm.

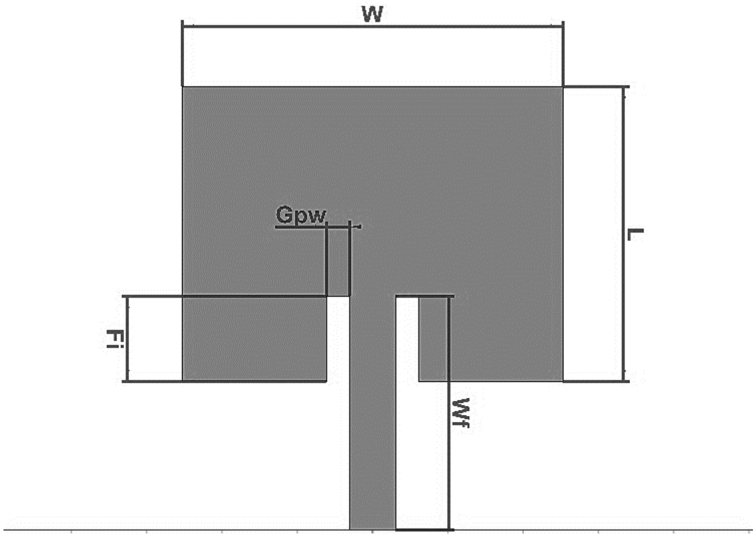


Figure 5 – Design of the proposed antenna

Table 2 – Antenna Dimensions: 2.45 GHz band

Dimension	**Base Antenna (mm)**	**Proposed Antenna(mm)**
W	37	31
L	28	25
Fi	5.70	5.70
Gpw	1.53	1.53
Wf	14	14

The optimized dimensions obtained with one decimal value precision are as follows: W (width) = 31 mm, L (length) = 25 mm, Fi (feed inset) = 5.70 mm, Gpw (gap width) = 1.53 mm, and Wf (feed width) = 14 mm. These dimensions represent a reduction of 25% in patch area when compared with the base antenna, and the algorithm's ability to converge to these values in 20 iterations demonstrates its efficiency in design optimization. Consequently, the PSO-based approach significantly reduces the number of iterations required to fine-tune the base antenna, leading to similar or improved performance in a shorter timeframe.

In order to further compare the performance of the proposed and base antennas, a more thorough analysis of the differences in their performances is needed. Specifically, the results of response parameters, such as reflection pattern (S11) and radiation pattern allow for an objective evaluation of the designs. Therefore, the CST was used again to simulate the base and PSO antennas. The S11 plots of both antennas are described in Figure 6, while the other parameters are listed in Table 3. Likewise, the 3D representation of the farfield of the antennas monitored in the 2.45GHz frequency is presented in Figure 7.

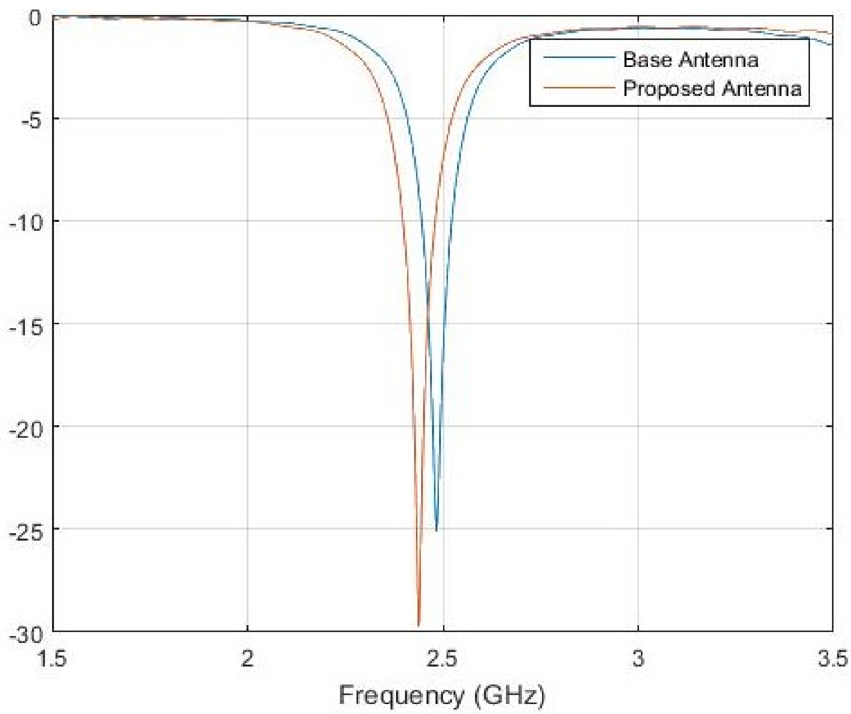
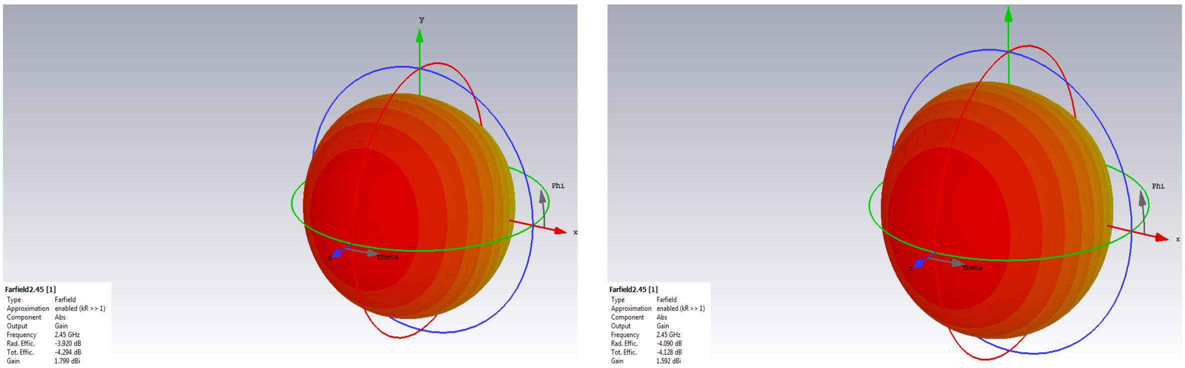


Figure 6 – S11 - Patch Antenna at 2.45 GHz

Table 3 – Comparison of Proposed and Base Antennas Parameters

Attributes	Base Antenna	PSO Designed Antenna
Resonance Frequency	2.45 GHz	2.4 GHz
Bandwidth	0.2 GHz	0.25 GHz
Return Loss	-25 dB	-29 dB
Area	1036 mm^2	775 mm^2

While both antennas had resonance close enough to the desired frequency, the PSO antenna achieved a lower magnitude with a minimum closer to the 2.45 GHz frequency. The base antenna reached -25dB and the PSO antenna -29dB of return loss, approximately, which is an improvement of 16%. Regarding the bandwidth, the two antennas



(a) Base Antenna (b) PSO Antenna

Figure 7 – Radiation Pattern at 2.45GHz

also fit the requirements of being broader than 80 MHz, with the PSO antenna having a slightly larger bandwidth than the base antenna. Finally, the radiation patterns plotted demonstrate that PSO antenna did not suffer disturbances since the proposed antenna continued following a similar pattern.

Because of its widespread applications, the 2.45 GHz antenna has a variety of research on the design assisted by artificial intelligence. Therefore, a comparison between related work can be done. Table 4 below presents a comparison of design parameters and operation results between the proposed antenna and other works that use PSO in the antenna design.

Table 4 – Comparative Study of Proposed Antenna and Existing Antennas

Ref	**Dimension (mm)**	**Area (mm²)**	**Return Loss (dB)**	**Fr**	**Iterations**
[2]	37.52x29.06	1090.3	-25	2.44 GHz	NA
[67]	46x55	2530	-22.5	2.45 GHz	NA
[68]	49x39.62	1941.4	-43	2.4 GHz	NA
[69]	29x15	435	-30	2.45 GHz	50
Proposed Antenna	31x25	775	-29	2.4 GHz	20

Compared to the base antenna, the proposed antenna featured smaller dimensions of 31x25 mm^2, significantly reducing the area to 775 mm^2. Despite the reduced size, the proposed antenna managed to improve the return loss to -29 dB, signifying better impedance matching at the desired frequency of 2.4 GHz. It's noteworthy that the proposed antenna achieved these results with just 20 PSO iterations, indicating efficient optimization with lower computational costs.

In contrast to the promising results achieved by the proposed antenna and the work by [69], the other related works employing PSO-related algorithms did not demonstrate significant improvements in both size reduction and return loss when compared to the base antenna. For instance, [67] presented a larger antenna with dimensions of 46x55 mm^2, resulting in an area of 2530 mm^2, while only achieving a return loss of -22.5 dB.

Similarly, [2] utilized an antenna with dimensions of 37.52x29.06 mm^2, resulting in an area of 1090.3 mm^2, with a return loss of -25 dB. Both of these works failed to substantially reduce the antenna size or improve the return loss when compared to the base antenna values. Moreover, [68] presented an antenna with dimensions of 49x39.62 mm^2, resulting in a considerable area of 1941.4 mm^2, but with a significant improvement in the return loss of -43 dB.

Comparatively, the work by [69] demonstrated a small antenna with dimensions of 29x15 mm^2, resulting in a compact area of 435 mm^2. This work achieved a return loss of -30 dB, similar to that of the proposed antenna, indicating effective impedance matching. However, it's important to note that [69] required 50 PSO iterations to reach these results, which is higher than the 20 iterations used for the proposed antenna.

Therefore, the proposed antenna successfully reduced the antenna's area while simultaneously improving the return loss, showcasing its efficiency in achieving desired performance metrics with fewer PSO iterations. On the other hand, the work by [69] managed a similar return loss but at the cost of a higher number of PSO iterations. When considering recurrent usage and computation costs, the proposed antenna presents a compelling advantage due to its efficient optimization process.

4.2 Case Study 1: 5G band at the 3.5 GHz frequency

Since the PSO-based optimization for the ISM band antenna achieved positive results, this work proceeded to apply it to the design of an antenna for 5G applications (3,300 to 3,800 GHz). For this antenna, the design requirements are set to an acceptable frequency error of $\pm 5\%$ (range of 3.32 GHz to 3.67 GHz) and bandwidth of at least 100 MHz. Following the same methodology, the algorithm with an adjusted cost function was employed and then compared to the base antenna for operation in the 3.5 GHz frequency. Table 5 describes the dimensions of the proposed and base antennas, revealing reductions in width (W) and length (L).

Table 5 – Antenna Dimensions - 5G Band

Dimension	**Base Antenna (mm)**	**Proposed Antenna(mm)**
W	26	25.4
L	20	18
Fi	5.70	5.70
Gpw	1.53	1.53
Wf	10	10

The reflection coefficient (S11) plot shown in Figure 8, presents the performance of the simulated base and proposed antennas. The optimized antenna achieved a return loss of -41 dB, surpassing the -34 dB of the base antenna, further enhancing its performance by 20%.

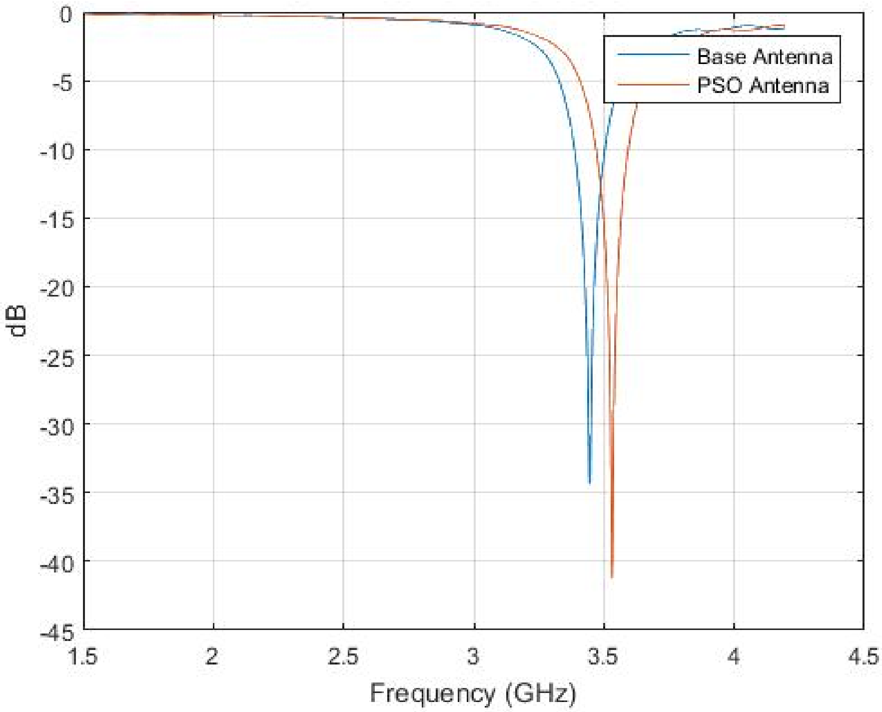


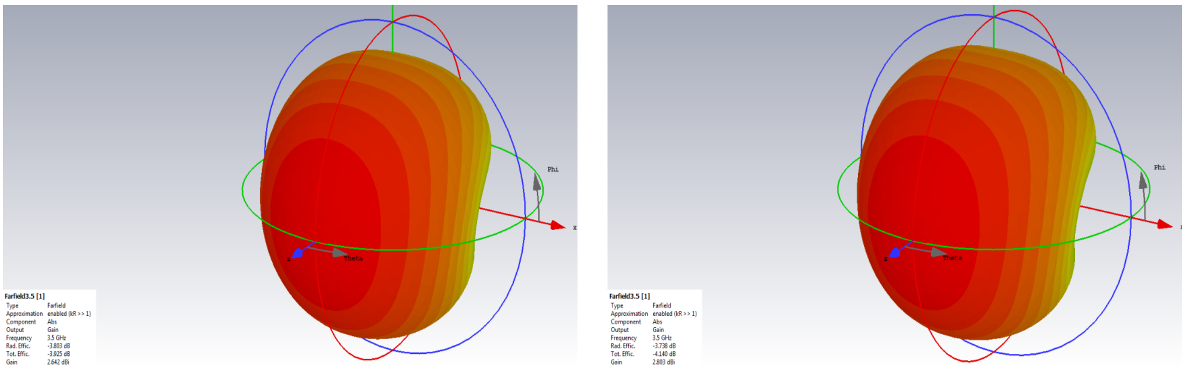
Figure 8 – S11 - Patch Antenna at 3.5 GHz

Table 6 provides a comparison between the base and proposed antennas. The optimized design maintains resonance at 3.5 GHz while broadening the bandwidth from 0.18 GHz to 0.22 GHz, which met the design requirements. Furthermore, the antenna area was reduced by 12%, demonstrating the efficacy of the PSO algorithm in optimizing antenna dimensions.

Table 6 – Comparison of Proposed and Base Antennas Parameters - 5G Band

Attributes	**Base Antenna**	**PSO Designed Antenna**
Resonance Frequency	3.5 GHz	3.5 GHz
Bandwidth	0.18 GHz	0.22 GHz
Return Loss	-34 dB	-41 dB
Area	520 mm^2	457 mm^2

Finally, Figure 9 illustrates the 3D far-field radiation patterns of both antennas at 3.5 GHz. The similarity in the radiation patterns confirms that the proposed antenna preserves the desirable radiation characteristics of the base antenna.



(a) Base Antenna (b) PSO Antenna

Figure 9 – Radiation Pattern at 3.5GHz

5 Conclusion

This thesis presented a comprehensive exploration of Particle Swarm Optimization as an approach for designing efficient and compact microstrip patch antennas applied to ISM and 5G bands. Motivated by the increasing demand for smaller, high-performance antennas in modern wireless communication systems, this work sought to overcome the limitations of traditional manual design methods and explore the potential of PSO optimization.

While recent works have explored PSO for antenna optimization, they often lacked a solution for multiple performance parameters and streamlined integration between the algorithm and simulation software, hindering potential broader applicability. Recognizing this gap, this research not only leveraged PSO to enhance antenna design but also developed a seamless interface between the algorithm and simulation software. This integration can facilitate the exploration of antenna designs across different frequency bands, including both ISM and 5G bands. With minimal modification of target parameters and cost function, the algorithm achieved optimization in another resonance frequency, attesting to the viability of the proposed approach.

The developed PSO-based methodology offered a flexible and adaptable framework for antenna design, seamlessly integrated with an electromagnetic field simulation software (CST). By considering multiple design parameters and optimization targets simultaneously, the PSO algorithm searched the complex design space to converge on optimal solutions. This approach not only streamlines the design process but also enables the exploration of non-intuitive designs that may have been overlooked using conventional methods.

The results obtained from the application of PSO to both the 2.45 GHz ISM band antenna and the 3.5 GHz 5G antenna demonstrate the significant advantages of this approach. In both cases, the PSO algorithm achieved reductions in antenna size while simultaneously enhancing performance metrics such as return loss and bandwidth. The 25% size reduction and 16% return loss improvement in the ISM band antenna, coupled with the 12% size reduction and 20% enhancement in return loss for the 5G antenna, showcased the versatility and effectiveness of the proposed algorithm across different frequency bands and application scenarios.

Moreover, the success in optimizing these antennas with relatively few iterations (20) highlights its computational efficiency. This efficiency is particularly valuable in scenarios where rapid design iterations are required.

Therefore, this thesis demonstrates that PSO based algorithms are powerful tools for antenna design optimization, capable of delivering compact, high-performance antennas across different frequency bands and applications. By automating and streamlining the design process, PSO based algorithms can not only accelerate the development of antenna solutions but also open new possibilities for exploring unconventional designs and optimizing multiple performance parameters simultaneously.

5.1 Future Work

The results obtained in this study can contribute for several avenues of future research to further explore and expand the capabilities of PSO in antenna design optimization. One important possibility is the adaptation of the algorithm to accommodate more complex antenna geometries beyond the simple rectangular shape explored in this work. This could involve adapting the current interface or incorporating geometric constraints to guide the optimization process towards desired shapes.

Another potential direction is to explore the impact of different substrate materials on antenna performance and optimize the PSO algorithm accordingly. By considering the dielectric properties of various substrates, it may be possible to achieve further enhancements in antenna efficiency, bandwidth, and size reduction.

Additionally, the current work focused on specific frequency bands (2.45 GHz and 3.5 GHz). Future research could investigate the effectiveness of PSO in optimizing antennas for a wider range of frequencies.

Extending the application of PSO to fractal antennas and MIMO configurations presents another promising area for future work. Fractal geometries offer unique advantages in terms of miniaturization and multiband operation, while MIMO configurations enable higher data rates and improved link reliability. Integrating PSO with these advanced antenna designs could offer new possibilities for optimizing their performance and expanding their application domains.

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