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Cycle XXIV

Optimized Antenna for Low UHF Band Wireless Power Transfer (WPT)

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My dream would not come true without them.

I did not know who would have become today without them.

Dedicate to my parents with love.

Acknowledgement

Success is a science, if you have the conditions, you will get the results.

"Oscar Wilde"

I would like to express my deepest gratitude to all those who provided me the condition to approach to my goal.

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Summary

Delivering power without requiring wire is an advance in transferring power technology; and it is named Wireless Power Transfer (WPT). Wireless power transfer makes possible to overcome drawback of conventional power transfer with wires, due to the wire resistance, wire routing, and so on; re-charging cell phones, game controllers, laptop, mobile robots, and electrical vehicles without being plugged in; making more reliable industrial systems and medical devices by eliminating trouble prone wiring and replaceable batteries; transmitting power in safe mode for human body and animals; providing continuous and instantaneous power transfer; and to miniaturize electrical systems and devices. Such advantages promote the interest of scientists, engineers, and researchers in studying and using wireless power transfer.

At present, the power is delivered wirelessly by employing such diverse physical mechanisms as: Radio Frequency (RF), and Resonance Inductive Coupling.

Radio Frequency: Recently, the availability of wireless standards for huge number of applications, from mobile phones, smart phones, to always-on WLAN devices shifted the attention on the extraction of energy from EM fields in the RF band. On other hand, Energy Harvesting Technology (EHT) allows to scavenge small amount of power from human activities or environment heat, light, vibration or Electromagnetic Field (EF). By availability the EM field in our daily life and using Energy Harvesting technology, nowadays the power is extractable from EM in RF range, and named Radio Frequency (RF) energy harvesting and it has the resulting benefit to product design (e.g. miniaturizing biomedical implanted devices and power supply), transfer power wirelessly over distance (e.g. Solar Power Satellite), in self-powering, where requires continuously available power source with lifespan (e.g. Wireless Sensor Network), and so on. Furthermore, RF Energy Harvesting provides the possibility of recycling EM radiation in the free space and using it as an alternative supply source that leads to reduce of the EM field pollution, miniaturization of the energy harvesting system with respect to energy harvesting system based on the other energy sources (e.g. large size of a photovoltaic).

One of the most important components in RF power harvesting system is called rectenna which is composed of a receiving antenna and rectifier. The receiving antenna plays a critical role in RF energy harvesting system, since it must extract the power from radiated electromagnetic waves.

Resonance Inductive Coupling: in this mechanism, resonance is used to deliver power wirelessly, by tuning transmitter and receiver at mutual EM frequency. coupling transmitter and receiver in resonant way has two main profits: exchange power efficiency without much leakage (minimizing energy leakage causes the maximization in the transferred energy to the receiver), and improve power efficiency over distances. Inductive coupling techniques have been reported to have high power transfer efficiencies (on the order of 90%) for very short lengths (1-3cm). However, the power efficiency of such technique decreases for longer distance drastically.

The biggest challenge in the design of RF energy harvesting system (rectenna) and wireless power transmitting systems via Resonance Inductive Coupling is the maximization of the transferred energy to the receiver, reduction of the size, and transmitting power in safe mode for human body and animals. This is possible by suitably redesigning the transmitting and receiving devices, trying to find the correct shape that allows on rising in performance, and tuning the transmitter and receiver at EM frequency to decrease leakage.

In this work, an approach based on a novel evolutionary technique is proposed for the design of loop wire antenna configuration, with the aim of increasing the transfer efficiency, the robustness of the coupling, and minimizing the average power loss, and miniaturization.

The new hybrid approach here proposed, called Genetical Swarm Optimization (GSO), and consists in a strong co-operation of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In particular, a key feature of the algorithm is that it maintains the integration of GA and PSO for the entire run. In each iteration, the set of solutions is divided into two parts and it is evolved with two techniques respectively. It is then recombined in the updated population for the next iteration; after that it is again divided randomly into two parts in the next run, in order to take advantage of both genetic and particle swarm operators. The population update concept can be easily understood thinking that a part of the individuals has been substituted by new generated ones by means of GA, while the remaining are the same of the previous generation but have been moved on the solution space by PSO. This kind of updating results in a more "natural" evolution, where individuals not only improve their score for natural selection of the fitness, or for good-knowledge sharing, but for both of them at the same time.

A driving parameter is introduced for the GSO algorithm, called Hybridization Coefficient (HC); it expresses the percentages of population that in each iteration is evolved with GA: so HC=0 means the procedure is a pure PSO (the whole population is processed according to PSO operators), HC=1 means pure GA(the whole population is optimized according to GA operators), where 0<HC<1 means that the corresponding percentage of the population is developed by GA, while the rest with PSO technique.

The output of the evolutionary optimization method or on other words, the candidate design is simulated at frequency range 450MHz- 600MHz by Matlab simulation in order to investigate the properties of the candidate design. Rao-Wilton-Glisson basis function and delta-gap feed model have been used to create a system of moment equations (Method of Moment) in home-built Matlab simulation tool. A wire is represented with the use of a thin strip model having one RWG edge element per strip width. The strip width should be four times of the wire radius. As the last step, the results obtained by Matlab are compared with the obtained results by FEKO- Lite (commercial software) to check and verify the reliability of the obtained results by Matlab for optimized antenna.

In this study, a novel antenna by means of optimization loop wire base on fractal variation has been proposed for application in WPT devices and RF energy harvesting component. The presented optimization approach is based on a recently developed evolutionary method. The design procedure is well suited in order to increase the transfer efficiency and the robustness of the coupling, with the aim of minimizing the average power loss and the size of the WPT systems.

Finally, Numerical results simulated with home-mode MoM-Matlab code have been verified by comparison with full-wave commercial simulator, FEKO-Lite.

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Chapter1

Introduction

Delivering power without requiring wire is an advance in transferring power technology and named Wireless Power Transfer/transmitting (WPT). Thus, *Wireless power Transfer* (WPT) as the name shows is the transfer of power ranging from milliwatts to kilowatts over a distance range from centimeters to several meters without interconnecting. Wireless power transfer makes possible to overcome drawback of conventional energy/power-transfer power with wires- due to the wire resistance, wire routing, and so on. Other benefits of the power transfer wirelessly include: re-charging cell phones, game controllers, laptop, mobile robots, and electrical vehicles without being plugged in, making more reliable industrial systems and medical devices by eliminating trouble prone wiring and replaceable batteries, transmitting power in safe mode for human body and animals, providing continuous and instantaneous power transfer, and to miniaturize electrical systems and devices. Such advantages promote the interest of scientists, engineers, and researchers in studying and using wireless power transfer.

Wireless Power Transfer (WPT) is made possible by various technologies, whereas conventional power transmitting is solely used wire technology to deliver power. The technologies and methods of WPT are as the following:

- **Inductive Coupling**

  The transfer of power takes place by electromagnetic coupling through a process known as mutual induction. The simplest example of the inductive coupling is *transformer.* The primary and secondary coils of transformer are connected base on principles of electromagnetism. For instance, the battery charge of a mobile phone and electric toothbrush are powered by this technology.

However, the main drawback of this technology is the short distance. The receiver must be kept very close to the transmitter.

- **Resonance Inductive Coupling**

The *resonance inductive coupling* technology is presented in order to overcome the main drawback of non-resonance inductive coupling technology.

The resonance inductive coupling is combination of inductive coupling and resonance frequency. Receiver and transmitter are tuned to mutual electromagnetic frequency. Resonance causes two resonance objects of the same resonance frequency interact very strongly and increases the transfer efficiency with respect to the distance range. A common use of the technology is for powering *contactless smart cards.*

- **Radio Frequency and Microwave Power Transmission**

High amount of the power is delivered over the long distance by converting into microwaves; the transmitting point and receiving point must be in the line of sight. The process of Microwave WPT is as the following:

1. Electrical energy to microwave energy.
2. Capturing microwaves by using rectenna.
3. Microwave energy to electrical energy.

One of the applications of Microwave WPT is in *Solar Power Satellite.* A satellite with solar panels is sent to orbit the earth and collect the sunlight. The satellite generates the electrical power with using solar cells. This energy is then converted into the microwave power and transmitting to the receivers of rectenna on the earth. At the end of the process, the microwave energy is converted back into electrical energy in the rectifier of rectenna. The similar procedure is employed to capture power from electromagnetic field at radio frequency band.

- **Laser Power Transmission**

Laser method of wireless power transfer is used a coherent light beam to transport very high power point to point in a line of sight. In this technology, the size of the antenna could be much smaller, and the light could be diffracted by atmospheric particles easily.

In this thesis, we focused on Radio Frequency Energy Harvesting and Resonance Inductive Coupling technologies. We proposed a novel hybrid technique of optimization in order to redesign and enhance the elements of the system of those technologies.

The chapter is started with a brief review on the history of the wireless power delivering, and the following sections have been devoted to describe Radio Frequency and Resonance Inductive coupling technologies in transferred power wirelessly in details.

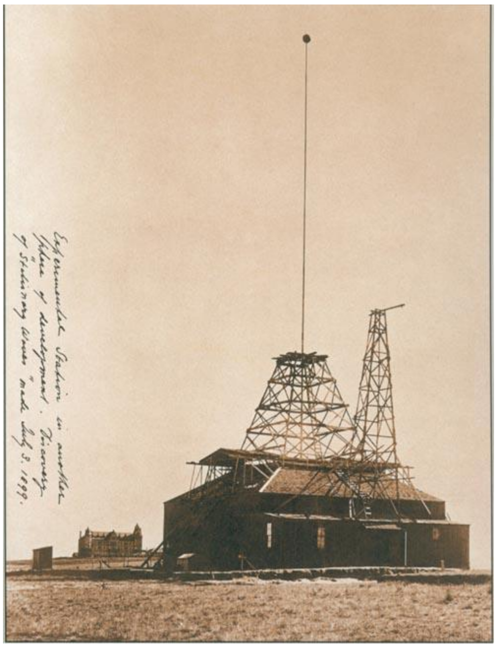
1.1 History of Wireless Power Transfer

In the early 1900's, the physicist Nikola Tesla conceived and explored the idea of the wireless power transmitting. Tesla managed to build a giant coil in a large square building over rose a 60 m mast with a 1m diameter copper ball positioned at the top. The coil was resonated at a frequency of 150 KHz and was fed with 300 kw of low-frequency power obtained from the Colorado Springs electric Company. As well, he succeeded to power the fluorescent lamps 25 miles from the power source without using wires. Nevertheless, Tesla's work was never commercially exploited due to the dangerous nature of the experiments, low efficiency on power transfer, and mainly by the deletion of financial resources. However, the work of Tesla was based on very long wavelength.

W. Brown was the first engineer who approached to use microwave and radio waves for effective power transmitting through long distances, in 1660's. The most research in this field focused on rectennas (J. A. G Akkermans & Visser-2005, Mohammad Ali &

Dougal-2005, Ren and Chang-2006, Shams & Ali-2007), which are antennas capable to collect energy from radio waves.

NASA for the first time in 2003 proposed a scheme to power satellites and wireless energy transfer by utilizing laser mechanism. The laser beam is capable to deliver very high energies in a line of sight. The laser mechanism is efficient to send power point to point, but it is dangerous mechanism for living beings.



Nikola Tesla's laboratory in Colorado Springs

Over the years, the idea of Tesla, wireless power delivery have been conceived, tried, and tested by many (Glaser, 1968; McSpadden et al., 1996; Shinohara & Mastsumoto, 1998; Strassner & Chang, 2002; Mickle, et al., 2006; Conner, 2007).

1.2 Radio Frequency Technology

Energy harvesting (EH) is the process of capturing and converting energy into usable DC voltage for items as small as cell phone or as large as satellites. There are various energy sources for energy harvesting technology. For instance, ambient energy sources (e.g. Solar; Wind; Biomass; Hydro geothermal; and Tides) or handmade-man ambient energy (e.g. emitted Electromagnetic waves (EM) from TV signals; wireless radio networks; and cell phone towers) [1]. Recently, the availability of wireless standards for huge number of applications, from mobile phones, smart phones, to always-on WLAN devices shifted the attention on the extraction of power from EM fields in the RF band [2]. On other hand, there is the possibility of recycling EM radiation in the air and use it as an alternative supply source by EH technique. In additional, scavenging the power from EM can allow to reduce the size of the harvesting system with respect to energy harvesting system based on the other energy sources (e.g. large size of a photovoltaic) [3].

Therefore, extraction power from electromagnetic waves to power devices is called Radio Frequency (RF) energy harvesting. RF power harvesting technology has the resulting benefit to product design (e.g. miniaturizing biomedical implanted devices and power supply); transfer power wirelessly over distance (e.g. Solar Power Satellite); in self-powering; where requires continuously available power source with lifespan (e.g. Wireless Sensor Network); and so on. Fig.1.1 shows the block diagram of a RF energy harvesting system. The system operates as: an antenna-receiving antenna picks up the incidence electromagnetic wave at RF band and then the picked RF wave is converted to a DC voltage via rectifier. The DC voltage is stored or used to power devices. In order to reduce the transmission loss and increase the voltage gain, the matching network between receiving antenna and rectifier is necessary [4, 5].

As been seen, the heart of a RF energy harvesting system is composed of a receiving antenna and rectifier that their composition is named “rectenna”. Hence, the main research fields focus on rectenna [6, 7, 8, and 9]. Since the role of the receiving antenna is, extraction the power from the radiated electromagnetic wave, rectifier’s role is conversion the picked power by antenna to the useful DC voltage. For enhancement of the performance of the RF energy harvesting, the receiving antenna and rectifier must be optimized and redesigned.

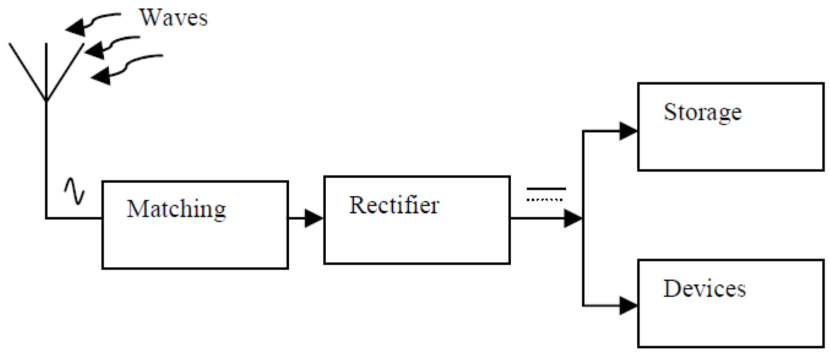


Figure1.1: Schematic of RF energy harvesting systems.

Many works could achieve sufficient power but provided low output voltage, which made them inadequate for using in some application [10] such as: passively powered wireless sensor networks. In addition, some previous studies have proposed a new design of the rectifier in order to increase the efficiency of the RF-DC conversion and recoverable power.

As been known, the power density decreases over longer distance. Thus, it is essential that the RF-DC conversion circuit be able to operate at very low receiver power. To overcome this, an optimized rectifier circuit has been introduced and the minimum-threshold of the RF-DC conversion has been improved [11].

In [12], in order to optimize the RF energy harvesting system, author has been employed a DC/DC voltage boost converter for elevation the voltage level. Moreover, author has been used a patch antenna array as collecting the RF power from the incidence electromagnetic waves with efficiency of 85% at 1.8 GHz.

However, in this work, we are more interested in raising the receiving antenna gain and we will address this case.

1.3 Resonance Inductive Coupling

The mechanism resonance is used to deliver power wirelessly by tuning transmitter and receiver at mutual EM frequency; and coupling transmitter and receiver in resonant way has two main profits: exchange power efficiency without much leakage (minimizing energy leakage causes the maximization in the transferred energy to the receiver), and improve power efficiency over distances.

Inductive coupling techniques have been reported to have high power transfer efficiencies (on the order of 90%) for very short lengths (1-3cm) [13]. However, the power efficiency of such technique decreases for longer distance drastically. Many works have been done on increasing power efficiency of such technique with respect to longer distances [14, 15, and 16]. In all those mentioned works, authors have developed a design, which consists of two helices and two singl loops [17]; as shown in Fig1. 2. In [14], authors have optimized the typical Strongly Coupled Magnetic Resonance, which has been illustrated in Fig1. 2. They are managed to achieve efficiencies 90.2% for 15cm distance to 35% for 45cm distance and increase the efficiency of the wireless power transfer to compare with conventional inductive coupling [18] and conventional Strongly Coupled Magnetic Resonance designs [19]. The same authors have analyzed the geometrical parameters of the SCMR and they showed that, the optimized SCMR in their previous work has a wide range of local optimum. Moreover, when they launched the system on that optimal range, the system reached the maximum efficiency [15]. In [16], the efficiency of wireless power transfer via magnetic resonance has been improved by using transmission coil array. Although, the previous works could have improved the power gain over larger distance, but they still require more work with respect to the size of the proposed model for resonance magnetic coupling. Because, in some applications such as implantable medical devices the size of the suggested model or system plays a key role. In additional, that is an important term in design of the electrical devices and systems.

Therefore, present a model for Resonance Inductive Coupling technology that could meet the three requirements: a) high efficiency, b) small size, and c) longer air gap, make the technology more adequate for more applications for instance: RFID, biomedical implant devices, and electrical car charging.

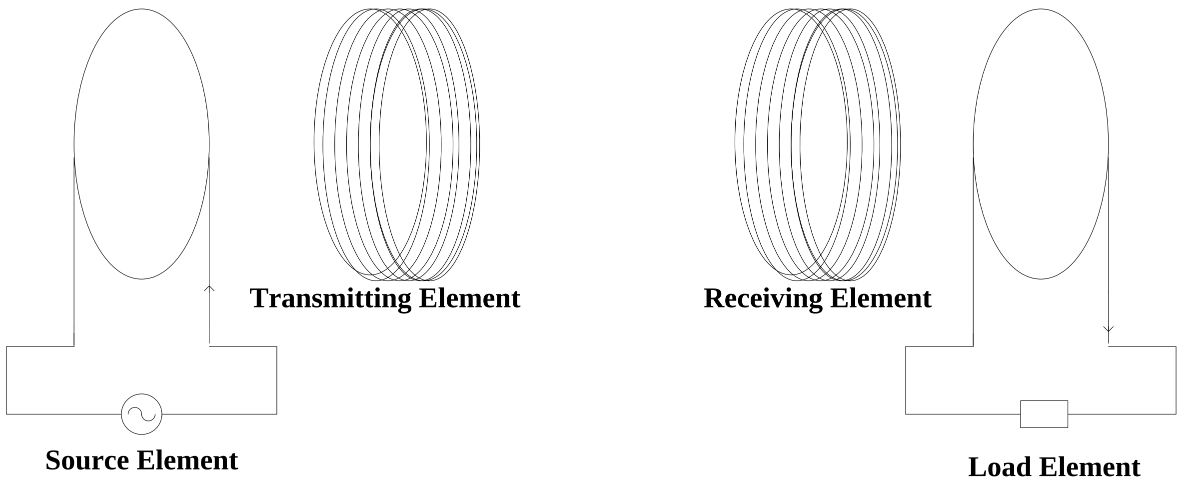


Figure1. 2: Schematic of an SCMR power transfer system. (From [17]).

Charging Electrical Vehicles with Resonance Inductive Coupling Technology

Resonance Inductive Coupling technology could introduce a convenient charging system for EVs and it makes possible to charge the vehicles, as they are parked in the parking or in your house's garage automatically without requiring of plugging and cord.

Powering vehicles by electricity is a new challenge in transportation technology. Nowadays, the attention of some scientists, researchers, and engineers have been attracted to EVs due to various advantages of EVs technology including: electric-powered vehicles are more economical than gas-powered vehicles, specially their electricity could be provided from renewable resources such as Solar, Wind, and so on; electric-powered vehicles pollute less than gas-powered vehicles, they are much reliable and require less maintenance to compare with gas-powered vehicles, and they can reduce the energy dependency.

In general, an electric motor and controller propel EVs; controller supplies the power of electric motor and obtains its required power from a rechargeable battery. Hence, the batteries are the heart of EVs, since the batteries should be powerful and long-lasting enough to move vehicles with minimum of recharging. As aforementioned, Resonance Inductive Coupling is a technology, which has been developed recently for charging batteries of the EVs. Inductive charging makes possible to charge EVs stationary and roadway electrification.

By roadway electrification, the power is deliverable to the vehicles as they move along an electrified section of roadway. In this method, the vehicles can provide their required power for traveling on freeways from the grid directly through the roadway. In additional, using resonance mechanism, in inductive charging roadway electrification allows to keep the efficiency high, as shown in Fig1. 3.

The entire system of wireless power transfer for EVs in stationary state is shown in Fig 1.4. high-frequency power source will produce high frequency alternating currents in the transmitting antenna that inductively transfer power to the receiving antenna. Among works, have been done for charging the EVs stationary through Resonance Inductive Coupling, we could refer to [20, 21]. Authors in [20, 21] have used the coil design as transmitting and receiving antenna over range 100mm-300mm for air gaps. The maximum efficiency has reported %98 and %100 at 100 mm air gap in [20, 21], respectively. However, in the mentioned works, authors have not considered the size of the designed coils and too big to be equipped on the bottom of EVs.

Figure1.3: Electrified roadway concept.

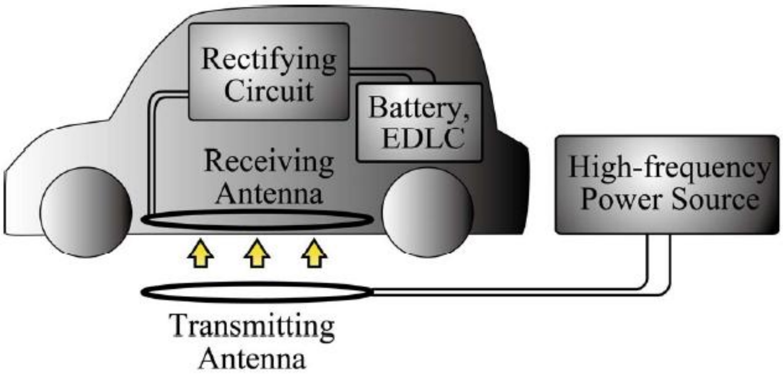


Figure1.4: Concept of wireless power transmitter for EVs.

This brings a new issue for car designers. Hence, in this study our aim is also to propose a model of antenna in resonance inductive coupling, with regard to the characteristic of antennas and its relation with power efficiency.

1.4 Field-to-Wire Coupling

In this section, we address the topic from different point of view and try to model the problem by equivalent circuits.

In Electromagnetic Compability field, the most effort of EMC engineers is to reduce electromagnetic interference and enhance performance of electronic devices in vicinity of interference. In order to that, some qualifications evolve to check the quality of the electronic devices; such as radiated emission and susceptibility.

Radiated Emission

Radiated emission is utilized to understand the factors that cause the unintentional radiated and the properties of those unintentional radiated in a system. As you known, the radiated electromagnetic field is produced, when an alternative current pass through a wire. Fig1. 5 illustrates two currents mode that produce the radiated emission on two wires parallel. The differential currents I_D mode are equal in magnitude, but they are in opposite direction; the common currents I_C mode are equal in magnitude, but they direct in the same direction. Therefore, the electromagnetic fields produced in opposite direction by the differential currents mode, tend to cancel each other but in practical, they are not able to cancel each other completely. In contrary, the electromagnetic fields produced in same direction by the common currents mode, add and produce larger electromagnetic fields.

In EMC fields, we are interested in having the minimum radiated emission as much as possible. In [22], the differential and common currents mode have been discussed in details and the following results have been obtained:

- The minimum radiated emission due to the differential and common currents mode is achievable by reducing the current level, the loop area (in differential currents mode), and the line length (in common currents mode)
- Reducing the loop area and length should be done early in the design.

In this study, we would like to propose a model antenna with the maximum radiated emission. Consequently, we present a model antenna for our system with either larger loop area or longer line length. The properties geometry of our model will be reported in the chapter 4.

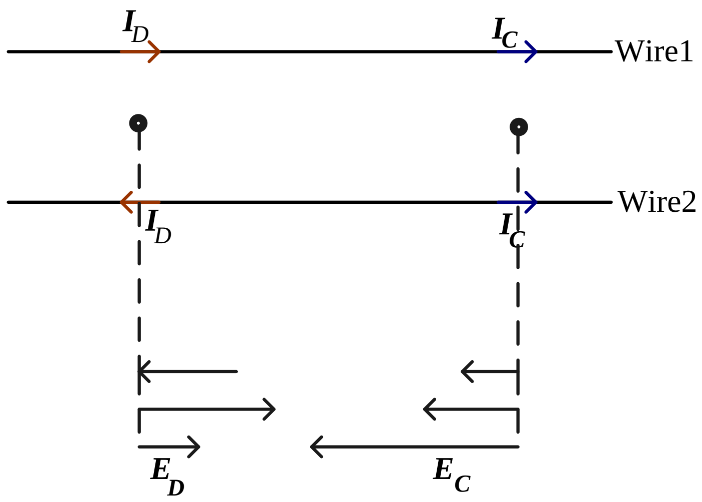


Figure1. 5: Illustration of the differential and common currents mode. (from [22]).

Radiated Susceptibility

Is the measurement of susceptibility of a system to an external disturbance such as radiated field from a Radio transmitters or radar. The susceptibility of devices to radiated emission is investigated by modeling field-to-wire coupling [22]. In this work, we utilize the derived model for investigation of radiated susceptibility testing of electronics devices in performance coupling between two antennas.

Field-to-wire coupling model is studied in order to give the better view of the coupling phenomena. Consider a lossless and uniform/parallel two-wire line with length ℓ

radius r_w, and separation by distance h . Uniform/parallel transmission line is assumed to be excited by an external plane wave, as shown in Fig1.6.

The two-conductor line is assumed electrically short at the frequency of interest. This leads to model the line with per-unit-length parameters of inductance l and capacitor c, whereas the effects of the external field are presented by distributed voltage and current along the line [22]. Distributed voltage V and current I are related to the normal magnetic field component and the transverse electric field component, respectively [22]. As long as the termination impedances are not extreme values such as short or open circuit, the line inductance and capacitance are neglected.

The equivalent circuit has been shown in Fig.1.6b. Under this condition, the Thèvenin voltage of the equivalent circuit of the line (Fig1.6b), at where the non-linear load is located, is derived, as shown in Fig1.6c. The voltage at points AB, as the loads are matched, is obtained as

$$\boldsymbol{V_{AB} = \frac{1}{2} j\omega \ell h \left[\mu_0 H + Z_c \left(\frac{\pi\varepsilon_0}{\ln\left(\frac{h}{r_w}\right)}\right) E\right], \quad Z_l = Z_c = Z_n} \qquad \textbf{(1.1)}$$

Where, $H = \frac{|E|}{n_0}$, and $n_0 = \mu_0 c_0$ impedance of free space. In order to predict incidence field picked-up of a two-conductor line $| V_{AB} |$ is plotted against frequency, as shown in Fig1.7. Specific values adopted for above model are listed in the following:

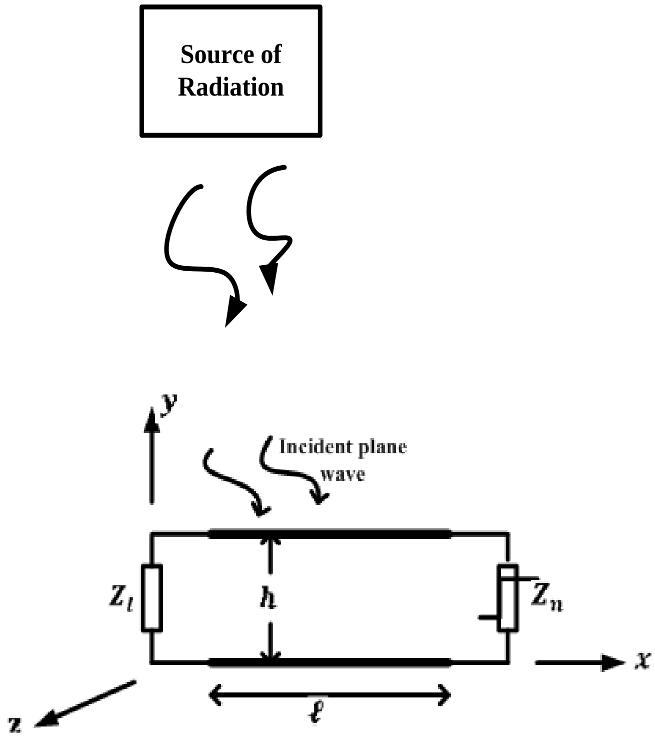
$$\boldsymbol{\ell = 10cm}$$

$$\boldsymbol{h = 3cm}$$

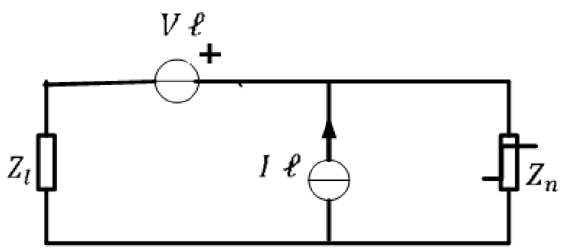
$$\boldsymbol{r_w = 0.5mm}$$

$$\boldsymbol{frequency = 0.9GHz - 2GHz}$$

$$\boldsymbol{| E | = 1v/m}$$


Source of Radiation
y
Incident plane wave
Z_l
h
Z_n
x
z
ℓ

(a)


$V\ell$
+
Z_l
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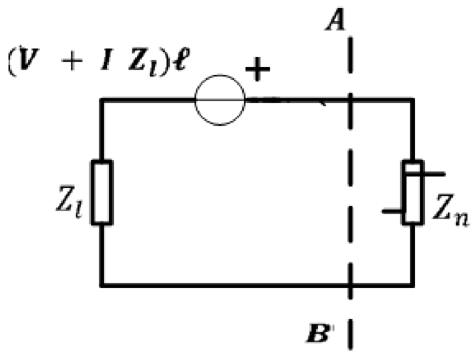
Z_n

(b)



(c)

Figure1.6: (a) A uniform/parallel two-wire line excited by an external electromagnetic wave, (b) circuit representation for one section of the line, and (c) Thèvenin equivalent circuit at where the non linear load is located.

Incidence uniform plane wave is considered with endfire incidence.

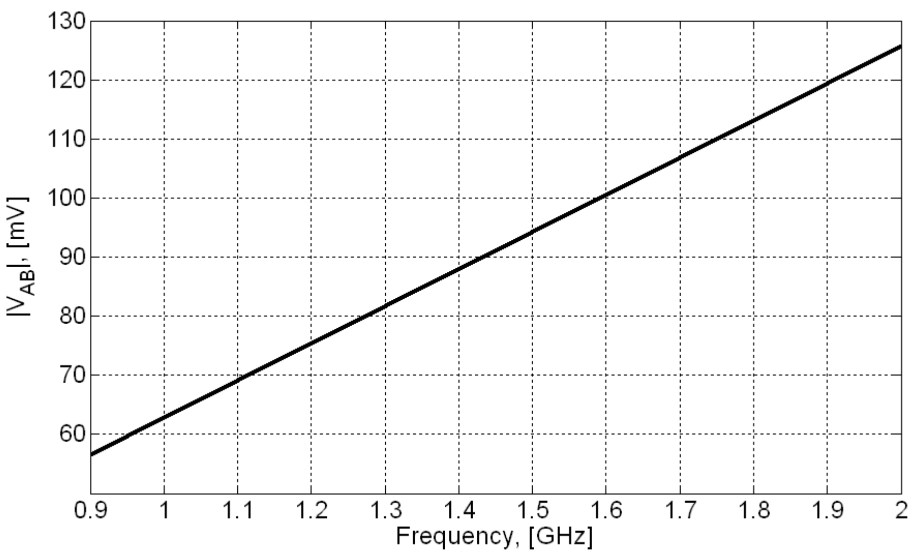


Figure1.7: | V_{AB} | versus frequency.

1.5 Antenna Design and Optimization Technique

Therefore, the biggest challenge in the design of RF energy system (rectenna) and wireless power transmitting systems is the maximization of the transferred energy to the receiver in order to increasing their performance of these technologies. This is possible by suitably redesigning the transmitting and receiving devices, reduction of the size, trying to find the correct shape that allows on rising in performance, and tuning the transmitter and receiver at EM frequency to decrease leakage, and transmitting power in safe mode for human body and animals. With this aim an approach based on a novel evolutionary technique is proposed for the design of an optimized antenna configuration.

As been known, when two antennas are placed closely, a coupled mode resonance phenomena are created between them. In order to maximize delivering power, the radiation antennas should be reduced. As well as, the distance between antennas is short with respect to the wavelength; if the distance between antennas could be extended over such coupled mode phenomena, they would benefit a number of applications. In this study, we chose *loop wire antenna* as structure for optimization due to several reasons: a) loop wire antennas are common structure in wireless power transfer system [23, 24], b)they have greater efficiency than monopole or dipole antennas in case of being electrically large, c) and they are useable in low-power short-range transmitter [25, 26].

Evolutionary optimization algorithms are global search techniques, thus they can overcome the drawbacks of the traditional optimization methods: in fact, they can face nonlinear and discontinuous problems, with a great number of variables. Among the main evolutionary optimization approaches, it is worth mentioning the *Genetic Algorithm* (GA) and *the Particle Swarm Optimization* (PSO).
In this work, a novel hybrid technique, named *Genetic Swarm Optimization* (GSO), is used: several comparative studies over different optimization tasks have shown the effectiveness of Genetic Swarm Optimization in exploring the problem hyperspace,

especially for the optimization of large domain objective functions; moreover, GSO has been already successfully applied to the optimization of antennas, wireless systems and energy harvesting devices [27,28], usually allowing to reduce the number of iterations, and thus the computational effort, requested to optimize complex EM problems.

Chapter 2

Numerical Method-Matlab

2.1 Introduction

A wire antenna is treated as one-dimensional segment model. Requirement theory behind of this model is a special integral equation. Too large ratio of the radius to the length in one-dimensional segment model causes some problem. Hence, to avoid this problem, Matlab is used to investigate the properties of the antenna under analysis. A wire is represented by a thin strip model having one RWG edge element for strip width; the width of the strip should be four times the wire radius [29].

2.2 Antenna Theory

Two methods that in the last three decades have been more successful in the analysis of many intractable antenna problems are the *Integral Equation* (IE) method and the *Geometrical Theory of differential* (GTD).

The Integral Equation method describes the solution of the antenna problems in form of an integral, where the induced current density is usually unknown and part of the integral. Then, *Method of Moments* (numerical technique) are used to solve the unknown induced current density. Afterwards, the radiation integrals are used to find the radiated fields and other systems parameters. These parameters include:

- Antenna near field
- Antenna far field

- Surface current distribution
- Input impedance and return loss
- Antenna transfer function and antenna-to-antenna link

There are two types of IE's: one is the *Electric Field Integral Equation* (EFIE), another one is the *Magnetic Field Integral Equation* (MFIE). Electric Field Integral Equation is convenient for wire-type antenna; whereas Magnetic Field Integral Equation is only valid for closed surfaces. Standard Matlab package is applied in order to solve and simulate the Integral Equation (to find the solution of the unknown induced current density) by using the Method of Moments. *Rao-Wilton-Glisson* (RWG) basis functions, the electric field integral, and the feeding –edge model are the background materials of the underlying Method of Moments (MOM) code.

2.3 Matlab Code

In Matlab, the numerical steps of the moment method (MM) are calculated by Matlab source codes and the antenna mesh generator files, successively. It is worth nothing that these codes are executed sequentially.

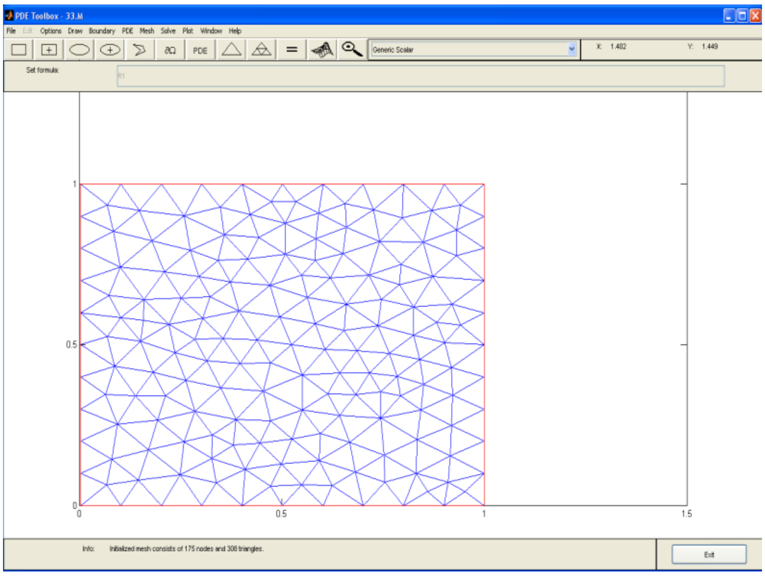
There are two main Matlab scripts. The first script impmet.m computes the impedance matrix Z [29] in order to determine electric current distribution on the antenna surface, and it is the basic and the most important step of the moment method. The second script point.m computes the radiated field of an infinitesimally small electric dipole or a group of dipoles at any points in space. This code allows us to determine the near and far field of an antenna. If the both mentioned scripts are programmed correctly, the rest of the work usually does not constitute any difficulties. The rest of Matlab codes are used to support and visualize the input and output data for an antenna. Those codes that their names start with rwg, e.g., rwg1.m, rwg2.m, rwg3.m are associated with the antenna structure operations. Those codes that their names start with efield such as efield1.m, efield2.m, efield3.m are associated with the near and far field antenna parameters.

2.4 Antenna Structure

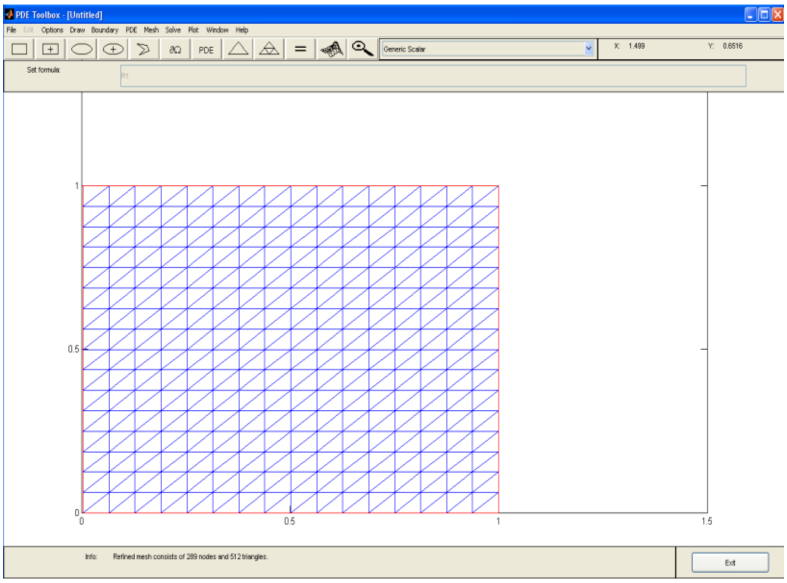
Antenna structures can be built in Matlab with two different ways. One way is the built-in mesh generator of the Matlab PDE toolbox (type command pdetool on workspace of Matlab). In this way, the mesh generator uses the convenient Graphical User Interface (GUI) to create planar structures of any rectangles, polygons, and circles. The design is able to be a 3D structure by writing a short script involving the z-coordinate dependency. For instance, a planar rectangle is created by PDE toolbox, as shown in Fig2.1.

An unstructured mesh could be created either by clicking on the Δ button on the top of the PDF Toolbox window or by selecting Initialize Mesh from the mesh menu. In order to have a structured mesh, selecting parameters option from the mesh menu and typing "inf" at maximum edge size part. Afterward, refine the mesh several times to obtain the structured mesh. Fig2. 2 represents unstructured and structured mesh for a circle with one diameter in PDE window.

The Second way is base on identifying the boundary of the antenna structure analytically. Matlab function Delaunay and function Delaunay3 are used respectively, to create mesh to the structure and to approach 3D structure. The advantage of this way is that 3D antenna surface and volume meshes are created arbitrary and the PDE toolbox is not requirement any longer. In this work, we utilized the *strip* mesh. The strip mesh is defined by cell size and strip width. Each cell is divided to two triangles by drawing the chord of the cells. The accuracy of the mesh depends on the number of the triangles. Obviously, we are able to obtain precise results by increasing the number of the triangles.

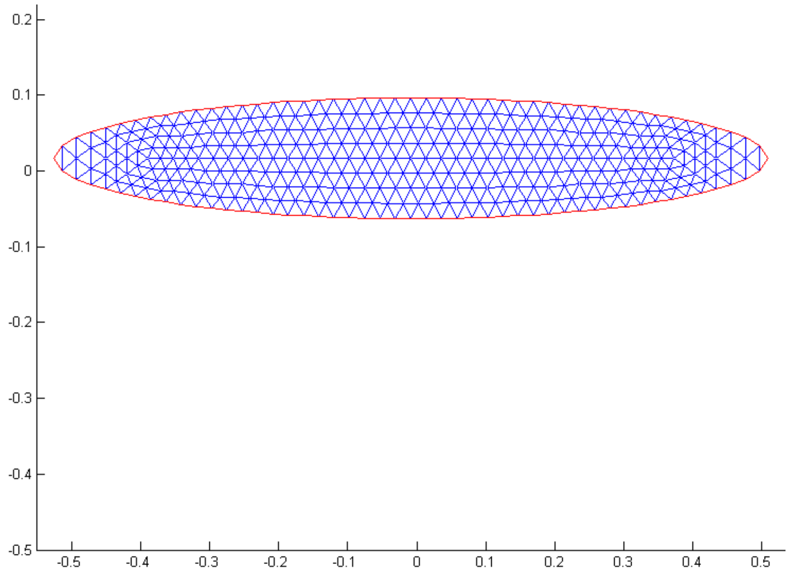


(a)

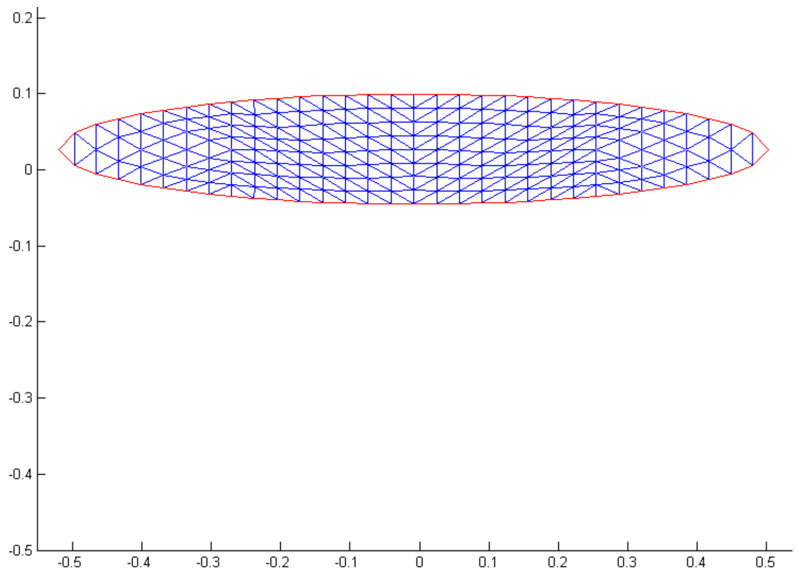


(b)

Figure 2.1: Two plate meshes create in PDE window: (a) Unstructured mesh; (b) Structured Mesh.



(a)



(b)

Figure2. 2: created circle with: (a) Unstructured mesh; and (b) Structured Mesh.

Fig2.3 shows a loop antenna and a helical antenna that have been created by identifying the boundary antennas.

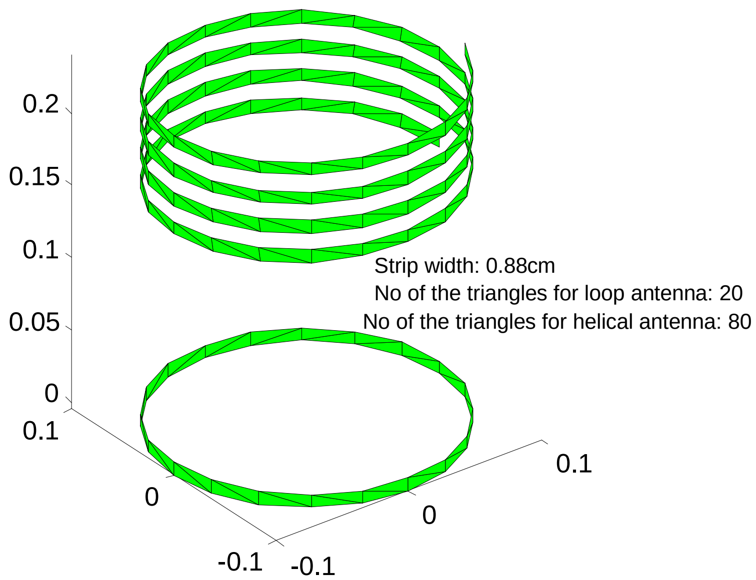


Figure 2.3: Loop and helical antenna created by the second way.

As aforementioned, the accuracy of the simulated model is controllable with the number of the triangles. In order to that, the created configuration in Fig2. 3 is again plotted in Fig2. 4 by decreasing the cell size. As well as, more examples have been given to show the flexibility of the method in various cases (Fig2.5).

2.5 Impedance Matrix and Surface Current

Consider a dipole antenna that whose surface is divided into separate triangles as shown in Fig. 2.6 (a). It is worth nothing that the used method of moments (MOM) relies on RWG (*Rao-Wilton-Glisson*) edge elements [30]. Each pair of triangles has a common

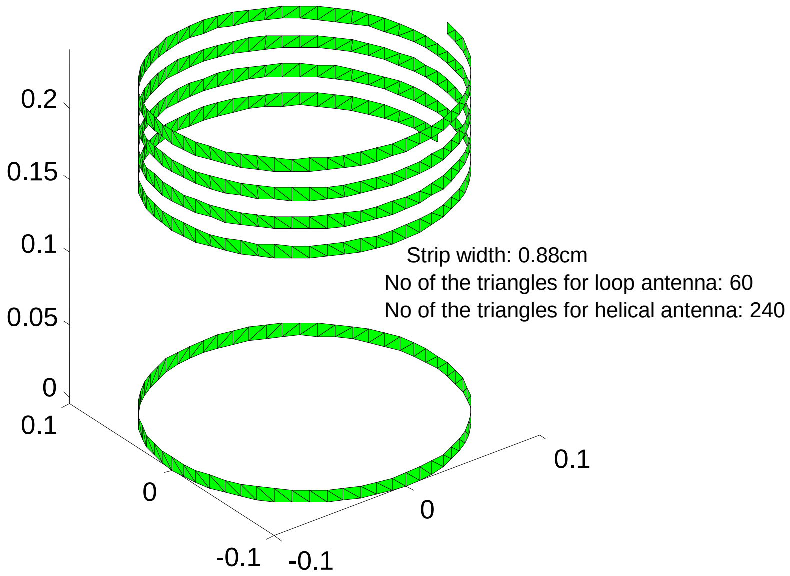


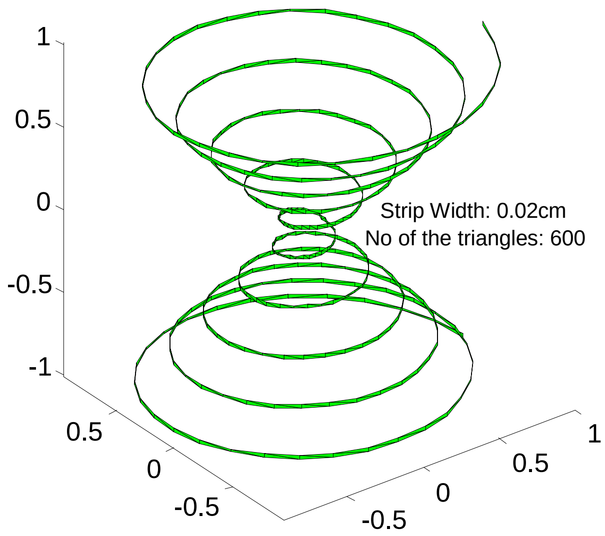
Figure2.4: Loop and helical antenna with small cell size.

edge which constitutes the corresponding RWG edge element; see Fig 2.6 (b). Triangles of each pair distinguish with a plus and minus sign($T^{\pm}$).

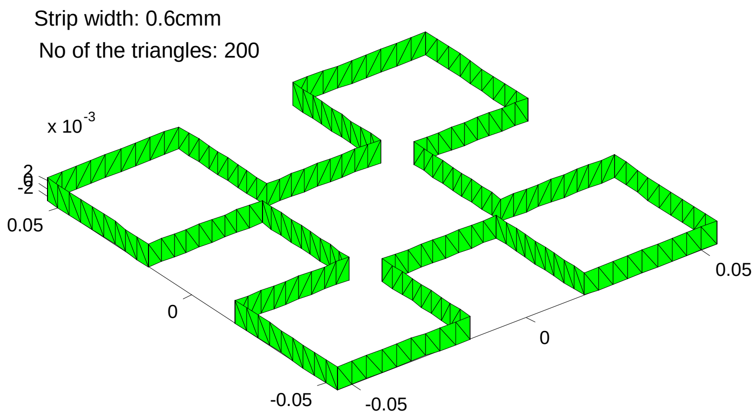
A basis function (or vector function) of the edge element

$$\boldsymbol{f}(\boldsymbol{r}) = \begin{cases} \left(\frac{l}{2A^{+}}\right)\boldsymbol{\rho}^{+}(\boldsymbol{r}) & \boldsymbol{r\ in\ T^{+}} \\ \left(\frac{l}{2A^{-}}\right)\boldsymbol{\rho}^{-}(\boldsymbol{r}) & \boldsymbol{r\ in\ T^{-}} \\ \boldsymbol{0} & \boldsymbol{otherwise} \end{cases} \qquad \textbf{(2.1)}$$

Where, l is the length of edge, $A^{\pm}$ is the area of triangle $T^{\pm}$, and $\rho^{\pm}$ connects the free



(a)



(b)

Figure2.5: Examples of the created antenna in Matlab: (a) Helical tapered antenna; (b) Fractal antenna.

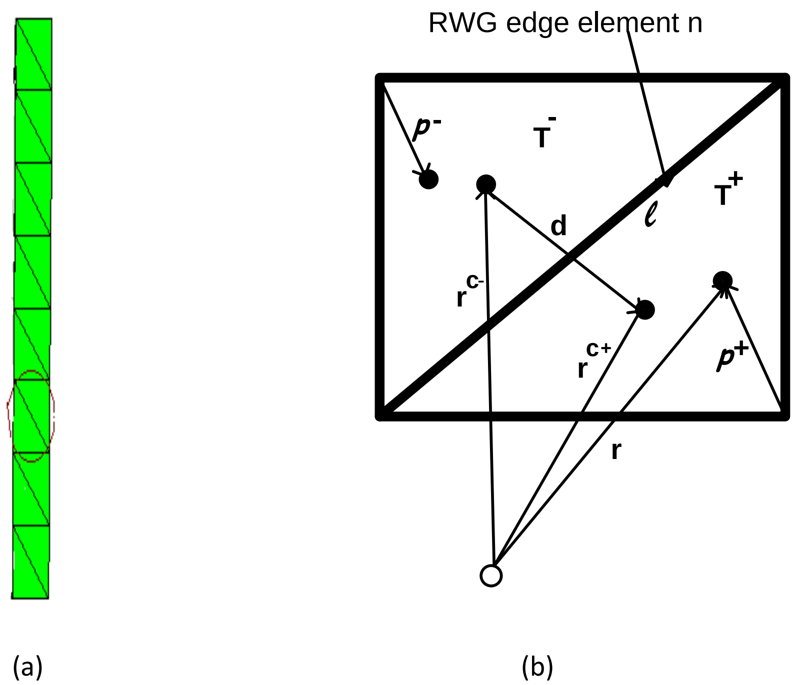


Figure 2.6: Schematic of a RWG edge element.

vertex of the plus/minus triangle to the observation point r; index c denotes the center of triangles $T^{\pm}$. Finally, the surface electric current on the antenna surface will obtain as the summation of the contribution (2.1) over all edge elements, with unknown coefficients.

$$\boldsymbol{J} \cong \sum_{n=1}^{N} \boldsymbol{I_n} \boldsymbol{f_n}(\boldsymbol{r}) \qquad \textbf{(2.2)}$$

Where, N is the number of edge element. **I** is unknown coefficient, which will obtain from the impedance equation (or the moment equation) as the unique solution of the equation. The linear impedance equation may be written in matrix forms

$$\boldsymbol{Z}.\boldsymbol{I} = \boldsymbol{V} \qquad \textbf{(2.3)}$$

Where, $Z = [Z_{mn}]$ is an $N \times N$ impedance matrix and $I = [I_n]$ and $V = [V_m]$ are column vectors of length N; indexes m and n correspond to two edge elements. Elements Z and V are given by

$$\boldsymbol{Z_{mn} = l_m[j\omega\left(A_{mn}+.\frac{\rho_m^{c+}}{2} + A_{mn}^{-}.\frac{\rho_m^{c-}}{2}\right) + \Phi_{mn}^{-} - \Phi_{mn}^{+}]} \qquad \textbf{(2.4)}$$

Where

$$\boldsymbol{A_{mn}^{\mp} = \frac{\mu}{4\pi}[\frac{l_n}{2A_n^{+}}\int_{T_n^{+}} \rho_n^{+}(r')g_m^{\pm}(r')ds' + \frac{l_n}{2A_n^{-}}\int_{T_n^{-}} \rho_n^{-}(r')g_m^{\mp}(r')ds']} \qquad \textbf{(2.4a)}$$

$$\boldsymbol{\Phi_{mn}^{\pm} = \frac{1}{4\pi j\omega\varepsilon}[\frac{l_n}{A_n^{+}}\int_{T_n^{+}} g_m^{\pm}(r')ds' - \frac{l_n}{A_n^{-}}\int_{T_n^{-}} g_m^{\pm}(r')ds']} \qquad \textbf{(2.4b)}$$

Where

$$\mathbf{g_m^{\pm}(r') = \frac{e^{jk|r_m^{c\pm}-r'|}}{|r_m^{c\pm}-r'|}} \qquad \textbf{(2.4c)}$$

And

$$\boldsymbol{V_m = l_m(E_m^{+}.\frac{\rho_m^{c+}}{2} + E_m^{-}.\frac{\rho_m^{c-}}{2})} \qquad \textbf{(2.5)}$$

Where

$$\boldsymbol{E_m^{\pm} = E^{i}(r_m^{c\pm})} \qquad \textbf{(2.5a)}$$

Note that E^{inc} is the electric field of an incident electromagnetic signal.

$$\boldsymbol{\rho_m^{c+} = r_m^{c+} - v_m^{c+}, \rho_m^{c-} = -r_m^{c-} + v_m^{-}}$$

When, $v_m^{c\pm}$ denote the centroil point.

2.6 Code Sequence

The source code in the Matlab directory is divided into two sequences; the first sequence includes the Matlab scripts rwg.m; the second one includes the Matlab codes efield.m. Fig 2.7 shows the flowchart of algorithm which determines the process of simulation by Matlab.

At the first step, the antenna structure is modeled analytically; then Delaunay triangulation is applied to the structure by using Matlab function Delaunay. The script rwg1.m and rwg2.m create RWG edge elements in order to compute the impedance matrix in the Matlab script rwg3.m. Calculation of the input impedance and radiation resistance are done in the script rwg4.m by determining excitation voltage. It is worth noting, the source of the induced current could be either the voltage source with 1 $^{v}/_{m}$ magnitude and zero phase or an incident electromagnetic wave with 1 $^{v}/_{m}$ electric field. The final script (rwg5.m) of the first sequence is devoted to visualize the surface current distribution of the antenna; as shown in Fig 2.8.

After the first code sequence is complete, scripts efield1.m, efield2.m, and efield3.m provide radiation signal at a point in the free space, radiation patterns of the antenna including 3D patterns, and the antenna gain. It is noticeable that the files with mat suffix (in Fig 2.7) are applied to save the information of each script; and using those information in the next script.

2.7 Electrically Large Loop Antenna

In this section, a square loop wire antenna with the length $l = 154mm$ and the cross-sectional radius $r_w = 1.1421\,mm$ at frequency $500MHz$ are created and the surface current distribution along the antenna is visualized. The loop contains 325 triangles.

The feeding edge of the structure is specified at point $(-0.07,0,0)$ by applying the delta gap model.

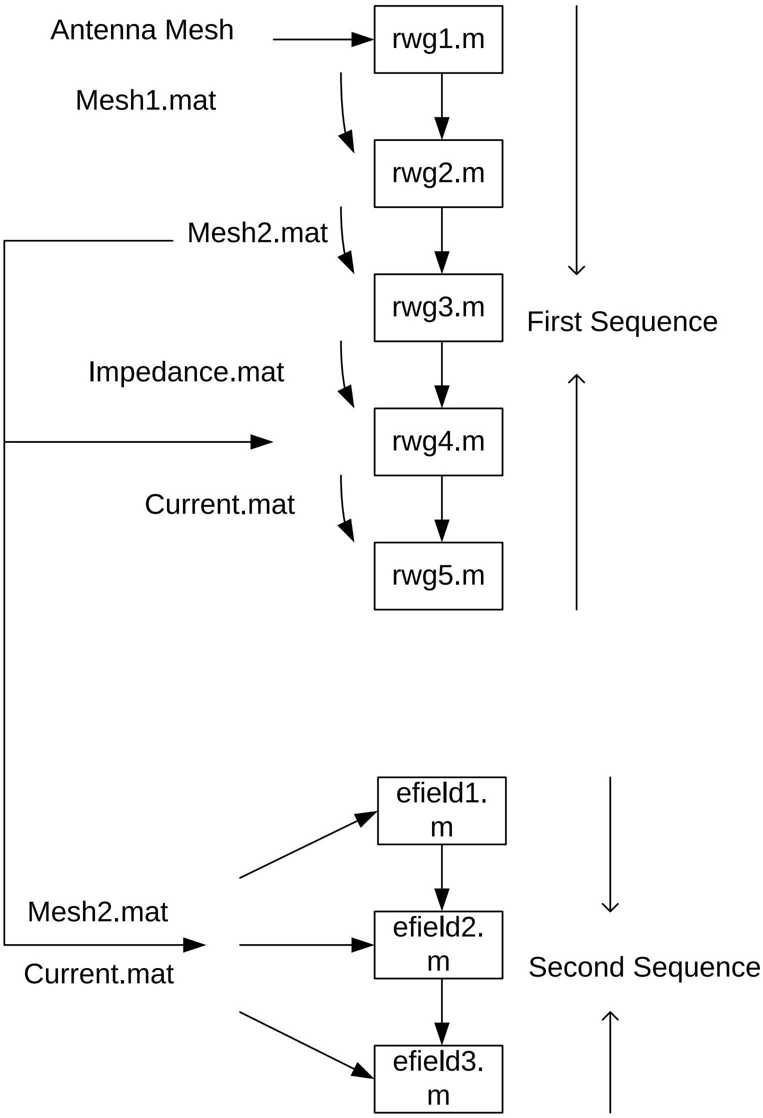


Figure 2.7: Flowchart of algorithm of antenna simulation by Matlab.

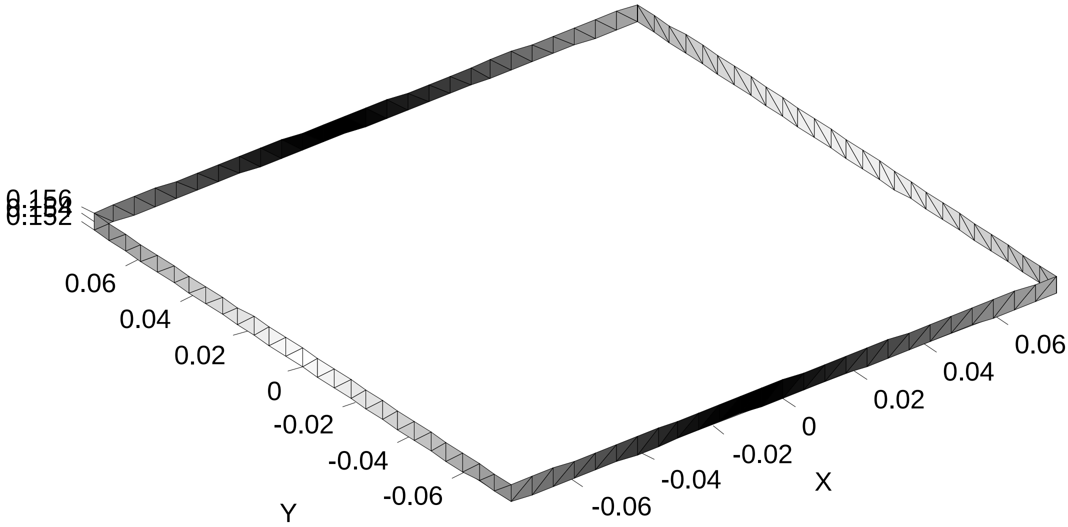


Figure 2.8: Surface current distribution along a square loop antenna at $500MHz$ frequency with a voltage source located at point $(-0.07,0,0)$.

As seen in Fig2.8, the surface current on the antenna is not distributed constantly. Thus, the simulated loop square wire antenna is an electrically large loop antenna at frequency $500MHz$. The white color corresponds to the maximum current density magnitude.

Chapter 3

Optimization Method

3.1 Introduction

In recent years several evolutionary algorithms have been developed for optimization of every type of electromagnetic problems. The general goal of the optimization is to find a solution that represents the global maximum or minimum of a fitness function. Electromagnetic optimization problems generally contains a large number of parameters; these parameters can be either continuous, discrete, or both, and often include constraints in allowable values. In addition, the solution domain of electromagnetic optimization problems often has non differentiable and discontinuous regions, and often utilizes approximations or models of the true electromagnetic phenomena to conserve computational resources.

Global search methods present two competing goals, exploration and exploitation: exploration is important to ensure that every part of the solution domain is searched enough to provide a reliable estimate of the global optimum; exploitation, instead, is also important to concentrate the search effort around the best solutions found so far by searching their neighborhoods in order to reach better solutions. Often global search methods are used together with other local search algorithm in order to improve efficiency and accuracy of the searching process [31].

The evolutionary computation algorithms (EA) are stochastic optimization methods that emulate biologic processes or natural phenomena. The capability of finding a global optimum without being trapped in local optima, and the possibility of well face nonlinear and discontinuous problems with great numbers of variables, are some advantages of these techniques. Besides these methods do not needs to compute any derivatives in order to optimize the objective function and this fact allows managing more complex fitness function.

Moreover, in contrast with traditional searching methods, EAs do not depend strongly on the starting point. Often a bad choice of the initial values can slow down the convergence of the entire process; or even drive the convergence towards a wrong solution (e.g. towards a local instead a global maximum or minimum). Although, these algorithms have strong stochastic basis, but they need a lot of iterations to get a significant result, in particular when the optimization problem has a big number of unknowns.

Among the main evolutionary optimization approaches it is worth mentioning the *Genetic Algorithm* (GA) and the *Particle Swarm Optimization* (PSO).

Msot of the times, PSO have faster convergence rate than GA early in the run, but they are often outperformed by GA for long simulation runs, or when the number of unknowns increases. This is due to the different types of search, adopted by the two algorithms.

The new hybrid technique here proposed is called *Genetical Swarm Optimization*, consists in a strong co-operation of GA and PSO, since it maintains the integration of the two techniques for the entire run of simulation. In fact, in each iteration, some of the individuals are substituted by new generated ones by means of GA, while the remaining part is the same of the previous generation but moved on the solution space by PSO.

Doing so, the problem of premature convergence of the best individuals of the population to a local optimum, one of the most known drawbacks found in tests of hybrid global-local strategies, has been cancelled.

The effectiveness of the proposed procedure has been validated with different electromagnetism problems, showing a good behaviour in particular for the optimization of large-domain functions.

3.2 Genetic Algorithm

Genetic Algorithms simulate the natural evolution, in terms of survival of the fittest, adopting pseudo-biological operators such as selection, crossover and mutation [32, 33]. In GA, the set of parameters that characterizes a specific problem is called an individual or a chromosome and is composed of a list of genes. Each gene contains the parameter itself or a suitable encoding of them. Each individual therefore represents a point in the search space, and hence a possible solution to the problem. For each individual of the population a fitness function is therefore evaluated, resulting in a score assigned to the individual. Based on this fitness score, a new population is generated iteratively with each successive population referred to as a generation. The GAs use three basic operators (selection, crossover, and mutation) to manipulate the genetic composition of a population. Selection is the process by which the most highly rated individuals in the current generation are chosen to be involved as “parents” in the creation of a new generation. The crossover operator produces two new individuals (i.e. candidate solutions) by recombining the information from two parents. Genetic Algorithms are very efficient at exploring the entire search space, but are relatively poor in finding the precise local optimal solution in the region in which the algorithm converges. Many efforts on the enhancement of traditional GAs have been proposed, by modifying the structure of the population or the role that an individual plays in it; the Genetic Algorithm developed for this application uses real encoded genes, since for high number of variables they result in faster than binary ones in convergence towards the maximum value.

Moreover, several additional operators have been developed for GA in order to get a faster convergence rate; Hybrid GAs, in order to solve the previous problem, use local improvement procedures as a part of the evaluation of the individuals of the population: these procedures complement the global search strategy of the GA. Evidently, each model is not optimal for all problems for many reasons. One of the most known drawbacks that were found during tests of hybrid GA is the problem of premature convergence of the best individuals of the population towards a local optimum.

3.3 Particle Swarm Optimization

The PSO has been introduced in the middle of 90's [34, 35, 36] and it is based on a"social interaction" metaphor in which the parameter space is searched by controlling the trajectories of a set of particles according to a swarm- or flock-like set of rules. The position of each particle is used to compute the value of the function to be optimized. Individual particles are then attracted, with a stochastic-varying strength, by both the position of their best past performance and the position of the global best past performance of the whole swarm.

PSO is akin to the other stochastic methods performing a global search in the parameter space without getting trapped in local minima. In the recent years the interest for its application to electromagnetic problems has been rapidly increasing [37, 38, 39], and several papers have been published comparing it with other optimization techniques, mainly with GA [40, 41, 42, 43].

3.3.1 Traditional PSO Implementation

Particle Swarm Optimization (PSO) is one of the more recently developed evolutionary techniques; it is based on a suitable model of social interaction between independent agents (particles) and it uses social knowledge in order to find the global maximum or minimum of a generic function [35]. While for the GA, as shown in section 3.2, the improvement in the population fitness is assured by pseudo-biological operators, such as selection, crossover and mutation, the main PSO operator is the velocity update that takes into account the best position explored during the iterations, resulting in a migration of the swarm towards the global optimum.

In the PSO the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories of a set of particles according to a swarm-like set of rules [37, 38].

In particular, the position of each particle is used to compute the value of the function to be optimized. Consequently every position is a particular solution of the optimization problem. Individual particles traverse the problem hyperspace and are attracted by both the position of their best past performance and the position of the global best performance of the whole swarm. Particles are moved in the domain of the problem with variable speeds and every position they reach represents a particular configuration of the variables set, which is then evaluated in order to get a score.

At each step the position of each swarm particle corresponds to one potential “optimal” solution for the problem, therefore the value of the function that mathematically models the problem, the fitness or cost function, is evaluated for all these possible solutions and the one that gives the best cost value.

As GA, the standard PSO algorithm is therefore an iterative procedure in which a set of $i = 1..,, Np$ particles, or agents, are characterized by their position Xi and velocity Vi with which they move in the M-dimensional space domain D of a cost function $f(X)$. A full treatment of the method can be found in [36] but for sake of clarity and uniformity of notation it is briefly summarized in the following. At the beginning positions and velocities have completely random values $X_i^{(0)}$and $V_i^{(0)}$, then they are updated iteratively according to the rules:

$$\boldsymbol{V}_i^{k+1} = \boldsymbol{\omega}^k \boldsymbol{V}_i^k + \boldsymbol{\phi}\boldsymbol{\eta}_1(\boldsymbol{P}_i - \boldsymbol{X}_i^k) + \boldsymbol{\phi}\boldsymbol{\eta}_2(\boldsymbol{G} - \boldsymbol{X}_i^k) \qquad \textbf{(3.1)}$$

$$\boldsymbol{X}_i^{k+1} = \boldsymbol{X}_i^k + \boldsymbol{V}_i^{k+1} \qquad \textbf{(3.2)}$$

being P_i the best position ever attained by particle i itself (personal knowledge) and G the best position ever attained by the particle swarm (social knowledge); $\omega^k = \omega_0 e^{-\alpha k} + \omega_1$ is a friction factor slowing down particles, η_1 and η_2 are positive parameters tuning the pulls towards the personal and global best positions and ϕ is a random number of uniform distribution in the [0,1] range. Please note that, if ϕ appears more than once in a given formula it is assumed to have different values each time.

The presence of random weights in the pull terms generated by the particle's best position P_i and the global swarm best position G causes wide oscillations and a random search in the entire parameter space. Such oscillations are precious whereas they broaden the search of each particle but they have some drawbacks since they can produce continuous oscillation around the optimal point. Such oscillation can be dampened, and so the convergence enhanced, via an effective use of the ω parameter.

Having a friction factor which is a function of k was suggested in [44]. Starting the optimization process with a high value for k and reducing it as k increases encourage the particles to explore the whole space domain in the beginning, in search of the global minimum, and then allow them to better investigate the region in which this minimum is supposed to be located.

An important aspect connected with the efficiency of the PSO is the way in which the particles moving towards the border of the solution space are handled; in [42] three different solutions are proposed: the first one consists in setting to zero the velocity of the particles arriving at the domain boundary, the second one models the boundaries as perfect reflecting surfaces, so that the particles impinging on them are reflected back in the solution space; finally the third one allows the particles to fly out from the solution space, without evaluating the cost function any more, until the particle eventually gets back in the domain. In this work the second technique has been adopted, since preliminary tests seem to suggest that this is the one guaranteeing the faster convergence.

If the iterative process is not yet arrived at the end (i.e. if the cost function has not yet reached the fixed threshold value or if the number of iterations does not equals the maximum allowed) a new step is performed: particles move from their position according to a swarm- or flock-like set of rules, being attracted, with a stochastic-varying strength, by both the position of their best past performance and the position of the global best past performance of the whole swarm. Note that the PSO completely differs from the typical GA based evolutionary algorithms since it does not implement any selection or mutation of individuals, but particles adapt themselves to the geometrical characteristics of the solution space they are moving in.

3.3.2 Some Consideration on PS

The PSO is gaining a big popularity, especially because of its simplicity in implementation, its robustness and its "optimization capability" for both single objective and multi-objective problems. PSO proved to be in all considered cases at least comparable, and often superior, to its most famous competitor, the GA [43, 45].

Besides the easiness of the implementation, the PSO presents the advantage of being well suited for optimization problems with both discrete and continuous parameters, and for parallel computing implementation [39, 46].

All these features make the PSO particularly appealing and attracted the interest of the electromagnetic community in the last years [42, 47]. However, the use of such a technique, requiring the evaluation of the cost function thousands of times needs particular care for electromagnetic problems, in which the cost function is often very computationally expensive. Moreover, there is some application in which PSO is by outperformed by GA [43]. For this reason, the development of new versions of the PSO algorithm with enhanced properties is a challenging issue.

3.4 The Class of Meta-Swarm Algorithm

Recently, the Particle Swarm Optimization (PSO) method has been successfully applied to different electromagnetic optimization problems. Because of the complexity of this kind of problems, the associated cost function is in general computationally expensive. A rapid convergence of the optimization algorithm is hence required to attain results in short time.

In this section some new PSO based techniques, aimed to improve the performances of the standard PSO with a negligible overhead in the algorithm complexity and computational cost are presented. All of them will exploit multiple interacting swarms.

In the literature, the use of more than one swarm or PSO is very sporadic, and, to the author best knowledge, previously completely absent in conjunction with electromagnetic problems. In [48] a division of the population in cluster is proposed. Contrarily to what is done here, in [48] the particles belonging to a cluster are chosen according to a ”minimum distance” criterion, and the equations that manage the evolution of the single particle are modified, substituting its personal and/or the global bests with those of the center of the cluster the particle belong to. In this way, however, the complexity of the algorithm increases since the particles division into clusters must be performed and managed. In [49] two separate PSOs are used to optimize a two-objective problem: each PSO focus on one aspect of the problem and they interact through the cost function. Finally, in [50] the Cooperative Particle Swarm (CPSO) method is introduced. This technique splits the domain in subspaces, each searched by a swarm, hence requiring additional functions to reconstruct the point where the cost function is to be evaluated and a more complex way, with respect to conventional PSO, to handle and store personal and global bests.

The most performing CPSO-H_k (H stands for Hybrid, k is the subspace dimension [50]) algorithms relies on the co-evolution of a CPSO and a PSO with exchange of information between the two, leading to an even more complex algorithm. On the other hand, the algorithms here presented exhibit just one or two terms to be summed to the velocity update function, and no other additional complexity.

3.4.1 Undifferentiated Meta-Swarm

Here three variations over the standard PSO algorithm are described. All of them use multiple swarms to enhance the capabilities of global search, but adopt different simple rules for describing the interactions among them; therefore the overhead to the traditional implementation is negligible.

The implementation here proposed is similar but simpler than those of Cooperative Particle Swarm (CPSO) methods [51,52]. These latter splits the domain in subspaces, each searched by a swarm, hence requiring additional functions to reconstruct the point where the cost function is to be evaluated and a more complex way, with respect to conventional PSO, to handle and store personal and global bests.

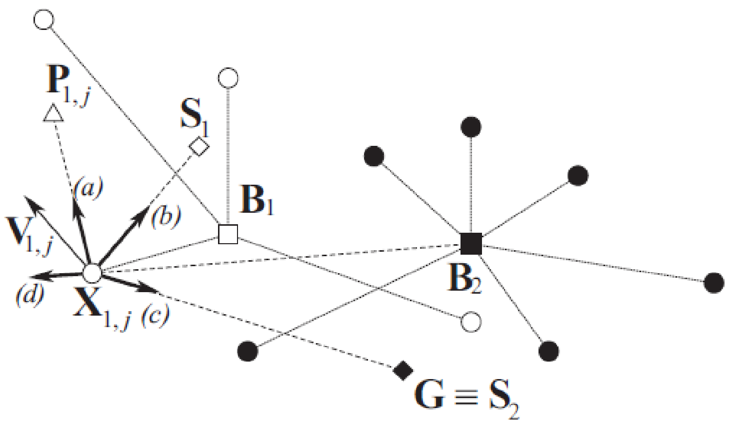


Figure3.1: Undifferentiated Meta-Swarm basic layout. Forces over a generic particle are: (a) pull toward personal best$P_{1,j}$; (b) pull toward swarm best S_1; (c) pull toward global best G (belonging to swarm 2); (d) repulsion from the other swarm's barycentre B_2.

Meta PSO

Meta PSO (MPSO) is the most straightforward of the methods here presented and simply consists in using more than a single swarm. Particles are now characterized by two indexes: an index $j = 1, \dots, Ns$ defining the swarm they belong to and an index $i = 1, \dots, Npj$ within the swarm. For sake of simplicity in the following all swarms will be considered as having the same number of particles $Np = Npj \ \ \forall j = 1, \dots, Ns$. The MPSO velocity update rule is:

$$\boldsymbol{V_{j,i}^{k+1} = \omega^k V_{j,i}^k + \phi\eta_1\left(P_{j,i} - X_{j.i}^k\right) + \phi\eta_3\left(S_j - X_{j,i}^k\right) + \phi\eta_2(G - X_{j,i}^k)} \qquad \textbf{(3.3)}$$

where $P_{j,i}$ is the particle personal best position, S_j is the global best position of swarm j (swarm social knowledge) and G is the global best position of all swarms (racial knowledge), while the other symbols have the same meaning as in (3.1).

Position update and boundary handling are the same as in standard PSO with just one more index.

Modified Meta PSO

As an enhancement to MPSO aimed at keeping swarms apart from each other, and hence widening the global search, an inter-swarm repulsion is introduced and a Modified $MPSO$ (M^2PSO) produced. The velocity update rule becomes:

$$\boldsymbol{V_{j,i}^{k+1} = \omega^k V_{j,i}^k + \phi\eta_1\left(P_{j,i} - X_{j.i}^k\right) + \phi\eta_3\left(S_j - X_{j,i}^k\right) + \phi\eta_2\left(G - X_{j,i}^k\right)}$$
$$\boldsymbol{- \sum_{s \neq j} \phi\xi \frac{B_s^k - X_{j,i}^k}{|B_s^k - X_{j,i}^k|^\gamma}} \qquad \textbf{(3.4)}$$

where the last term is a sum of the repulsions between each single particle and all the other swarms barycenters $B_j^k = (1/N_p)\sum_{i=1}^{N_p} X_{j,i}^k$ weighted by a random value ϕ and a fixed weight ξ The repulsive force introduced is a function of distance according to power γ. If $\gamma = 2$, as used here, force decays as the inverse of distance.

Stabilized Modified Meta PSO

As a further enhancement to the M^2PSO it can be ruled that the swarm which is performing best, i.e. the swarm j whose social knowledge coincides with the racial knowledge $S_j = G,$ is not repelled by other swarms, or, in other words, stabilizes it-self. This allows for the best swarm to keep exploring the surroundings of the current best position, refining it, whereas other swarms extend the search in other points of the space, hence greatly enhancing the possibility of escaping a local minimum.

Figure 3.1 shows graphically the basics of all these algorithms. Only two swarms are depicted, for sake of clarity. Swarm 1 is represented via white symbols, swarm 2 via black symbols. Only forces on a single particle $X_{1,j}$, with velocity $V_{1,j}$ belonging to swarm 1 are shown. Of course not all these forces are present, depending on the algorithm.

3.4.2 Differentiated Meta-Swarm

The multiple swarm techniques presented above use several swarms spanning the whole domain in order to have better and faster exploitation of the whole space domain without being trapped in local minima. The three techniques, presented also in [47], differ in the rule that manages particles, exhibiting just one or two terms to be summed to the velocity update function. The added complexity is hence negligible and of course the intrinsic parallel nature of PSO is maintained.

These three techniques will be identified in the following as Undifferentiated Meta PSOs, the word Undifferentiated meaning that all the particles of all swarms obeys to the same rules.

The simplest of these Meta PSOs is further modified here, and two other new schemes have been obtained, named in the following Differentiated Meta PSOs, in which the behavior of the particles within a swarm is managed with different rules.

Despite of their simplicity, both the Undifferentiated and the Differentiated Meta-PSO work better than the standard PSO. The effectiveness of the Undifferentiated and Differentiated Meta-PSO algorithm can also find a confirmation in the analysis on the different possible social interaction models reported in [53], in which it is hypothesized that tightly connected particle swarms, as in the standard PSO scheme, may not be so good in finding the problem optimum, since they can be entrapped in local sub-optima, while this risk is lower in case of moderately connected societies, as the proposed schemes are.

As opposed to the Meta-Swarms presented in section 3.4.1, in which each agent was equal to any other agent, in the Differentiated Meta-Swarm algorithms proposed here below different velocity update laws holds on agent-by-agent bases. In particular both the proposed algorithms are still based on a multi-swarm approach, but in each swarm a particle is bestowed a special ’leader’ status. If the bee similitude often used for PSO holds, we can think of this special particle of each swarm as the ’queen bee’.

It is worth noticing that two different flavors for each of the algorithms described above can be implemented, one where the leader particle never changes, and these will be referred to as Absolute Leader algorithm, and one where the leader particle can change within a swarm, usually by setting as leader the particle exhibiting the best performance (the one whose personal best coincides with the swarm’s best). This second family will be indicated as Democratic Leader algorithms. In this work the Leader paradigm will be applied only to the MPSO algorithm.

In principle it can be applied to any Meta PSO algorithm but preliminary analyses showed that the MPSO is the one taking the larger benefit. The resulting algorithms will be denoted as ALMPSO or DLMPSO (Absolute Leader Meta-PSO and Democratic Leader Meta-PSO), respectively. In these algorithms the leaders behave indeed as the agents of a MPSO, with an attraction towards the leader personal best (personal knowledge) an attraction towards the swarm best (social knowledge) and an attraction towards the global best of all leaders (racial knowledge). On the other hand all other swarms agents obey to interactions which are confined within the swarm itself, that is, they are not subject to racial knowledge. The updating rule for the velocity of the MPSO algorithm [47] can therefore modify as

$$\boldsymbol{V}_{j,i}^{k+1} = \boldsymbol{\omega}^{k}\boldsymbol{V}_{j,i}^{k} + \boldsymbol{\phi\eta_1}\left(\boldsymbol{P}_{j,i} - \boldsymbol{X}_{j.i}^{k}\right) + \boldsymbol{\phi\eta_3}\left(\boldsymbol{S}_j - \boldsymbol{X}_{j,i}^{k}\right) + \boldsymbol{\phi\eta_2}\left(\boldsymbol{G} - \boldsymbol{X}_{j,i}^{k}\right) + \boldsymbol{\delta}_{j,i}^{L_j}\boldsymbol{\phi\eta_2}\left(\boldsymbol{G} - \boldsymbol{X}_{j,i}^{k}\right) \qquad \textbf{(3.5)}$$

while the updating rule for the position remains the same as in (3.2):

$$\boldsymbol{X}_{j,i}^{k+1} = \boldsymbol{X}_{j,i}^{k} + \boldsymbol{V}_{j,i}^{k+1} \qquad \textbf{(3.6)}$$

In (3.5) $\delta_{ij}^{L_j}$ is a function which value is 1 only if $i = L_j$, being L_j the index denoting the leader of swarm j, otherwise it is 0.

Equation (3.5) holds of course both for Absolute and Democratic algorithms. In the former case the value of L_j is chosen at the beginning and never changed (in this case it is computationally simpler to consider $L_j = 1, \forall j = 1 \ldots, N_s$); whereas in the latter case L_j is updated at each time iteration k by having L_j pointing to that agent for which $P_{j,i} = S_j$. In both cases the algorithm complexity is not significantly different than that of a MPSO.

Fig3. 2 shows this algorithm graphically. As in the previous case only two swarms are depicted, for sake of clarity. Swarm 1 is represented via white symbols, swarm 2 via black symbols. The leader of each swarm is highlighted with an additional circle. The swarm leader is subject to three forces, whereas each other particle in the swarm only to two.

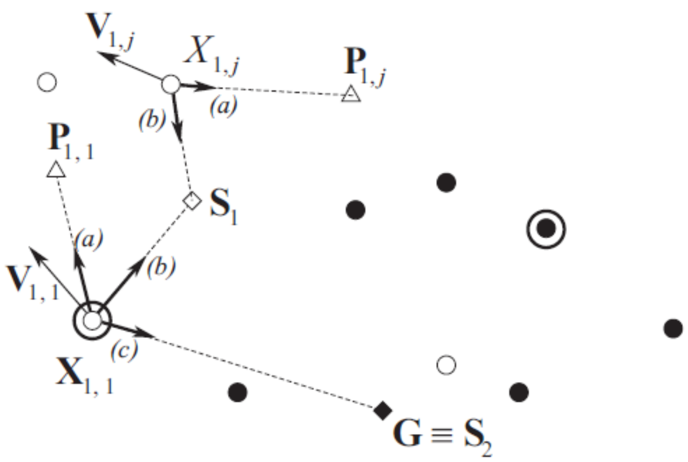


Figure3.2: Differentiated Meta-Swarm basic layout. Forces over the genetic particle are: (a) pull toward personal best $P_{1,j}$; (b) pull toward swarm best S_1. For what concerns the leader, he is subjected also to (c) pull toward global best G (belonging to swarm 2).

3.5 Genetical Swarm Optimization

Some comparisons of the performances of GA and PSO are present in literature [54], underlining the reliability and convergence speed of both methods, but continuing in keeping them separate.

Due to the different search method adopted by the two algorithms, the typical selection-crossover-mutation approach versus the velocity update one, both the algorithms have shown a good performance for some particular applications but not for other ones. For example we noticed in our simulations that sometimes GA outperformed PSO, but occasionally the opposite happened showing the typical application driven characteristic of any single technique. In particular PSO seems to have faster convergence rate than GA early in the run, but often it is outperformed by GA for long simulation runs, when the last one finds a better solution.

Anyway, the population-based representation of the parameters that characterizes a particular solution is the same for both the algorithms; therefore it is possible to implement a hybrid technique in order to utilize the qualities and uniqueness of the two algorithms.

Some attempts have been done in this direction, with good results, but with a weak integration of the two strategies. Precisely, most of the times, one technique is used mainly as a pre-optimizer for the initial population of the other technique. In [55], for example, the authors test two different combinations of GA and PSO, using the results of one algorithm as a starting point for the other (in both the orders) to optimize a profiled corrugated horn antenna.

Another hybridization strategy is proposed in [56], where the upper-half of the best-performing individuals in a population is regarded as elite and, before using GA operators, it is first enhanced by means of PSO, instead of being reproduced directly to the next generation.

The hybrid technique here proposed, called Genetical Swarm Optimization (GSO), and consists in a strong co-operation of GA and PSO, since it maintains the integration of the two techniques for the entire run. In fact, this kind of updating technique yields a particular evolutionary process where individuals not only improve their score for natural selection of the fitness or for good-knowledge sharing, but for both of them at the same time.

In each iteration, the population is divided into two parts and they are evolved with the two techniques respectively. They are then recombined in the updated population, that is again divided randomly into two parts in the next iteration for another run of genetic or particle swarm operators. Fig3. 3 and Fig3. 4 show the flowchart of the developed algorithm, the idea that stands behind the algorithm and the way to mixing the two main techniques, respectively.

The population update concept can be easily understood thinking that a part of the individuals is substituted by new generated ones by means of GA, while the remaining are the same of the previous generation but moved on the solution space by PSO.

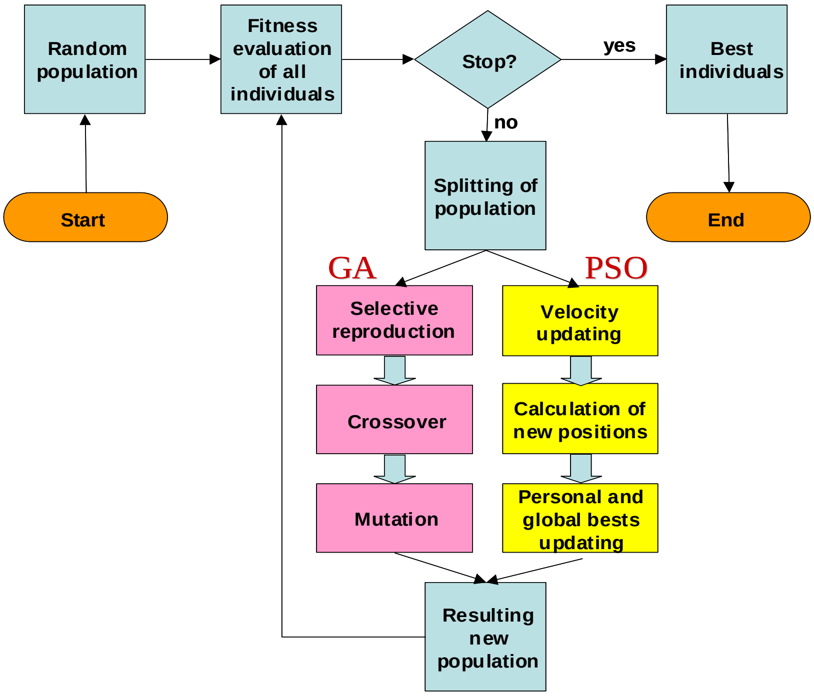


Figure3. 3: The flow-chart of the GSO algorithm.

The driving parameter of GSO algorithm is the Hybridization Coefficient $hc(i)$; it expresses the percentage of population that in each iteration is evolved with GA: so $hc(i) = 0$ means the procedure is a pure PSO (the whole population is processed according to PSO operators), $hc(i) = 1$ means pure GA (the whole population is processed according to GA operators), Whereas, $0 < hc(i) < 1$ means that the corresponding percentage of the population is developed by GA, while the rest with PSO technique.

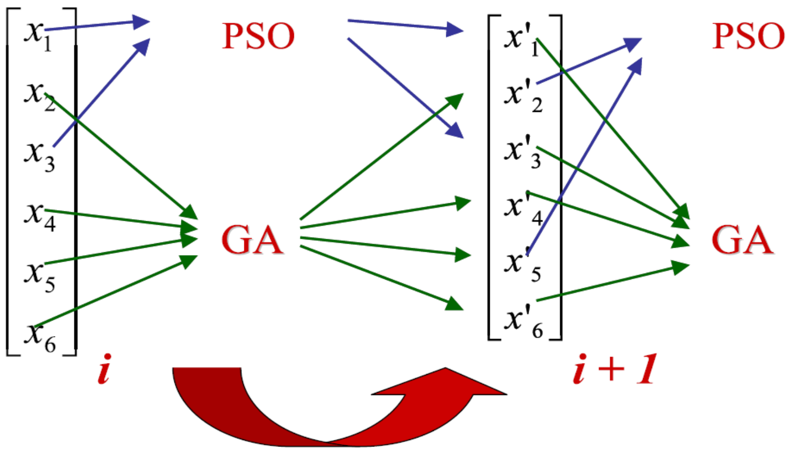


Figure3. 4: Splitting of the population in subgroups during the iterations.

3.5.1 The GSO Algorithm Class

The *hc* approach opens a wide spectrum of possible merging strategies between GA and PSO, since the *hc* itself can be varied during the optimization run. In fact, the number of individuals evolved by a particular procedure, in each iteration, can change according to predefined variation rules of the *hc* parameter, in order to exploit a better convergence. This feature essentially extends the GSO concept to stand as a class of hybrid evolutionary algorithms.

For instance, a step variation of *hc* between 0 and 1 (or vice versa) occurring after half the run, realizes an hybridization approach similar to the one used in [55], where the population is initially evolved by PSO, then the resulting individuals, after about 50% iterations, are evolved by GA (and vice versa).

The different rules of variation of $hc(i)$ during iterations identify several "flavours" in the class of GSO algorithms, as shown in [57]: both traditional implementations of PSO and GA can be obtained too, by keeping $hc(i) = 0$ and $hc(i) = 1$ for the entire run.

The best value of $hc(i)$ or its best variation rule for a given problem are hardly known a priori. Therefore the two different adaptive rules were proposed, in order to combine in the most effective way the properties of the GA and the PSO approaches also for unknown problems.

The first one is the so-called *Dynamical GSO*, as referred in [57]; in this implementation the hc parameter is updated during iterations according to the following rule:

$$\boldsymbol{f(x)} = \begin{cases} \boldsymbol{hc(i)} + \boldsymbol{v}\dfrac{\boldsymbol{e}^{-\xi\frac{i'}{N}}}{\boldsymbol{k}}, & if\boldsymbol{\Delta\hat{f}(i')} < \boldsymbol{\Delta\hat{f}(i)} \\ \boldsymbol{hc(i)}, & if\boldsymbol{\Delta\hat{f}(i')} \geq \boldsymbol{\Delta\hat{f}(i)} \end{cases} \qquad \textbf{(3.7)}$$

Where N is the total number of iterations, K is the number of individuals in the population, $i' = i + \Delta i$, $v = \pm 1$ (versus), $\xi = 2$ (damping), and $\Delta\hat{f}(i') = \hat{f}(i') - \hat{f}(i)$; here $\hat{f}(i')$ is the best fitness value obtained after i'iterations and $\Delta i = 5$.

The second implemented technique is the so-called *self-Adaptative GSO* that derives the hc updating rule from the traditional PSO technique: in fact, if we consider the value of $hc(i')$ in the i' -th iteration, then we can call $V_{hc}(i')$ the variation between $hc(i')$ and $hc(i)$ and so we can write:

$$\boldsymbol{hc(i')} = \boldsymbol{hc(i)} + \boldsymbol{V_{hc}(i')} \qquad \textbf{(3.8)}$$

Therefore, the problem is simply to find the right velocity update to properly change $hc(i)$ during the run; following the PSO similarity, we can define a personal best P_{hc} value that has been obtained during the run and therefore write:

$$\boldsymbol{V_{hc}(i')} = \boldsymbol{\omega}.\boldsymbol{V_{hc}(i)} + \boldsymbol{\phi}.\boldsymbol{\eta}.(\boldsymbol{P_{hc}} - \boldsymbol{hc(i)}) \qquad \textbf{(3.9)}$$

Where P_{hc} is chosen analyzing the slope of the increasing of the fitness score during the iterations, i.e. if in iteration $\bar{\iota}$ the increment of fitness is higher than in the previous history, then $P_{hc} = hc(\bar{\iota})$.

However, differently from the traditional expression for the velocity update of standard PSO, in this case the problem is mono-dimensional and there is only one single agent, therefore the personal best of P_{hc} is also the global best, and so the definition of (3.9) is simpler than (3.1). It is worth noticing that this updating procedure can not take advantage of the cooperation among several particles, therefore, to avoid stagnation in sub-optimal values, a random mutation is added to the $hc(i)$ value when the slope of the fitness curve and the velocity are equal to zero.

Preliminary analyses are here presented with respect to the other optimization techniques dealing with classical optimization problems. The application of these tools to the antennas developed for this work will be presented in the next chapter.

3.5.2 Preliminary Analysis

With the aim to validate the effectiveness of the developed technique, we used different values of hc in order to discover the best hybridization parameter and to compare GSO with pure PSO and GA, simply by setting $hc = 0$ or $hc = 1$.

A first comparison of the different performances has been made on a classical optimization problem, i.e. finding the maximum of an N-dimensional $sinc$ function given by the equation:

$$\boldsymbol{f}(\boldsymbol{X}) = \prod_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} \frac{\sin(\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{x}_{\mathbf{0},\boldsymbol{i}})}{(\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{x}_{\mathbf{0},\boldsymbol{i}})} \quad \mathbf{(3.10)}$$

where N is the dimension of the domain, $x_i \in (0,1)$ and $x_{0,i} = 0.3 \quad \forall i$.

To analyze the efficiency of the different approaches when the solution space dimension increases, three different cases of growing complexity were chosen , thus considering N = 5, 10 and 20.

The results reported in Fig3. 5-7 shows the fitness behaviour related to different *hc* values for the *sinc* function for different problem dimensions. In additional, from preliminary analyses it has been clear that the value of $hc(i)$ plays a role in affecting the speed of convergence, for instance very good performances have been obtained for the optimization of the *sinc* function by considering $hc(i) = 0.2, \forall\ i$ for the N-dimensional *sinc* function and it does not depend on the dimension of the problem. Furthermore, the obtained best *hc* value (0.2) means that, for a big sized problem, the basic PSO can be strongly improved by adding a small percentage of genetic operators on the population.

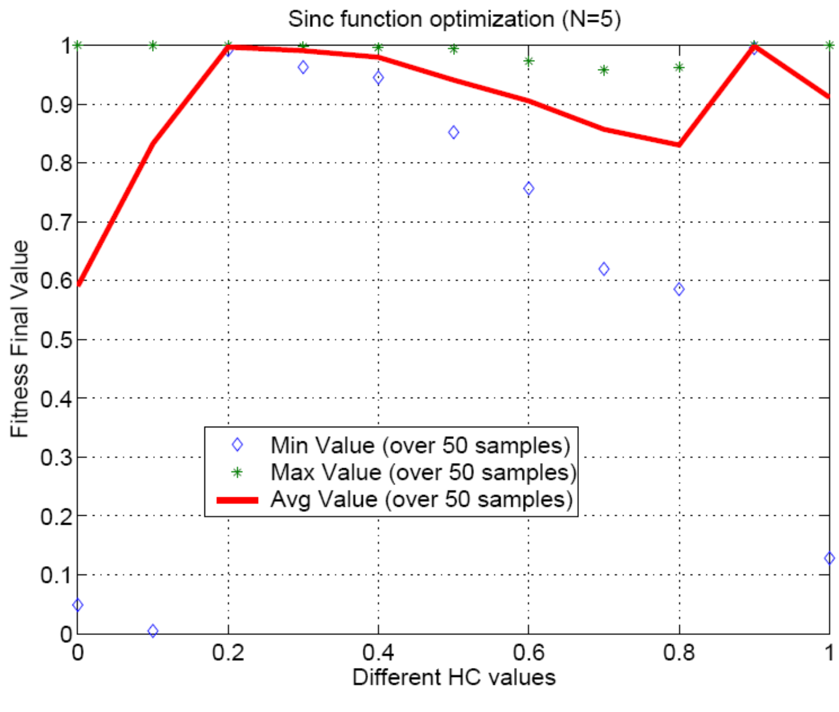


Figure3. 5: Final fitness for different *hc* values (5-D *sinc* function optimization, average over 50 samples).

Moreover, while for a small number of unknown GSO performance is similar to GA and PSO ones (Fig. 3.5), if the size of the problem increases (Fig. 3.6, 3.7), GSO behaviour improves and outperforms GA and PSO during iterations.

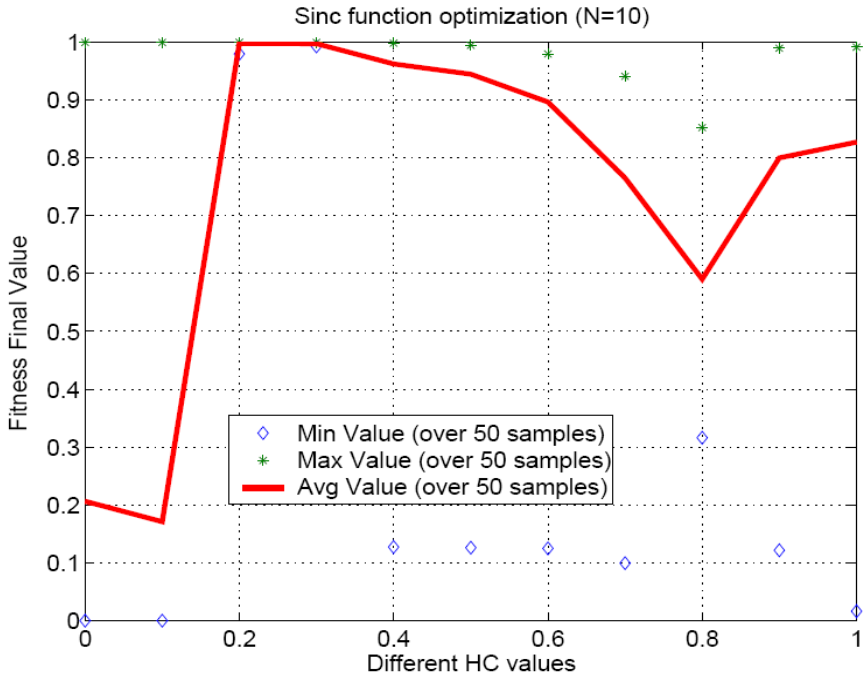


Figure3. 6: Final fitness for different *hc* values (10-D sinc function optimization, average over 50 samples).

It is important to notice that the evaluation of the fitness function is the most relevant time consuming task, while the computational overhead of the optimizer operators, different for the considered techniques, is negligible. This is particularly true in electromagnetic optimization. Therefore the larger the population, the longer is the single iteration, since several evaluations of the fitness function must be performed to complete the step. For this reason, the different techniques have been compared in terms of performed fitness evaluations rather than iterations, in order to fairly compare the different algorithms regardless of the number of individuals in the population. Furturemore, as results reported in Fig3.8-10 show, it seems that the improvments introduced by the hybridization are increasing with the dimention of the problem to be

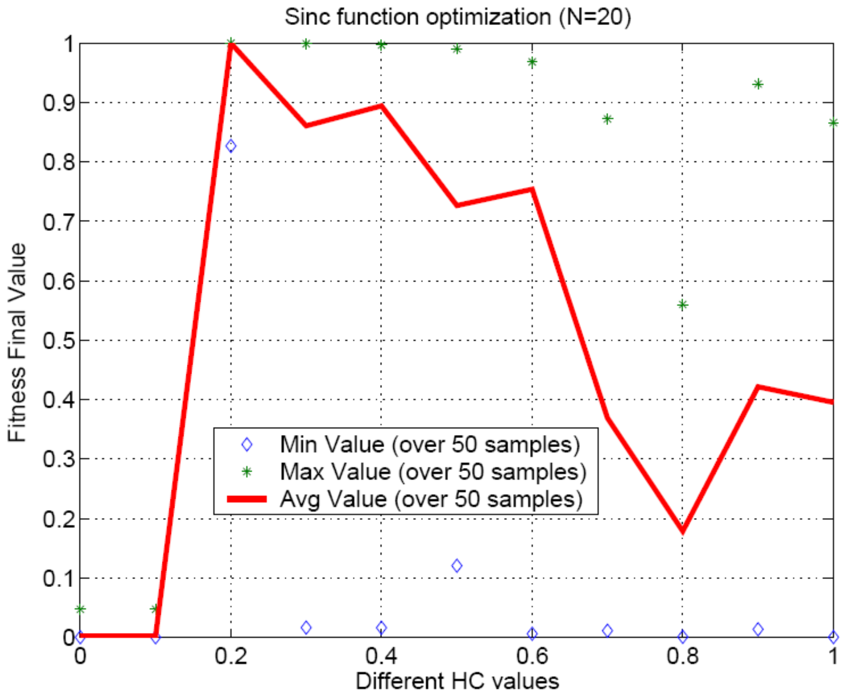


Figure3. 7: Final fitness for different *hc* values (20-D sinc function optimization, average over 50 samples).

optimized: if we consider the optimization of the well-known N-dimensional *sinc* function, for $N = 5$ average performance of all the considered method (increasing GA and PSO, for comparison) are almost the same , although the traditional methods sometimes fails in finding the optimal value, as shown by the bar indicating the worst performance (over 100 independent trials) in Fig3. 8. When $N = 10$, the average performances of GSO as slighty better than GA and significantly better than PSO (Fig3.9), while, for $N = 20$, the improvement introduced by the hybridization is not negligible, since just the different GSO implementations are able to locate the optimal value, as shown by the bar indicating the best performance in Fig3. 10, while, for the considered number of iterations, neither GA nor PSO are able to get the optimal value in 100 trials and their average performance is lower than GSOs'one. Moreover, the best performance is here obtained using $hc = 0.2$, since this value has been found to be the optimal for this kind of problem, but anyway the adaptive straegies are still better than the traditional technique.

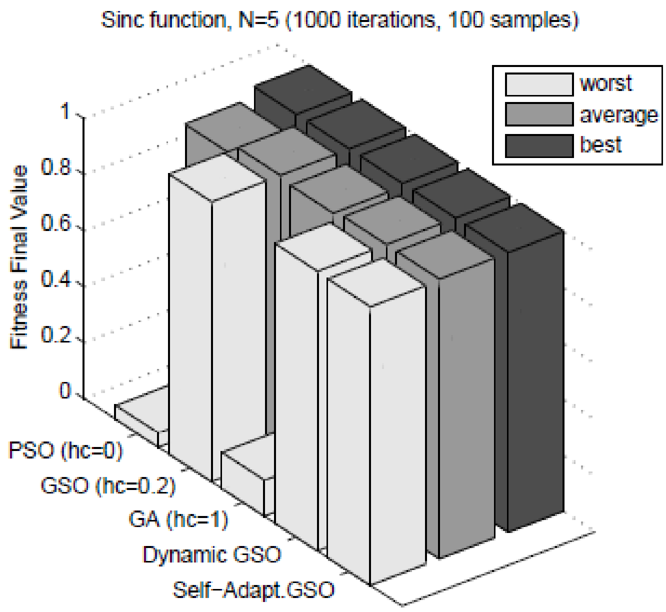


Figure3. 8: Final values of the *sinc* function optimization with $N = 5$ variables obtained with different hybridization strategies (average results over 100 trials).

3.5.3 Performance Analysis

With the aim of validating the effectiveness of the developed technique for electromagnetic applications, the author chose the optimization of a linear array of 100 elements. This application has been already considered in literature in order to compare the performances of the different algorithms in the determination of the complex phased array weights to best meet a specified far-field side-lobe requirement.

The antenna is a linear phased array of one hundred half-wavelength spaced radiators. The far-field radiation pattern to be optimized is $F.F.(\theta) = E.P.(\theta) \cdot A.F.(\theta)$, where

$$\boldsymbol{A \cdot F(\theta) = \sum_{i=1}^{N} A_n e^{j2\pi n(d/\lambda)\sin\theta}} \qquad \textbf{(3.11)}$$

is the array factor in which is the number of radiative elements, are the complex element weights to be determined. The voltage element pattern, according to [54] is assumed to be:

$$\boldsymbol{E \cdot P \cdot (\theta) = \sqrt{cos^{1.2}\theta}} \qquad \textbf{(3.12)}$$

The cost measure to be minimized is the arithmetic mean of the squares of the excess far-field magnitude above the specified side-lobe level. The side-lobe mask is the same used in [54] which include a 60 dB notch on one side.

In the present work, the GA engine implemented in GSO uses real encoding of genes with tournament selection; uniform crossover occurs with probability $P_{cross} = 80\%$ while the random mutation rate is $P_{mut} = 5\%$. For PSO we use $\phi_1 = 2$, $\phi_2 = 2$ and $\omega = 0.7$ in equation (3.1). Each run has been conducted with a population of 10 individuals and stopped after 50 000 iterations.

Several hybridization techniques have been tested for the optimization of the linear array: Fig3.11 and Table 3. 2 show the results of the best four procedures, after 400 000 fitness evaluations, as well as the average of 100 trials.

The effectiveness of GSO method emerges both for the static case ($hc = 0.2$) and for the self-adaptive case, that results a fast and reliable hybridization strategy.

This technique is exploiting the distinctive attributes of the two algorithms, results in a general purpose tool that can represent a fast method for optimization of large domain objective functions. This feature makes it suitable for application on a wide range of electromagnetic problems.

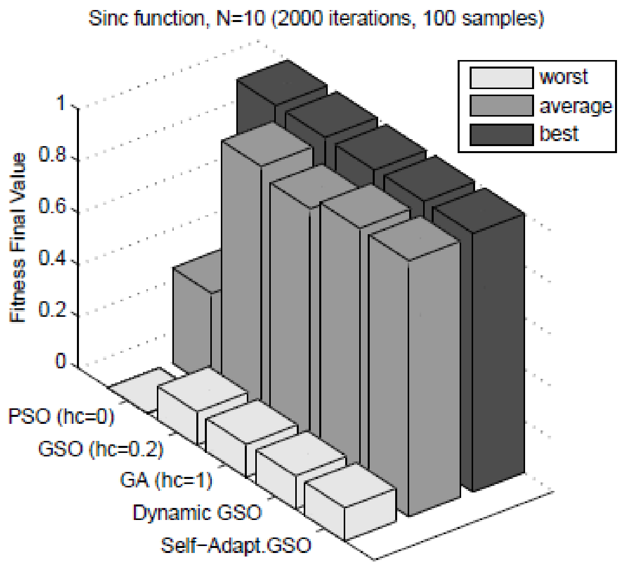


Fig.ure3. 9: Final values of the *sinc* function optimization with $N = 10$ variables obtained with different hybridization strategies (average results over 100 trials).

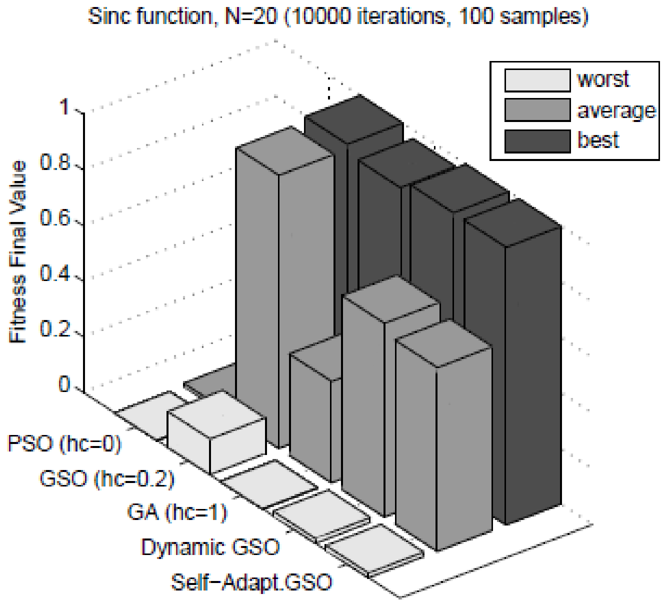


Figure3. 10: Final values of the *sinc* function optimization with *N* = 20 variables obtained with different hybridization strategies (average results over 100 trials).

	Dimension of the considered optimization problem					
	$N = 5$		$N = 10$		$N = 20$	
	function evaluations		function evaluations		function evaluations	
Optimization Strategy	$5 \cdot 10^3$	10^4	$25 \cdot 10^3$	$5 \cdot 10^4$	$2 \cdot 10^5$	$4 \cdot 10^5$
Static GSO ($hc = 0.2$)	0.999 (0.000)	1.000 (0.000)	0.982 (0.122)	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)
Dynamical GSO	0.998 (0.001)	1.000 (0.000)	0.990 (0.087)	1.000 (0.000)	0.743 (0.402)	0.832 (0.345)
Self-Adaptive GSO	0.989 (0.081)	0.999 (0.001)	0.989 (0.087)	0.999 (0.001)	0.732 (0.408)	0.838 (0.337)
GA	0.977 (0.139)	0.988 (0.091)	0.955 (0.169)	0.996 (0.003)	0.505 (0.412)	0.776 (0.339)
PSO	0.884 (0.301)	0.961 (0.184)	0.415 (0.445)	0.510 (0.459)	0.020 (0.053)	0.026 (0.057)

Table3. 1: results of the *sinc* function optimization for different problem dimensions and rules of variation for the *hc* parameter during iterations: average final values over 100 independent trails and, in parentheses, their standard deviation.

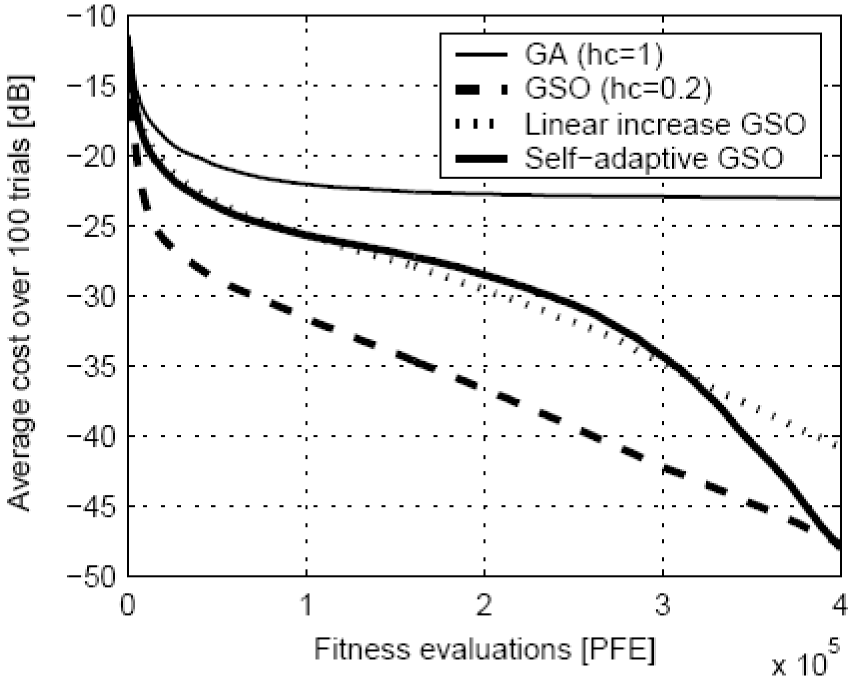


Figure 3.11: Performance comparison between different techniques for the linear array optimization (100 trials).

Hybridization strategy	Cost value [dB] after					
	$2 \cdot 10^5$ PFE		$3 \cdot 10^5$ PFE		$4 \cdot 10^5$ PFE	
	μ	σ	μ	σ	μ	σ
GA ($hc = 1$)	-22.75	3.34	-22.94	3.32	-23.05	3.33
GSO ($hc = 0.2$)	-36.65	4.71	-42.19	7.27	-47.65	7.57
Linear increase	-29.55	2.84	-34.79	5.47	-40.74	8.23
Self-adaptive	-28.52	2.24	-34.33	5.95	-47.95	8.94

Table 3.2: Linear Array Optimization.

Chapter 4

Design and Numerical Results

4.1 Introduction

In chapter two, we described the Method of Moment –Matlab Codes, which later in this chapter will be employed to investigate the properties of the loop wire antenna under analysis. Whereas, we devoted chapter three to explain two dominate evolutionary optimization methods- Genetic Algorithm and Particle Swarm Optimization- and we showed Particle Swarm Optimization in detail for electromagnetic problems. At the end of the chapter three, Genetic Algorithm and Particle Swarm Optimization has been merged in well cooperation to present a new evolutionary optimization method, is called Genetical Swarm Optimization.

In this chapter, the proposed evolutionary optimization method (Genetic Swarm Optimization) will be applied to optimize the square loop wire antenna by considering fractal variation.

And then, the candidate antenna is analyzed by electromagnetic solver (MoM-Matlab Code); automated design procedure is illustrated in Fig4.1. We should mention that, for the first time, Kim and Jaggared [58] introduced the application of the fractal to the field of antenna theory. At the final section of this chapter, we will simulate the structure under analysis by commercial simulator such as FEKO-Lite [59] and compare those with the obtained results by Matlab in order to check and verifying the reliability our design.

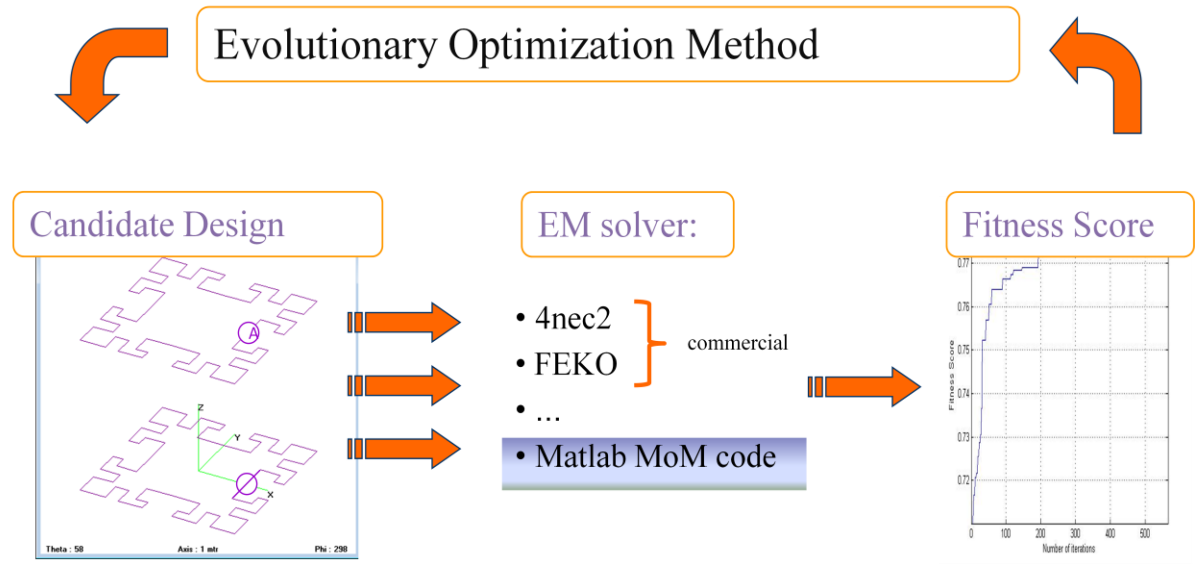


Figure4.1: Illustration of design procedure.

4.2 Considered Geometry

In order to optimize antenna for wireless energy transfer, and to improve the wireless link performances of WPT, preliminary analyses have been conducted on an equivalent model based on two identical square loop wire antennas, as reported in Fig4.2, separated by an air gap. The choice of such geometry is due to the need of reducing antenna dimension [60].

The starting geometry is a square loop antenna. The following geometries are the results of Genetical Swarm Optimization with respect to the fractal variation, as shown in Fig4. 3. The direction of the arrows, pointes in the output of Genetical Swarm Optimization order.

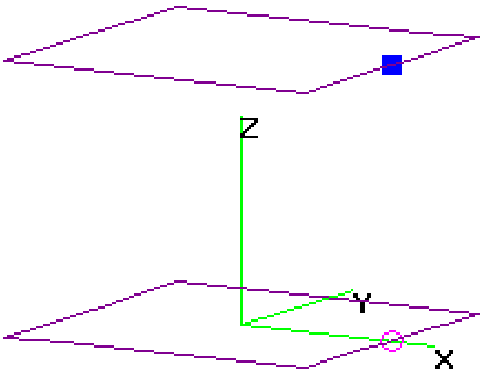


Figure4. 2: A schematic of idea of the two identical antennas.

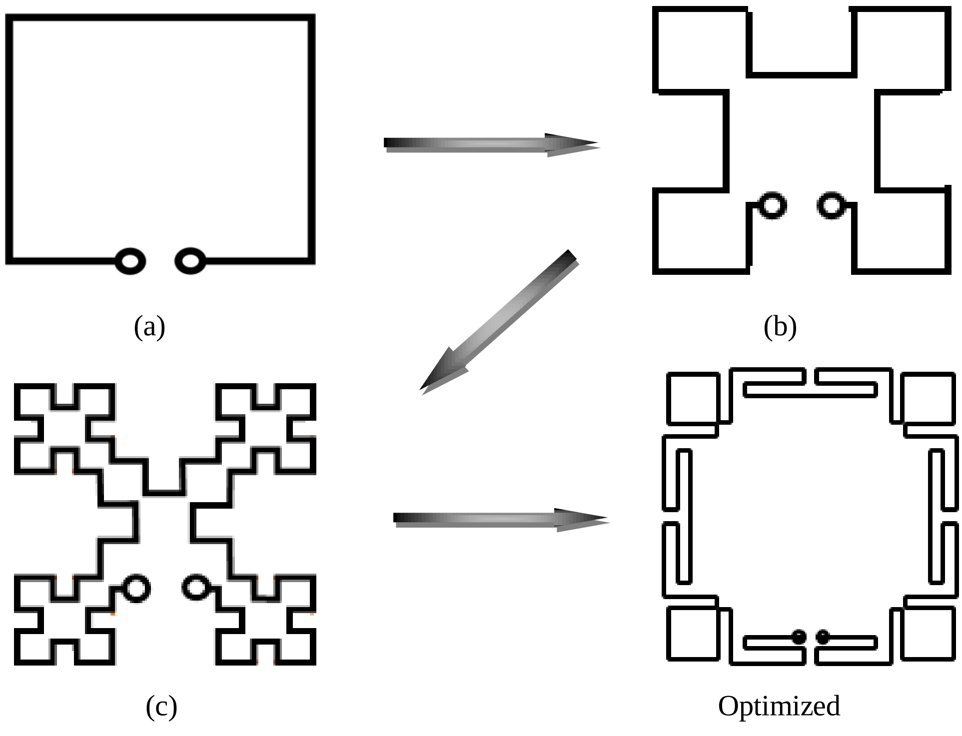


Figure4. 3: Loop wire antenna shape and its optimization.

4.3 Simulation Analysis

Scattering Parameters

Scattering parameters or S-parameters are used to describe the behavior of a network at high-frequency, where the network is complex and it is difficult to present the characteristics of the network with lumped parameters. On other hand, S-parameters make possible to treat a network as a "black box"; as shown in Fig4.4.

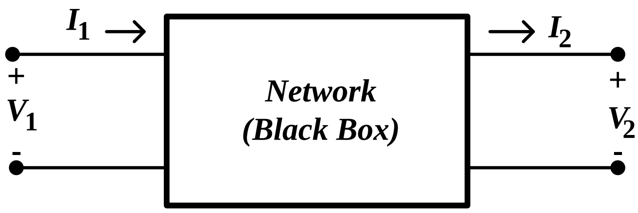


Figure4. 4: Two ports network.

We considered the "black box" contents two antennas in communication. The transmitting power from antenna 1 and the receiving power by antenna 2 are defined in term of S-parameters matrix as the following:

$$\begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \qquad \textbf{(4.1)}$$

S_{11} and S_{22} refer to the reflected power by antenna1 and 2, respectively. S_{12} and S_{21} represent the transferred power from antenna 1 to antenna 2 and vice versa. Hence, the small value of S_{11} means, the most of the transmitting power has radiated in the free space from antenna 1 and the less amount of the transmitting power has reflected at port of the antenna 1. Whereas, the big value of S_{21} implies that the most of the delivered power from the antenna 1 to the antenna 2 has been absorbed by antenna 2.

Therefore, if we would be able to redesign two antennas in communication with small value for the reflection coefficient (S_{11}) and big value for the transmission coefficient (S_{21}), it is worth saying that we increased performance between antennas.

S-parameters could be cast in terms of the terminal voltages and currents at two ports network; shown in Fig4 .5:

$$\boldsymbol{S_{11}} = \frac{(\boldsymbol{1} - \boldsymbol{y_{11}})(\boldsymbol{1} + \boldsymbol{y_{22}}) + \boldsymbol{Z_0 y_{12} y_{21}}}{\Delta} \qquad (\boldsymbol{4.2})$$

$$\boldsymbol{S_{21}} = \frac{-\boldsymbol{2y_{21}}}{\Delta} \qquad (\boldsymbol{4.3})$$

Where, $Z_0 = 50$

$$\Delta = (\boldsymbol{1} + \boldsymbol{Z_0 y_{11}})(\boldsymbol{1} + \boldsymbol{Z_0 y_{22}}) - \boldsymbol{Z_0 y_{12} y_{21}}$$

$$\boldsymbol{y_{11}} = \frac{\boldsymbol{I_1}}{\boldsymbol{V_1}}|_{V_2=\boldsymbol{0}}$$

$$\boldsymbol{y_{22}} = \frac{\boldsymbol{I_2}}{\boldsymbol{V_2}}|_{V_1=\boldsymbol{0}}$$

$$\boldsymbol{y_{12}} = \frac{\boldsymbol{I_1}}{\boldsymbol{V_2}}|_{V_1=\boldsymbol{0}}$$

$$\boldsymbol{y_{21}} = \frac{\boldsymbol{I_2}}{\boldsymbol{V_1}}|_{V_2=\boldsymbol{0}}$$

Reciprocity Theory

The *reciprocity theorem* is utilized in simplifying the antenna theory, it is named base on its application in the antenna theory. *Strong Reciprocity Theorem* allows deducing the properties of receiving antennas from those of transmitting antennas and vice versa, where receiving and transmitting antennas are identical. *Week Reciprocity Theorem* allows interchanging in the performance of receiving and transmitting antennas, where all the differences are in the construction of receiving and transmitting antennas (refer to [61] in order to more understanding of week reciprocity theorem). In this study, we have applied strong reciprocity theorem in order to simplifying our designed antennas.

Strong Reciprocity Theorem

Assume two identical antennas by a gap separation. A voltage source is placed at the terminal port of the antenna I and the flowed current through the antenna, produces the electromagnetic force E_1. Antenna II is excited by the electromagnetic force E_1 and a current is induced through the antenna.

Strong reciprocity theorem states that if this time, the voltage source is applied at the terminal port of antenna II, the induced current through antenna I, while antenna I is exposed to the radiated electromagnetic force E_2 from antenna II, is equal to the induced current through antenna II by the radiated electromagnetic force E_1 from antenna I.

Thus, S-parameters of a network with strong reciprocity and symmetric characteristic could be simplified as:

$$\boldsymbol{S_{21} = S_{12}}$$

$$\boldsymbol{S_{11} = S_{22}}$$

4.3.1 Antenna Optimization Procedure

The procedure of optimization and design is described as the following:

Each candidate antenna (the output of Genetical Swarm Optimization) is simulated by Matlab in the frequency rang $450MHz - 600MHz$. We are interested in this range frequency (Low Ultra High Frequency) due to being ideal for a whole range of applications indoors/outdoors and appearing perpetually in urban areas.

Matlab simulation is interactively called by the presented optimization procedure, in order to evaluate the coupling performances of the proposed antenna geometrics, as shown in Fig4.3.

The aim of the analysis was to design the geometry in order to maximize the coupling versus the displacement.

The data interface between optimization algorithm and numerical modeler is managed by a built-in function called "fitness function". The fitness function (FF) decodes the information provided by GSO into geometrical dimensions to assign to the antenna design; afterwards, FF analyses the new configuration and then it evaluates the feasibility, the S_{11} and S_{21} of parameters of the wireless system.

In order to maximize the energy transfer it is desirable to have antenna matched in the frequency band of interest, and minimizing S_{11} that is the return loss at port 1. Moreover, it is necessary to maximize the coupling performance S_{21}.

To reach out these different objectives, we chose a multi-objective approach called ε-constrained method [62] by adopting thresholds for the fitness function in order to identify different phases into fitness score evaluation: In the first stage, fitness score value f is then defined as:

$$f = -\mathbf{50}\ (\boldsymbol{until\ geometry\ is\ feasible})$$

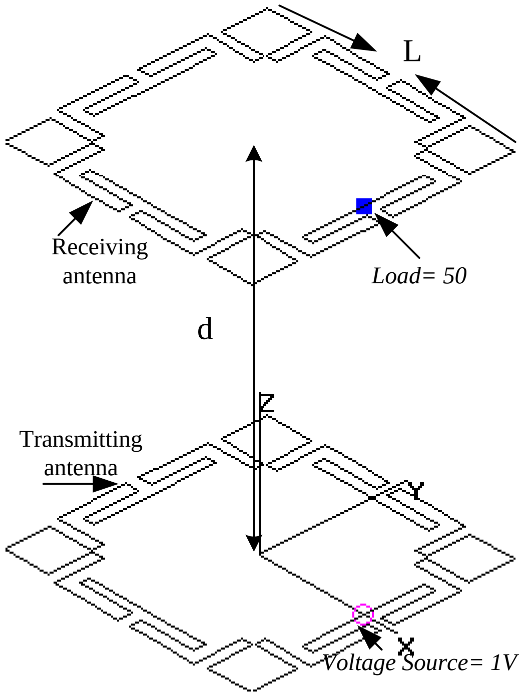


Figure4. 5: case study analyzed with Matlab.

In order to penalize unfeasible solutions; when geometrical feasibility is obtained, f is computed as:

$$f = -\mathbf{30} - \boldsymbol{S_{11}} \quad (\boldsymbol{if}\ \boldsymbol{S_{11}} > -10)$$

To minimize, return loss at the considered working frequency. Finally, when return loss has reached the desired value:

$$f = \boldsymbol{S_{21}} \qquad\qquad (\boldsymbol{if}\ \boldsymbol{S_{11}} < -10)$$

In order to, maximize antenna matching at the considered working frequency.

Here, the optimization procedure considers a population of 10 candidate solutions per iteration and it runs for 500 iterations, thus leading to 5000 cost function calls. Self-adaptive hc is considered to maximize the GSO performances, as reported in [63].

A sample evolution of fitness value is reported in Figure4. 6; where the stage 2 and 3 are highlighted. Moreover, in the same figure the hc value during iterations is reported, showing that, in this particular case, self-adaptive GSO goes towards an almost exclusive application of PSO operators. For each configuration mentioned in 4.2 section, S_{11} is plotted, versus S_{21} to observe the reflection of the optimization procedure in the antenna size and the antenna matched. As presented in Fig4. 7, the optimized antenna has the best matching and size.

As well as, the scattering parameters and the dimensions of the considered geometries in section 4.2 are shown in Fig4 .8, Fig4. 9 and Fig4. 10, respectively.

As been observed in Fig4. 8 and Fig4. 9, the smallest value of $S_{11}$and the greatest value of S_{21} are belonged to the optimized antenna; moreover, the size of antenna is minimized by the optimized antenna. It means the optimized candidate met the all requirements for having robustness coupling between antennas.

In wireless power transfer technology, the power efficiency is a key parameter. The power gain or efficiency of the analyzed geometrics can be expressed as follows:

$$\boldsymbol{\eta = \frac{Power\ delivered\ to\ the\ load}{Power\ from\ source} = \frac{|\ S_{21}\ |^{2}}{1 - |\ S_{11}\ |^{2}}}$$

And the efficiency of each candidate is plotted in Fig4. 11. The optimized candidate reached the highest efficiency, as shown in Fig4. 11. The candidate (b) also has the good efficiency as the optimized candidate; as you have observed in Fig4.7, the candidate (b) is not however well-matched and sized to compare with the optimized configuration. The design procedure is well suited in order to increase energy efficiency and the robustness of the coupling, with the aim of improving the transmission power wirelessly.

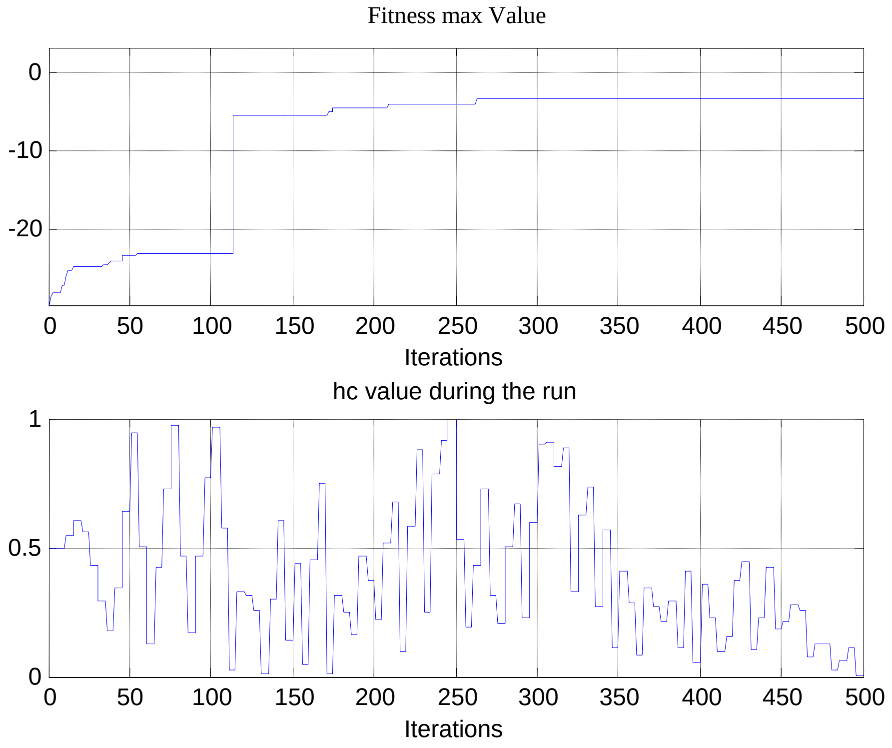
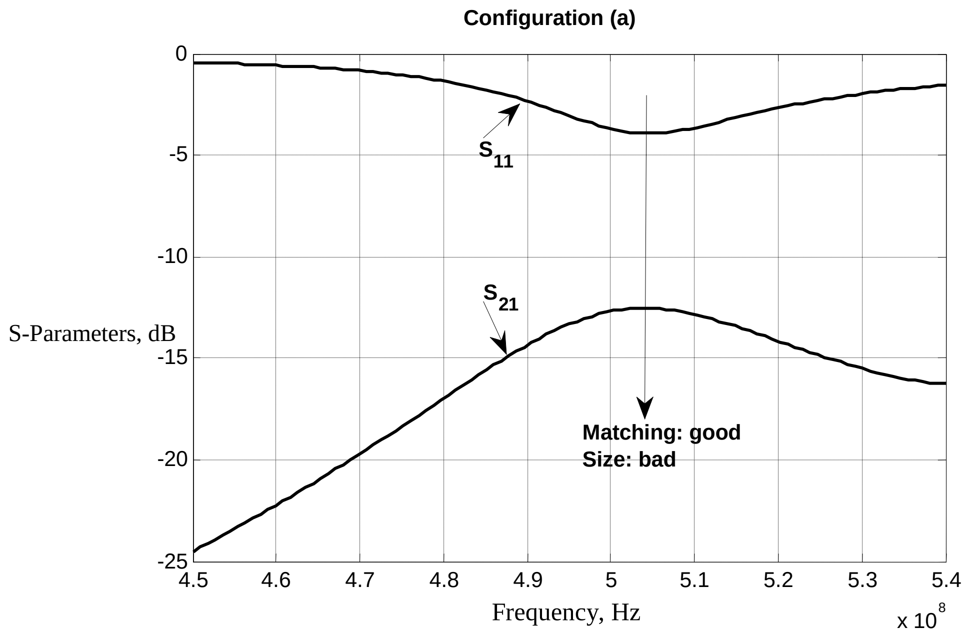
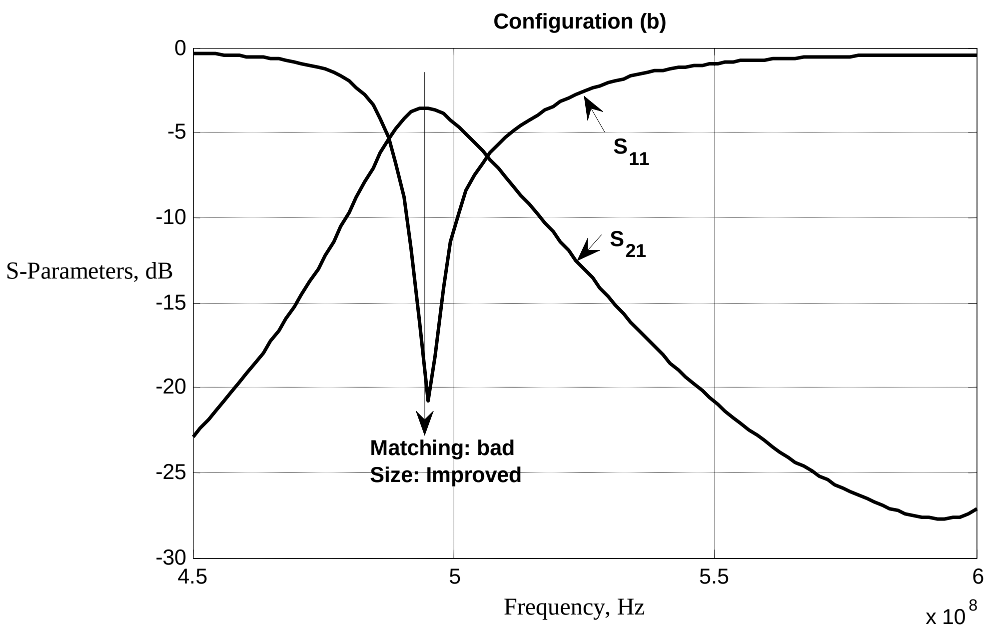


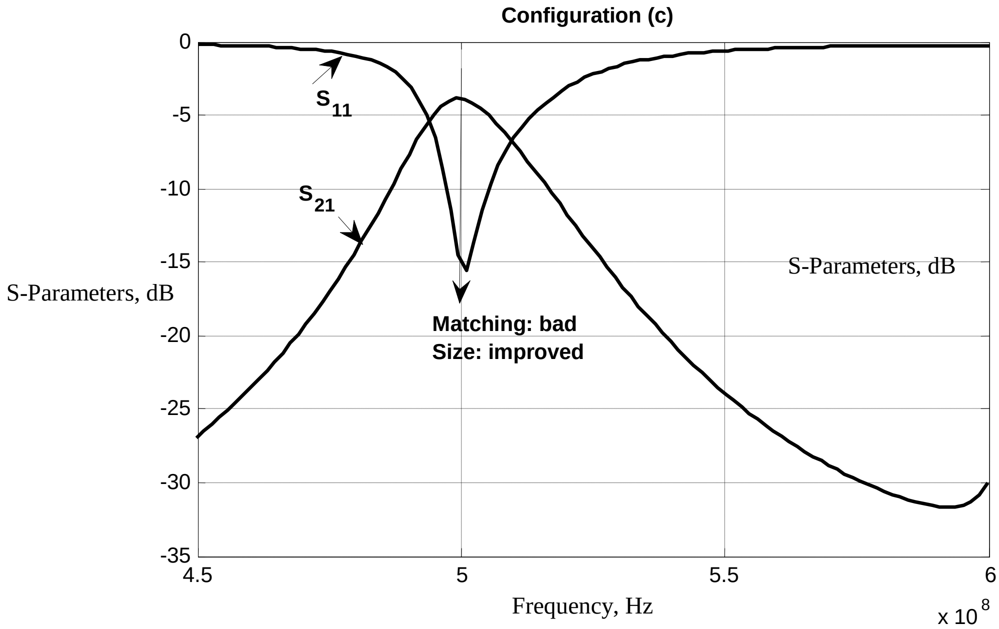
Figure4. 6: Evolution of fitness score and *hc* values during iterations.

4.4 Distance and Power Gain

Parameter d in Fig4. 5 indicates the distance between the origin point of the transmitting antenna and the receiving antenna; the parameter d is fix in pervious simulations and models. The distance d between two candidate antennas was considered equal to the length of the one side of the antenna; for instance, the parameter d in Fig4. 5 equals to the length of the side of the optimized antenna $L= 91mm$.


Configuration (a)
0
-5
-10
-15
-20
-25
S-Parameters, dB
4.5
4.6
4.7
4.8
4.9
5
5.1
5.2
5.3
5.4
Frequency, Hz
x 10^8
S11
S21
Matching: good
Size: bad


Configuration (b)
0
-5
-10
-15
-20
-25
-30
S-Parameters, dB
4.5
5
5.5
6
Frequency, Hz
x 10^8
S11
S21
Matching: bad
Size: Improved



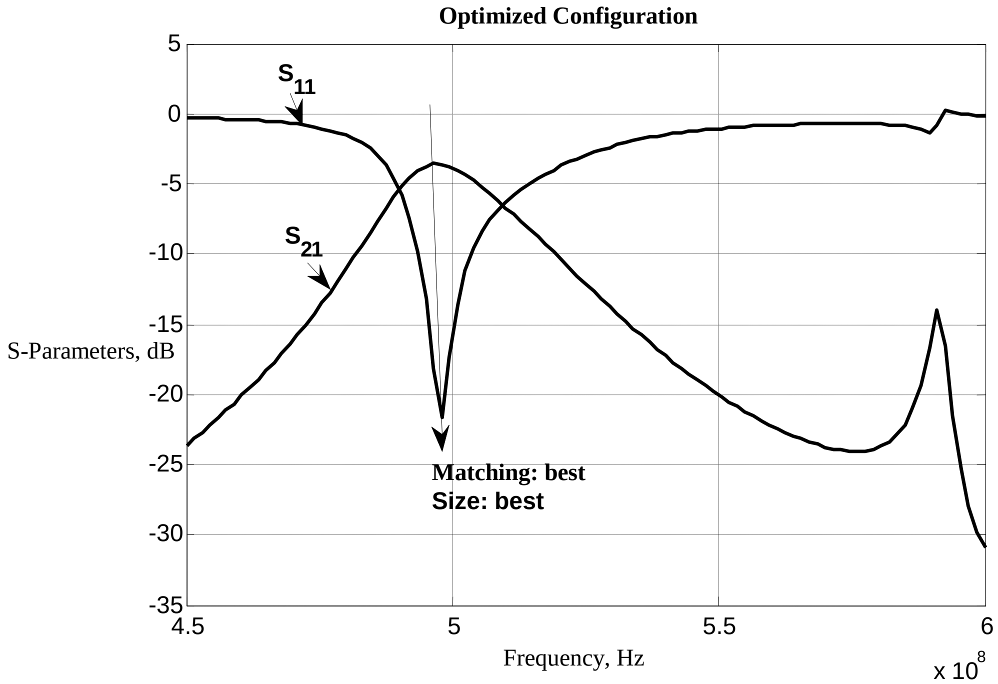


Figure4. 7: The matching antenna for each geometry.

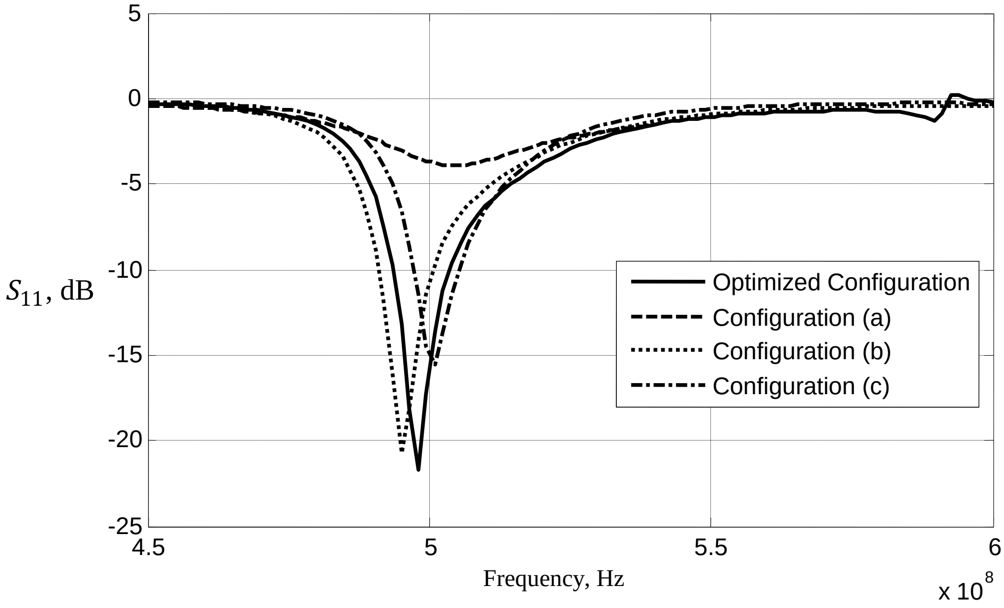


Figure4. 8: Return loss comparison of each configuration.

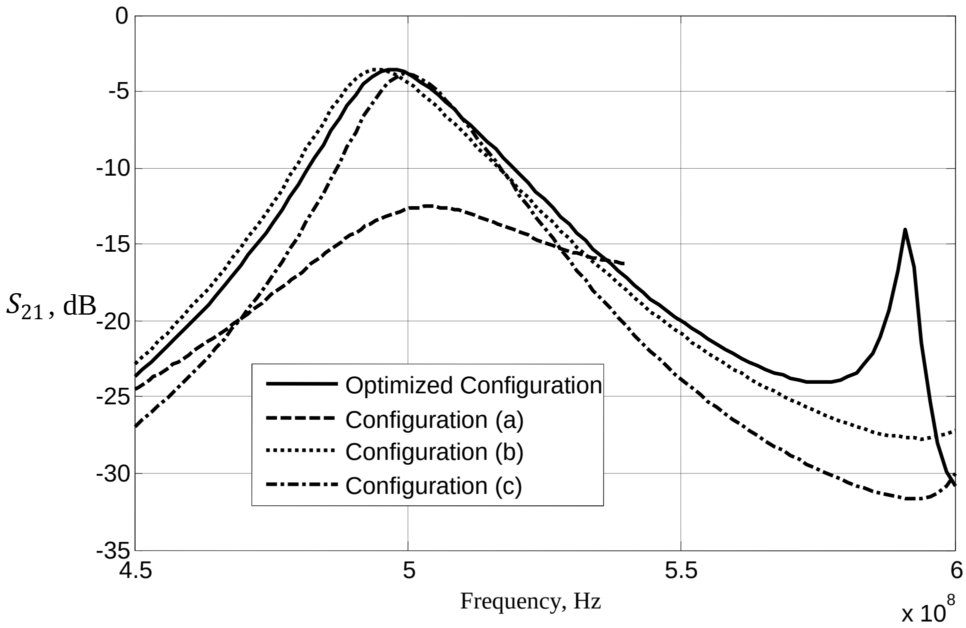


Figure4. 9: Coupling performance of each configuration.

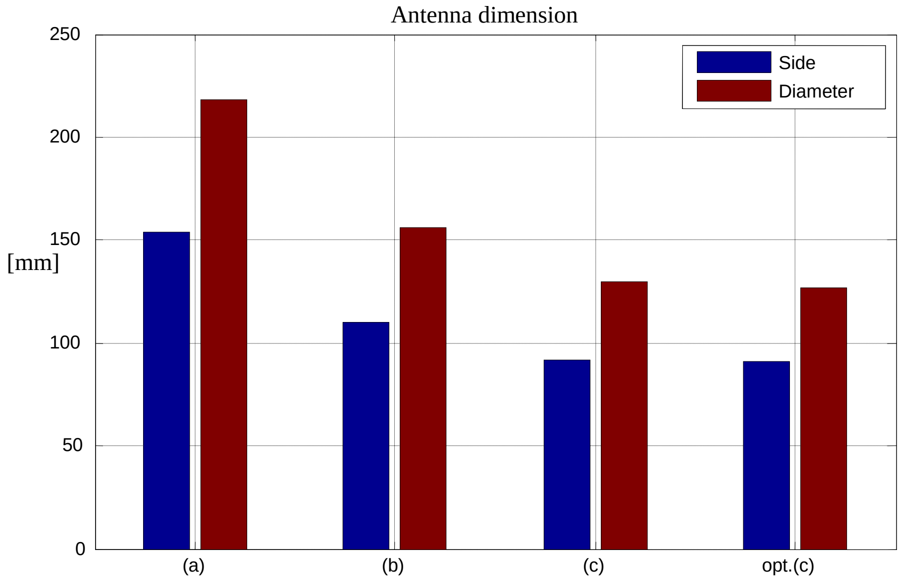


Figure4. 10: Size comparison of analyzed geometrics.

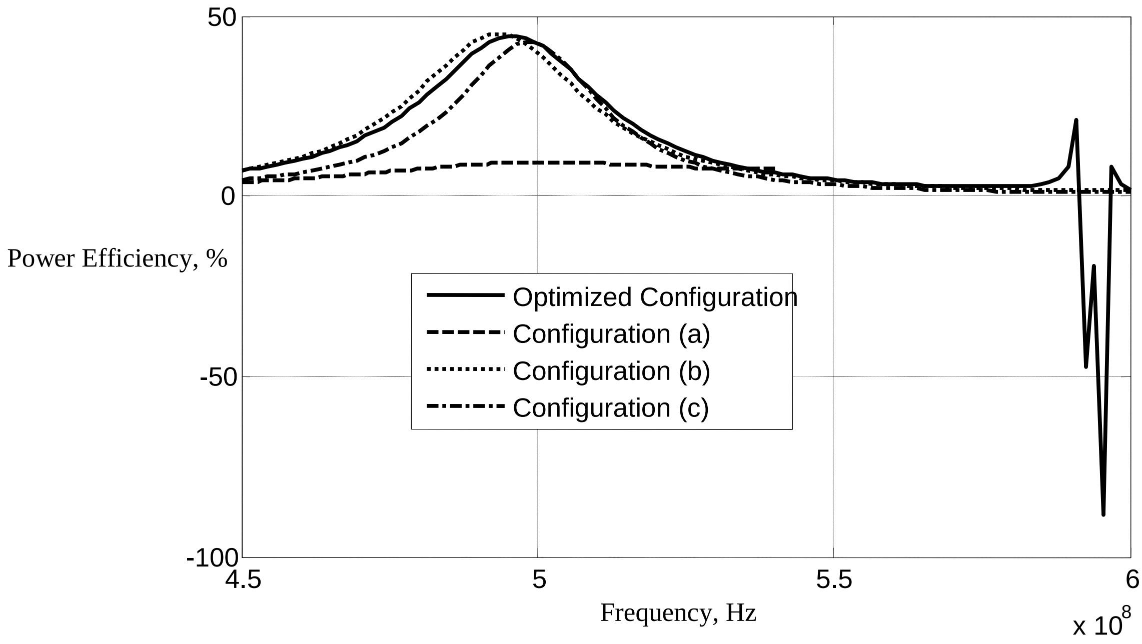


Figure4. 11: The power efficiency of the considered configurations.

As mentioned in *Resonance Inductive Coupling* section of chapter one, the coupling performance of the antennas would decrease by increasing the distance between them. Thus, improving the power gain over the longer distance, gives possibility to extend the applications of this technology.

In this section, we supposed that the distance d is a variable parameter. The power gain or efficiency is computed and plotted for several different values of the d in order to investigate the impact of the longer distance on our optimized model, see Fig4. 12. At the end, the worse case (the model with the longest d) is compared with the configuration (a) with $L = 154\, mm$ and the same d as the worse case, shown in Fig4. 13.

As been seen in Fig4. 12, increasing the separated gap of antennas cause the decreasing of the antenna coupling. However, the worse case ($d = 250\, mm$) of the optimized antenna has still higher efficiency than two square loop antennas with the same separated gap and longer length; as presented in Fig4. 13. This means that we are managed to optimize the simple square loop antenna structure, which is able to deliver more power over longer distance.

4.5 Frequency Analyzing

The loop antenna is named *the electrically large antenna*, when the perimeter of the loop antenna is greater than ${}^{\lambda}/_{10}$.

$$\boldsymbol{P_{loop} \gg {}^{\lambda}/_{10}} \qquad \textbf{(4.4)}$$

Large loop antenna usually has either a circular or square shape. Both circular and square loops are usually operated near the first resonance point, which occurs for a perimeter of slightly greater than one wavelength [64].

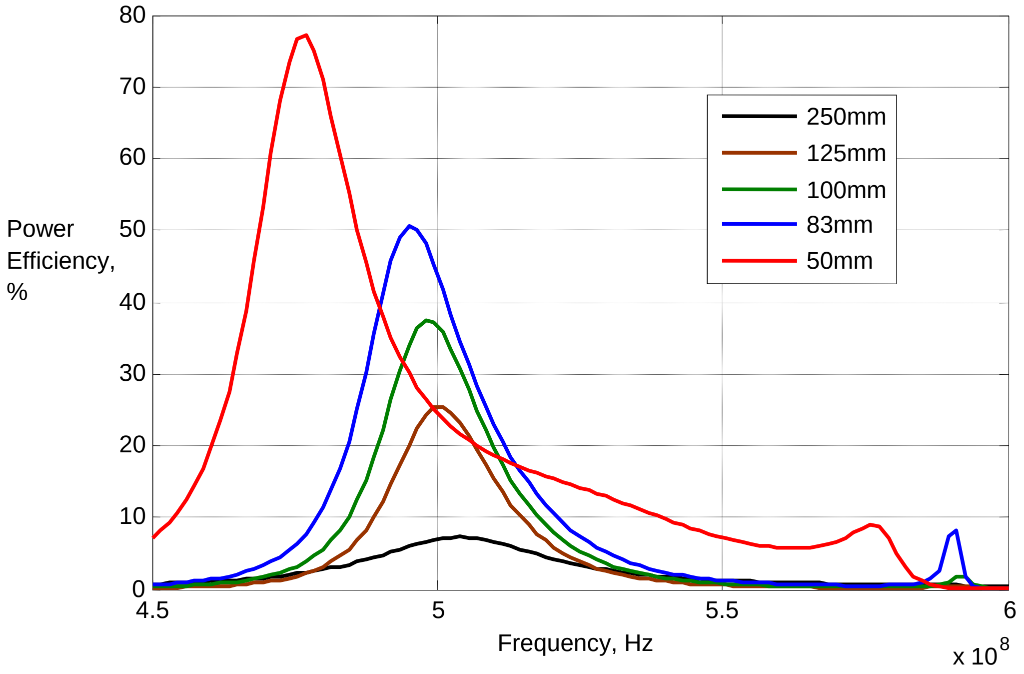


Figure4. 12: the efficiency of transferred power in each distance.

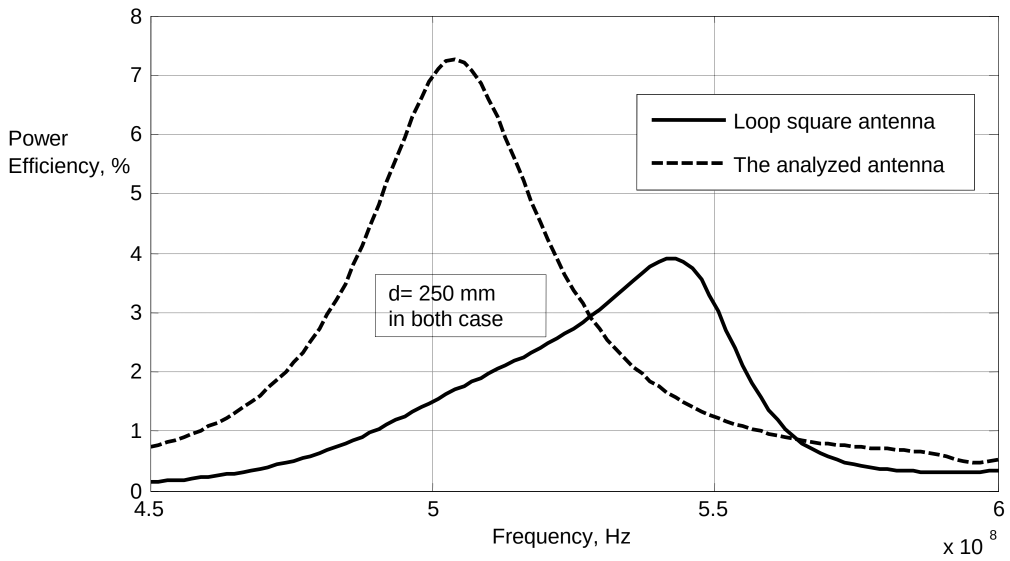


Figure4. 13: Comparison the worse case and two loop square antennas.

$$P_{loop} > \lambda_{f_r} \qquad \textbf{(4.5)}$$

Where, λ_{f_r} is the wavelength at the resonance frequency.

$$\lambda_{f_r} = \frac{3*10^8}{f_r} \qquad \textbf{(4.6)}$$

The following table I reports the perimeter and one wavelength at the resonance frequency for the candidate antennas. The configuration (a) and the optimized antenna are only which meet the equation (4.5). And it could be said that the resonance frequency of the configuration (b) and (c) are not practical. It is worth noting that, the equations (4.5) and (4.6) give the ability to design and tune an electrically large loop antenna at the interested resonance frequency.

For instance, the perimeter of antenna Shape (a) is increased to $p = 0.626$ in order to tune antenna at frequency the same as frequency of the optimized antenna ($479.7MHz$), as shown in Fig 4. 14.

4.6 Validation of the results

In this section, for checking and verifying the reliability of the results, the return loss at port 1 of the configurations reported in Fig4. 3 plotted by Matlab have been compared with the return loss of the simulated configurations (Fig4. 3) by FEKO-Lite [59]. As we expected, there is a good agreement between the Matlab and FEKO-Lite results, as shown in Fig4. 15.

Configuration	Perimeter $P\ (m)$	$f_r\ MHz$	λ_{f_r}
a	0.616	506	0.592
b	0.309	494.55	0.606
c	0.27	497.52	0.602
Optimized	0.770	479.7	0.625

Table I.

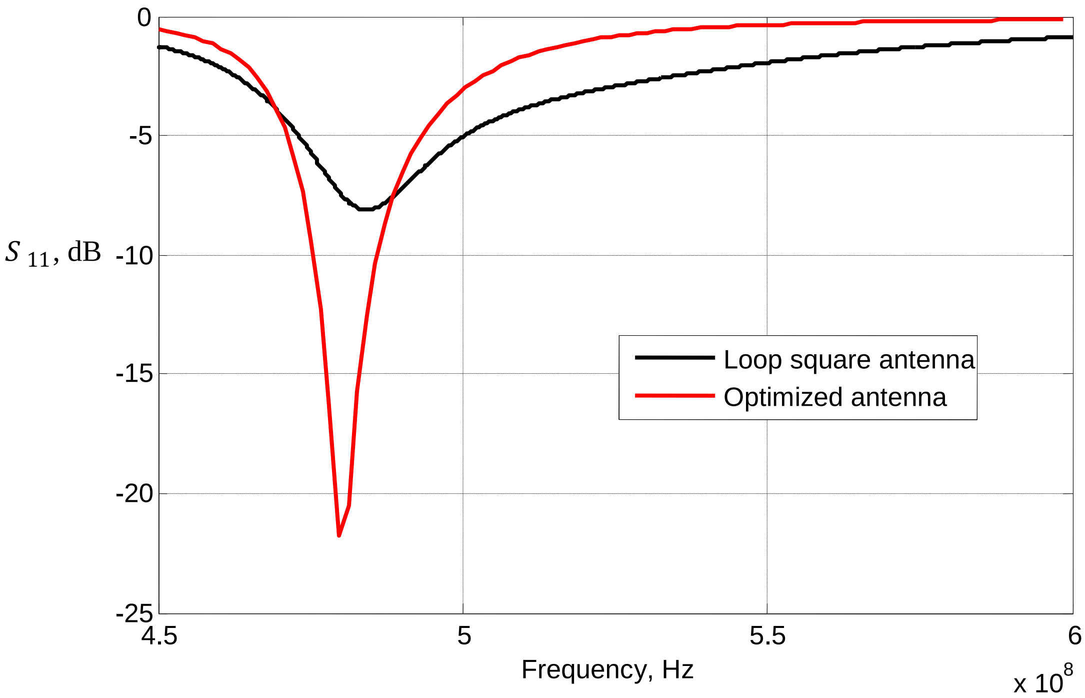
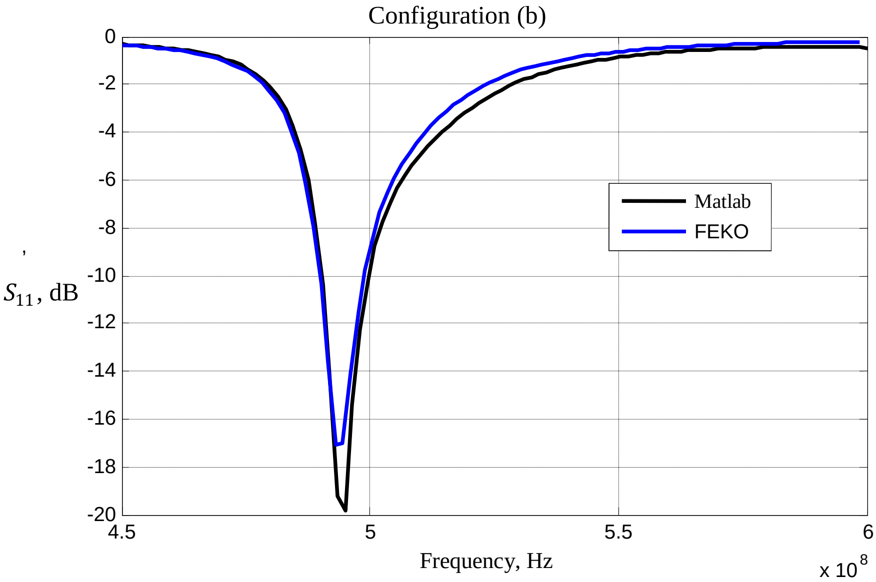
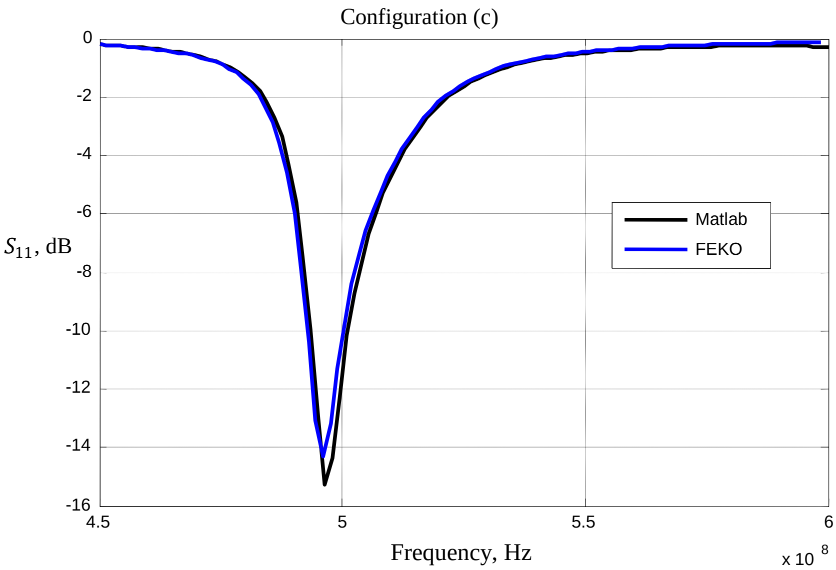


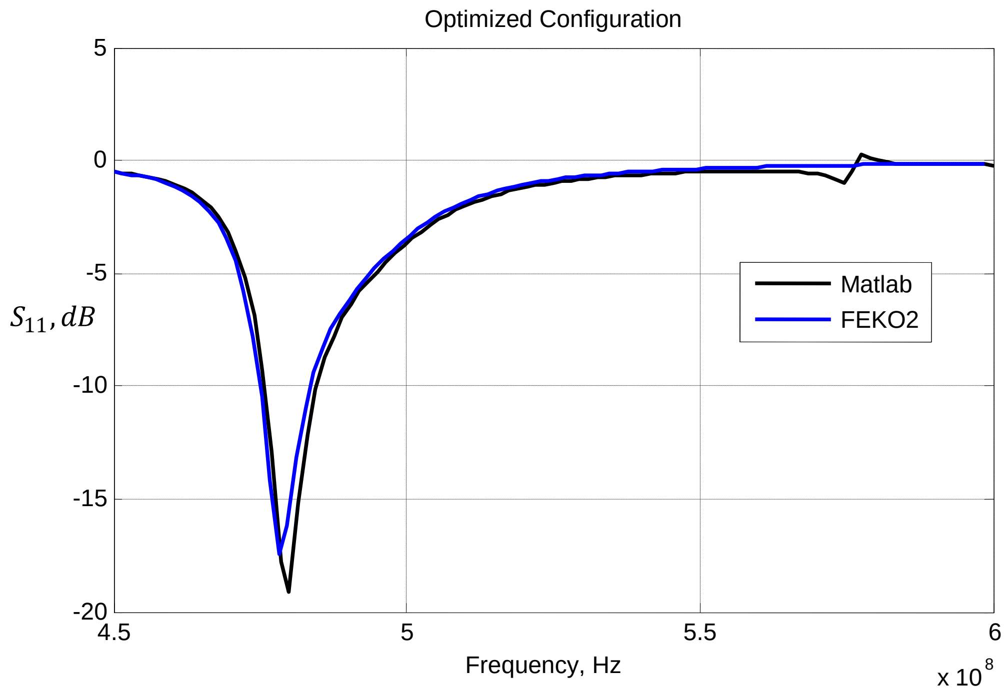
Figure4.14: represents the increased perimeter loop square antenna to obtain the same frequency as frequency of the optimized antenna.


Configuration (b)
0
-2
-4
-6
-8
-10
-12
-14
-16
-18
-20
S_{11}, dB
4.5
5
5.5
6
Frequency, Hz
x 10 8
Matlab
FEKO

(1)


Configuration (c)
0
-2
-4
-6
-8
-10
-12
-14
-16
S_{11}, dB
4.5
5
5.5
6
Frequency, Hz
x 10 8
Matlab
FEKO

(2)



(3)

Figure4. 15: Comparison of the obtained S_{11} parameter by Matlab and FEKO for configuration 1) (b), 2) (c), and 3) Optimized.

Chapter 5

Conclusions

In this study, we have designed an antenna configuration to exploit the Radio Frequency and Resonance Inductive Coupling mechanisms for transferring power wirelessly. For designing antenna a merged optimization technique by the name of Genetic Swarm Optimization has been applied, and the candidates of the antenna that have been produced by the optimization procedure, have been characterized with electromagnetic solver (MoM-Matlab).

As been described in chapter 1, the role of the antenna in Radio Frequency energy harvesting system is providing RF-power for rectifier; whereas, the rectifier must convert this RF-power to DC-power for supplying electrical devices. Thus, it would be tricky to design and propose an antenna model with the high gain power for the RF energy harvesting system in primary step of process. Since, we have observed that the most previous works have been presented and suggested models for improvement and development the performance of the rectifier. In additional, in chapter 1, we have also shown that the Resonance Inductive Coupling mechanism has benefits in wide range of applications such as Electrical Vehicles, if the coupling phenomena between two antennas could be kept robust by increasing their distance. In order to have the maximum coupling or in other words the maximum power efficiency, we should keep two factors in the mind during redesigning antennas: a) decreasing radiated emission, and b) increasing transmission coefficient.

Genetic Swarm Optimization is a merged technique of Genetic algorithm technique and Particle Swarm Optimization technique (GA and PSO are described in more details in chapter 3), which is utilized for reaching to our purpose in this work. As aforementioned in chapter 3, GSO has advantages in: solve large domain objective function, face non-linear and discontinuous problems, and reduce the number of iteration and the computational efforts. It is worth noting that, as well authors in [43, 65, and 66] have been shown the reliable and effective of the presented procedure (GSO) for a wide spectrum of applications in electromagnetic.

The outputs of the optimization method have been simulated in home-built MoM solver. We used the Matlab environment in this thesis due to the drawbacks of the other Electromagnetic solver software, when the ratio of the wire diameter to its length is becomes too large. The structure of the antenna out-coming from the optimization procedure has been built by identifying boundary of its geometry in home-built solver and we controlled the accuracy of our results with the number of the meshes. In chapter 2, several examples have been given to show the impact of the number of triangles in the structure and alternative way (Graphical User Interference) of building the antenna structure in Matlab. As verifying and checking our results obtained with Matlab, they have been compared with the same results obtained with a well-assessed commercial software such as FEKO-Lite. As have been illustrated in Fig4. 13 in chapter4, there is a good agreement between the results.

It could be said we succeed to propose a model antenna by optimization methods with the power efficiency more than the power efficiency has been reported in [18]. Furthermore, the designed antenna is miniaturized to compare with the models presented in [20, 21] for charging Electrical Vehicles; and the small size feature of the optimized antenna makes the designed antenna suitable to install at the bottom of the vehicles. Most relevant results of this study have been published in [67].

Of course, additional features could be required in order to raise the power gain of the designed antenna over the longer distance and make them sufficient in Electrical Vehicles' recharging system. Therefore, a perspective future work might be studying the integration of the optimized antenna in an array system, to improve the coupling with displaced objects.

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