Antenna - Final Project

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Particle Swarm Optimization in Antenna Engineering

Introduction

Nature and Science have constantly exchanged ideas for a very long time in mankind's history. This has become a popular method to approach complicated problems in the past few decades. Computer scientists have developed computational algorithms based on natural behavior of humans, animals, etc. in a framework known as **computational intelligence**. One of the most outstanding ideas presented in this domain is originally inspired by the role of teamwork in various species in our ecosystem. This family of methods rely on "**Swarm Intelligence**", the hidden collaboration among species of one kind. On the other hand, many **engineering problems** (usually design problems) are **simplified as an equivalent optimization problem**. Each problem should be dealt with a proper algorithm according to their **parameter space**, **objectives, power and computation limits** and **design constraints**. Antenna design problems as a major part of electromagnetic engineering problems are usually defined in a parameter space with **lots of local optimums**. Traditional optimization methods such as Gradient Descent or even their stochastic variations of them such as SGD and BGD have a poor performance in such problems due to **low exploration power** and **local trapping**. Heuristic methods such as Swarm Intelligence methods become handy in these situations. This report is a **comprehensive review** on **Particle Swarm Optimization** (PSO) in Antenna Engineering Problems.

Chapter 1. Basics of PSO

Particle Swarm Optimization (PSO) is a subset of Swarm Intelligence family of algorithms which itself is a subset of Heuristic approaches in Computational Intelligence.

- **Swarm Intelligence**:

  A branch of computational intelligence inspired by co-operation of species with the goal of **solving** a cognitive problem by **two or more individuals** who **independently collect information** and **process it through social interactions.**

  - Population, Knowledge and Information Sharing (co-operation) and are the main components of swarm intelligence.

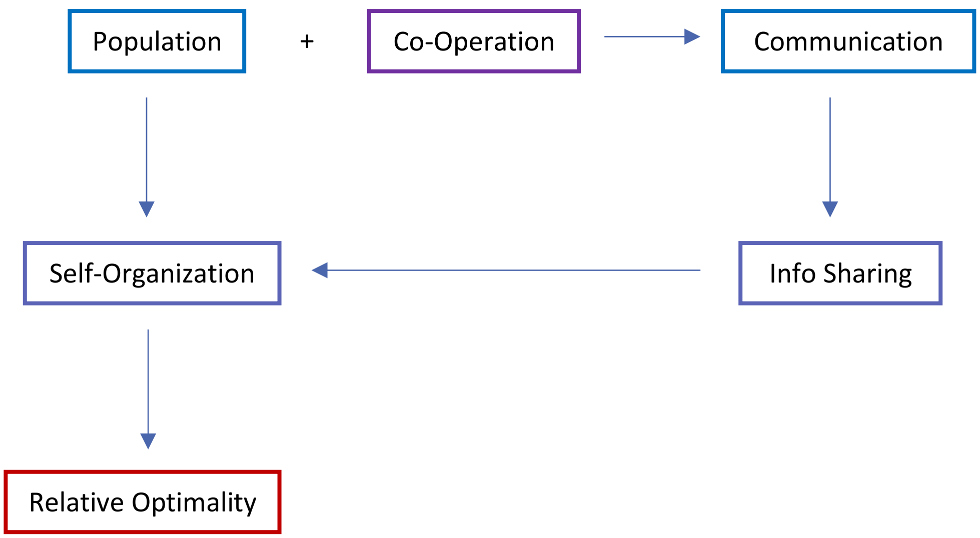


Figure 1.1 – Main Structure of Information Flow in Swarm Intelligence

  - Swarm Intelligence is observed in the daily life of bee and ant colonies, flocks of birds, school of fish, etc.

Figure 1.2 – Swarm Intelligence in the Nature

- **Particle Swarm Optimization**:

Many optimization algorithms use swarm intelligence as their core to solve complicated problems. Solving these problems is usually entangled with:

- High dimensional parameter space searching
- Wide range search in a field full of local maximums and minimums
- Several constrains on power, time and physical factors
- Multi-Objective Optimization

These issues make **traditional algorithms** such as GD, BGD and SGD to become **less suitable for complex problems**. In contrast, there are algorithms which have more degrees of freedom and search these complicated high-dimensional spaces by controlling an **exploration – exploitation balance**, and using wiser initializations.

One of the algorithms which uses multiple points in a swarm intelligence framework is the PSO (Particle Swarm Optimization). PSO relies on **distributing** multiple points called **particles** in the search space in such a way that nearly every important local maximum and minimum is **visited** by **at least one particle**.

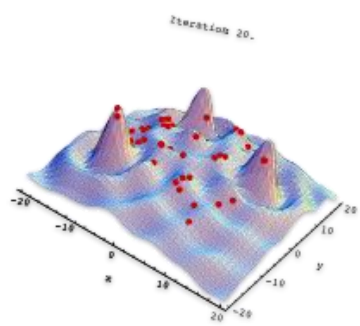


Figure 1.2 – Geometrical Demonstration of PSO running in the parameter space

The **information** is **shared** by **storing each particle's best record** (the point which yields the lowest value for the cost function among all other visited points) and also the **best global record** (among all particles).

A record can be thought of as a **struct** containing the **parameter vector** in the record place and also the **cost function** of the **record point**.

Chapter 2. Dynamics of PSO

The movement of particles in PSO is based on **Newtonian Mechanics**. The fact that adding a velocity (movement) vector to a position vector will result in the new position for a given optimizer is used in almost all optimization algorithms, but the key to the truth that "What kind of problem can an algorithm solve? ", is hidden in the **factors which define how the velocity vector should be calculated each time step.**

- Position Update:

$$\boxed{\overrightarrow{x_i^{t+1}} = \overrightarrow{x_i^t} + \overrightarrow{v_i^t}}$$

- Position Initialization (Multidimensional Uniform pdf)

$$\boxed{\overrightarrow{x_i^0} = U(x_{min}, x_{max})}$$

- **Movement Factors in PSO:** (what affects the velocity vector)

  - **Inertia (**current velocity**)**
  - **Particle's Cognition (**best personal record**)**
  - **Social Cognition (**best global record**)**

- Velocity Update:

$$\boxed{v_i^{t+1} = w_i v_i^t + c_1 r_1 (x_i^{t\,(best)} - x_i^t) + c_2 r_2 (x^{t\,(best)} - x_i^t)}$$

The constants which appear in the velocity update formula define **how much** each of the **factors** (inertia, local best, global best) are **important** and also how should we **deal** with the **exploration, exploitation dilemma.**

$\boldsymbol{W}, \boldsymbol{c_1}, \boldsymbol{c_2}$ are constants that control the **learning rate** relative to each factor, thus **control relative importance, convergence speed and optimization accuracy**

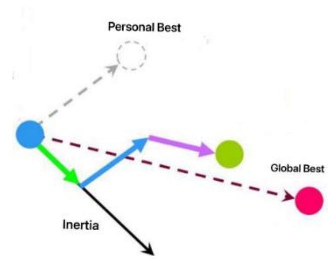


Figure 2.1 – Velocity vector as a superposition

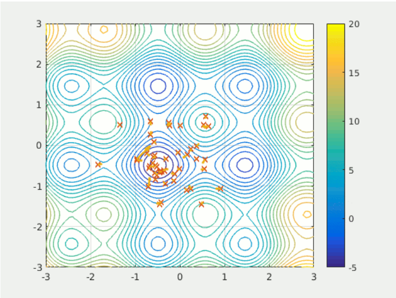
$\boldsymbol{r_1}, \boldsymbol{r_2}$ are random values usually with a **standard uniform** distribution. They **control exploration and exploitation** within angles **between global and local bes**t.

- Record Update:

Each particle has **knowledge** about **global best** and **personal best** record. If the current position yields a **cost function value lower than the personal best record**, personal best record is updated:

$$x_i^{t+1\,(best)} = \begin{Bmatrix} x_i^{t\,(best)}, & J\left(x_i^{t+1}\right) > J(x_i^{t\,(best)}) \\ x_i^{t+1}, & J\left(x_i^{t+1}\right) < J(x_i^{t\,(best)}) \end{Bmatrix}$$

If the **current position** yields a **cost function lower** than the **global best record**, both personal and global best records are updated:



$$x^{t+1(best)} = \begin{Bmatrix} x^{t\,(best)}, & J\left(x_i^{t+1}\right) > J(x^{t\,(best)}) \\ x_i^{t+1}, & J\left(x_i^{t+1}\right) < J(x^{t\,(best)}) \end{Bmatrix}$$

Figure 2.2 – PSO convergence shown on a contour plot

- Termination Conditions:

  - Based on **Step Size:**

    Terminate the process when the average or maximum step size.

  - Based on **Number of Iterations**

    Terminate the process when a maximum number of iterations are passed.

  - Based on **Swarm Radius**

    Terminate the process when the swarm radius is smaller than a specific value.

- Variations of PSO:

- **Local PSO:** A neighborhood of points (physical or not) share record values and the swarm communicates via interleaving neighborhoods

  There are many cases where neighborhoods based on particle indices are preferred, due to:

  1. Computation Efficiency
  2. Spreading information to all particles regardless of their point in space

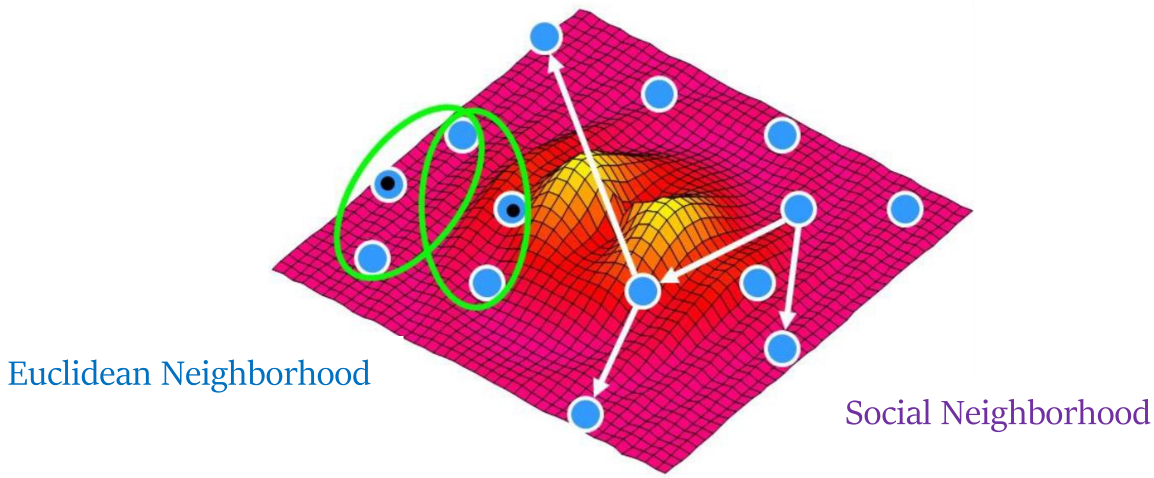


Figure 2.1 – Local and Social Neighborhood

- **Binary PSO:** Used when some or all the parameters in the parameter space are binary variables.

  The parameter space is represented by a binary string and each bit represents a parameter. The update equations in BPSO are based on the probability of each parameter bit being 1. Usually, sigmoid function is used to map values to a range of [0, 1]

$$\pi = s\left(v_j^i[t+1]\right)$$

$$s(z) \triangleq \frac{1}{1+e^{-z}}$$

$$\Pr\left\{x_j^i[t+1]=1\right\} = \pi\left(x_j^i[t], v_j^i[t+1], x_j^{i,best}[t], x_j^{gbest}[t]\right)$$

Chapter 3. PSO in Antenna Engineering

Optimization problems in Antenna Engineering are usually related to minimizing the return loss in operation frequencies, maximizing bandwidth and finding proper configurations that yield a desired radiation pattern (sufficiently low SLL, desired beam width and directivity, number of side lobes, etc.)

$$BW = f_h - f_l = (f_{max} - f_{min})\ (\forall f \mid S_{11}^{f} < -10\ dB) \qquad S_{11}(f) = 20\log_{10}\frac{V_{\mathrm{inc}}(f)}{V_{\mathrm{ref}}(f)}\ (\mathrm{dB}),$$

We should define necessary components of a PSO algorithm for an Antenna Design usage:

- Objectives:

$$\{S_{11}, BW, SLL, Directivity, Gain, etc.\}$$

- Parameters:

  Points in the parameter space are mapped in to **candidate configurations** of the Antenna (Ex: Aspect Ratio for Patch Antenna)

  These parameters can be continuous or discrete (Why?)

  - Antenna design problems are classified into 2 sets.

    - **Topology-known**: the designer has a prior knowledge about the general topology of the antenna, Fine-tuning will be done using continuous PSO.

    - **Topology-unknown:** no prior knowledge about the initial shape is provided. An initial plane is divided into pixels which are parameters of the BPSO algorithm, where the existence or absence of material within the pixels corresponds to the parameter bit being 1 or 0.

    - **Hybrid Design:** Some of the parameters are generally known and constrained, but some other ones should be optimized using BPSO, thus we use a hybrid method to combine PSO and BPSO for mixed spaces.

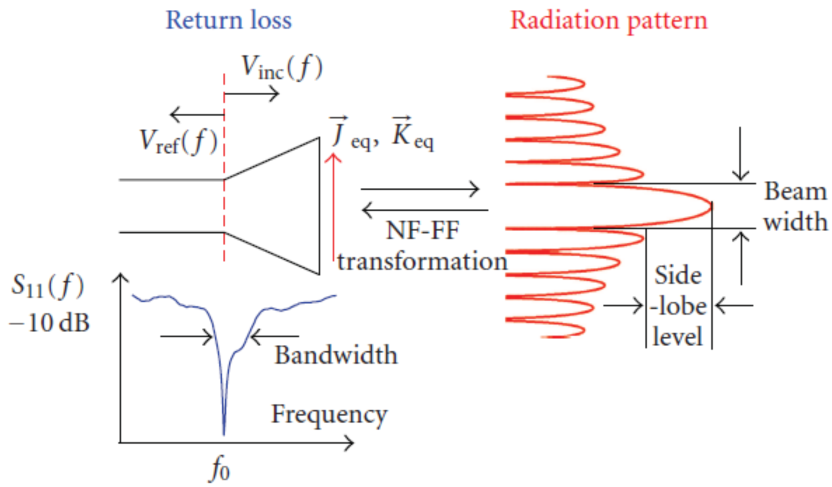


Figure 3.1 – Objectives in an Antenna Engineering optimization problem

- Cost-function Evaluation:

According to our objectives **fitness functions** should be **defined** and **evaluated** in **each iteration** of the PSO algorithm for **all particles** (agents).
If we have **power**, **computation** or **time limitations**, this may be considered as a **downside to PSO**, because each evaluation is equivalent to **solving** the **maxwell equations** regarding **boundary conditions** for the point in the parameter space, in which the particle is located.

$\nabla \cdot \mathbf{D} = \rho$	(1)	Gauss' Law
$\nabla \cdot \mathbf{B} = 0$	(2)	Gauss' Law for magnetism
$\nabla \times \mathbf{E} = -\dfrac{\partial \mathbf{B}}{\partial t}$	(3)	Faraday's Law
$\nabla \times \mathbf{H} = \dfrac{\partial \mathbf{D}}{\partial t} + \mathbf{J}$	(4)	Ampère-Maxwell Law

Figure 3.2 – Maxwell Equations are solved for Fitness Evaluation

This is usually done via **EM analyzers** which are **powerful tools** for calculating Electric and Magnetic fields through various methods such as finite-element, method of moments, variational methods, etc.

- Setting weighting coefficients:

  Weighting functions are the important component of optimization algorithms which can be set by various methods. The. An **alternative** is to make our problem a multi objective problem to **decrease** the **search complication** for an **increase** in **fitness** complication. **MO-PSO** (Multi-Objective Particle Swarm Optimization) is used to **optimize multi-objective problems**.

\- Pareto Front in MO-PSO:

Usually, we reach a point on our multi-objective optimization where there is **no dominant solution**. At this point **improving** one objective is **bounded** to **deteriorating** the other.

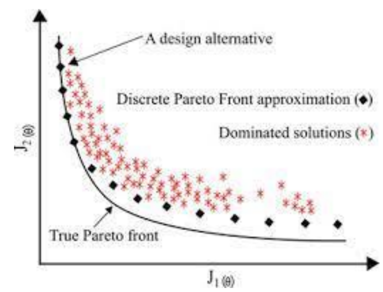


Figure 3.3 – Pareto Front in Multi-Objective optimization problems

- Implementing a PSO engine:

  After all, to implement a PSO algorithm suitable for a specific problem we have a **set of candidate variations (**PSO, BPSO, MO-PSO) and a **set of objectives** (Fine-Tuning physical parameters, Topological parameters, or designing desired radiation patterns) on the **other side**.

  An **EM analyzer** acts as an **interface** that connects the objectives to the algorithms information by **evaluating fitness functions**, and **driving particle velocity** vectors in a **feedback loop.**

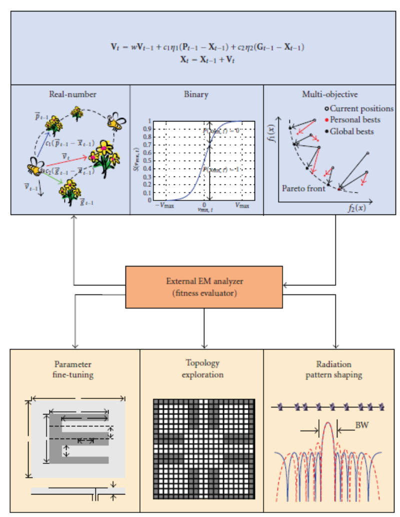


Figure 3.4 – General scheme of a PSO engine in Antenna Problems

Chapter 4. Review on an e-shaped Dual Band Patch Antenna designed with PSO

In this section, I'll review a design for an E-shaped Dual Band Patch Antenna, which was aided by PSO in the Antenna Laboratory of the University of UCLA.

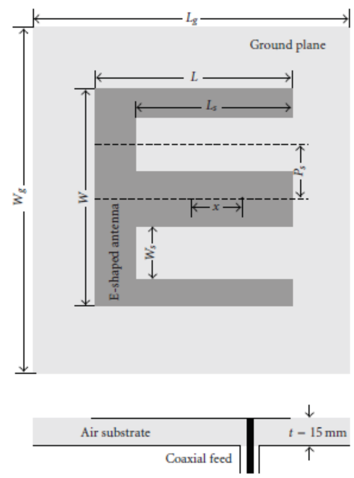


FIGURE 3: The topology of an E-shaped patch antenna. Each candidate design is represented by six geometrical parameters.

Figure 4.1 – General scheme of a PSO engine in Antenna Problems

- The E-shaped antenna is used for Digital Communication in 1.8 GHz operation frequency and for WLANs in 2,4 GHz. The current design is a **dual-band** design in order to obtain low **return loss** in both operation frequencies with a sufficiently wide bandwidth around them.

- Parameters:
  1. Patch Length (L)
  2. Patch Width (W)
  3. Slot Length (L_S)
  4. Slot Width (W_S)
  5. Slot Position (P_S)
  6. Feed Position (x)

- This problem will be classified as a **topology-known problem**. Because the general structure is known (E-shaped) and the **optimization problem** will be described as **fine-tuning** the physical parameters of the Antenna.

- Objectives:
  1. Resonant frequencies (minimum S_{11}) should be on 1.8, 2.4 GHz.
  2. Sufficient Bandwidth should be provided around operation frequencies

- Optimization Constrains:

$$L \in (30, 96), \quad W \in (30, 96), \quad L_s \in (0, 96),$$
$$W_s \in (0, 96), \quad P_s \in (0, 96), \quad x \in (-48, 48).$$

For each candidate design, the following equations also need to be satisfied to maintain the E-shape of the patch and to retain the desired dual-band performance:

$$L_s < L, \qquad P_s > \frac{W_s}{2}, \qquad P_s + \frac{W_s}{2} < \frac{W}{2}, \qquad |x| < \frac{L}{2}.$$

- Cost-function:

$$f = 50 + \max\{S_{11}(1.8\ \text{GHz}), S_{11}(2.4\ \text{GHz})\}.$$

As we observe, the cost function is proportional to the maximum value of S_{11}, in the operation frequencies which is a wise choice.

- Interpreting the Results:

This algorithm used for this simulation is a 10-agent PSO:

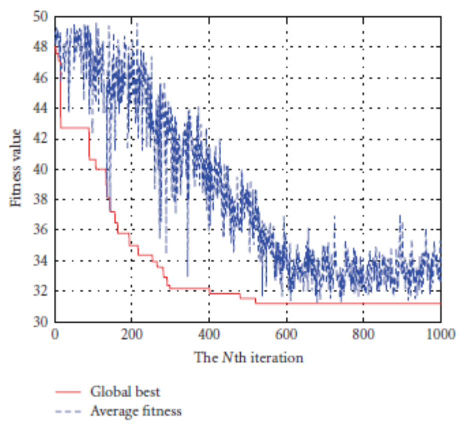


FIGURE 4: Convergence curves of the RPSO optimization by using a 10-agent swarm for 1000 iterations and applying the fitness function defined in (6).

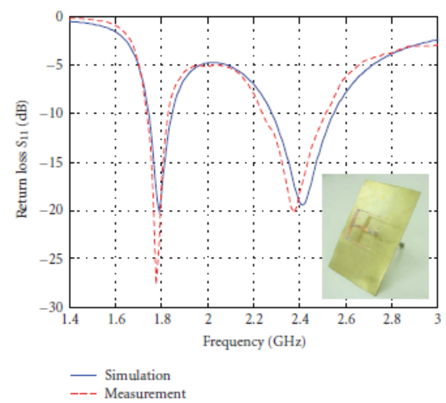


FIGURE 5: Simulated and measured S_{11} curves of the optimal dual-band antenna, which is prototyped and shown by the inset. Measurement results show a -15 dB return loss at both 1.8 GHz and 2.4 GHz.

Figure 4.2 – Simulation Results, Fitness Values and Return Loss plots

- According to the figure on the left the average fitness has a lot of fluctuations because of the random and big changes in the particle positions, especially at the beginning

- The global record fitness will remain constant after the algorithm has converged (500 iterations) and will decrease rapidly at the beginning where the particles are far from the final solution.

- The figure on the right shows that experimental implementation has even achieved a better performance in return loss, yet has a small deviation on the operation frequencies.

Chapter 5. References:

1. Computational Intelligence, An Introduction, Andries P. Engelbrecht, University of Pretoria, Wiley Publications, Second Edition – 2007

2. PSO for Antenna Design in Engineering Electromagnetics, Nambo Jin, Yahya Rahmat Samii, UCLA, Dec 2017