Instructor: Prof. Rashed

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PSO in Antenna Engineering

When Nature Gives Ideas…

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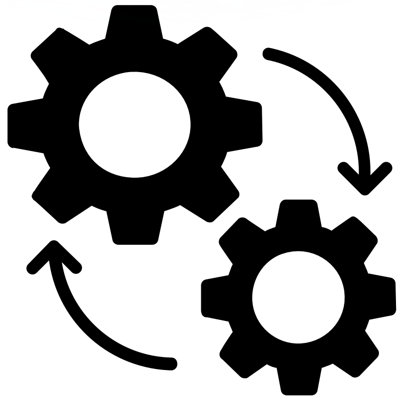
Chapter 1.

Introducing Swarm Intelligence and PSO

Origins of PSO

What is swarm intelligence and how is it related to optimization ?



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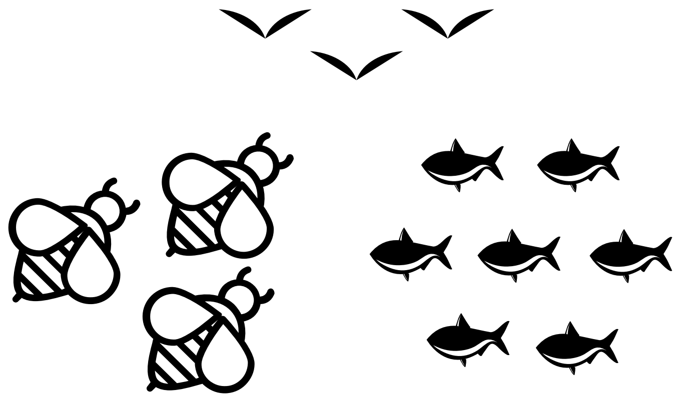


Engineers are dealing with optimization problems everyday, usually constrained, high dimensional and multi-objective

Nature has always shown us how social lifestyle and teamwork, solve massive problems

Optimization Problems

1. Too much parameters
2. Large parameter space
3. Non-Differentiable Cost Functions

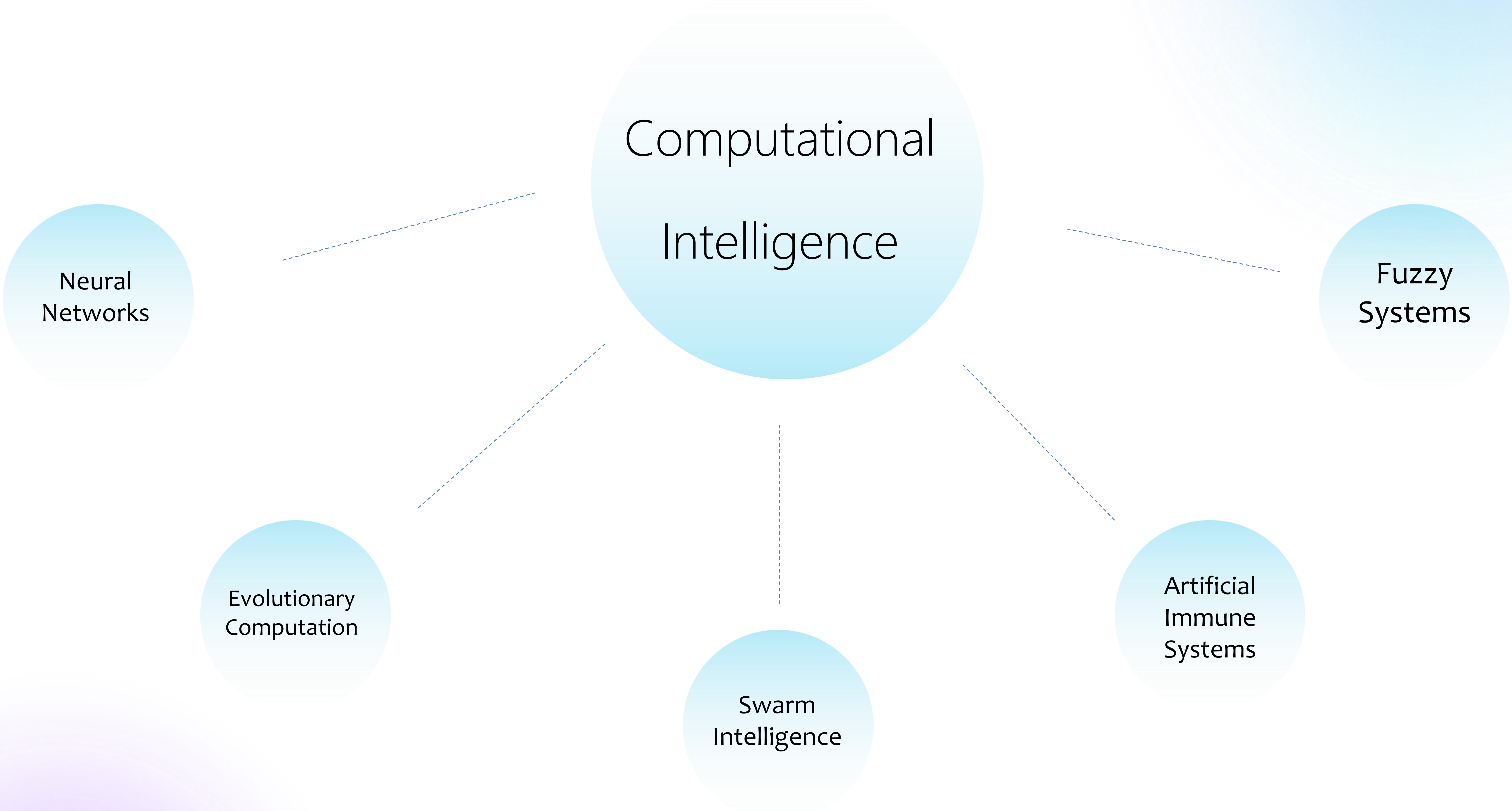
Traditional Algorithms such as Gradient Descent are not successful

Using SGD, BGD

We can’t perform back propagation in some cases !

Search space is still too large to be computation efficient !

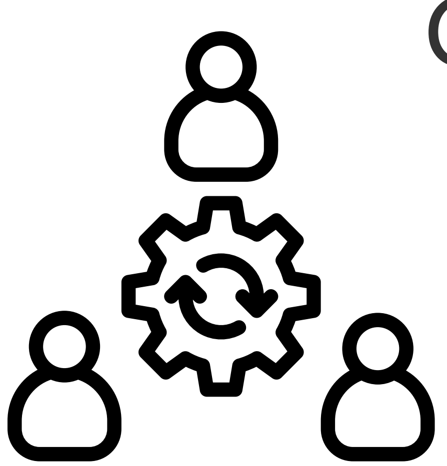
Use Metaheuristics !


Computational Intelligence
Neural Networks
Fuzzy Systems
Evolutionary Computation
Swarm Intelligence
Artificial Immune Systems

Swarm Intelligence

Originated from the study of:
colonies, swarms and social organisms

Definition:
Solving a cognitive problem by **two or more individuals** who **independently collect information** and **process it through social interactions**



- Introduced in 1989 Gerardo Beni, Jing Wang in the context of cellular robotic systems

Swarm Intelligence

Let's see some examples...

Ants do such tasks together that are impossible or time consuming individually

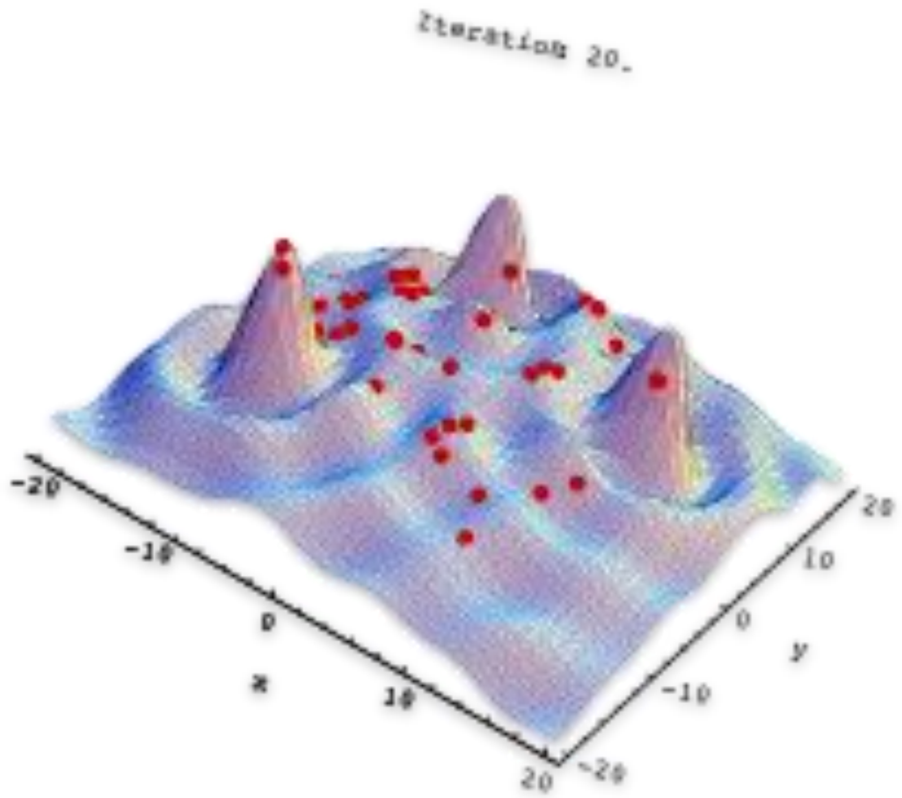
Bees create honeycombs through a teamwork process

Flock of birds move in such an intelligent way during migration

Migration of a school of fish

Each particle is placed in an initial position in the parameter space field

Particle Swarm Optimization



Movement vector is a superposition of 3 vectors:

1. Current direction
2. Direction towards best local point
3. Direction towards best global point

Chapter 2.

Dynamic Equations of PSO

1. Global Best PSO

Let x_i^t denote position of particle i, at time step t.

The position of the particle is changed by adding a velocity v_i^t to the current position.

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

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

The velocity drives the particles within the optimization process. How should we define it?

$$\overrightarrow{v_i^{t+1}} = w_i \underbrace{\overrightarrow{v_i^t}}_{\substack{\text{Current}\\ \text{Velocity}\\ \text{Inertia}}} + c_1 r_1 \underbrace{\overrightarrow{(x_i^{t\,(best)} - x_i^t\,)}}_{\substack{\text{Distance}\\ \text{from Best}\\ \text{Personal}\\ \text{Memory}\\ \text{Cognitive}\\ \text{Component}}} + c_2 r_2 \underbrace{\overrightarrow{(x^{t\,(best)} - x_i^t\,)}}_{\substack{\text{Distance}\\ \text{from Best}\\ \text{Global}\\ \text{Memory}\\ \text{Social}\\ \text{Component}}}$$

Record Update Conditions

Each particle has knowledge about global best and personal best record.

If the current position yields a cost function lower than the personal best record, personal best record is updated:

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

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

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

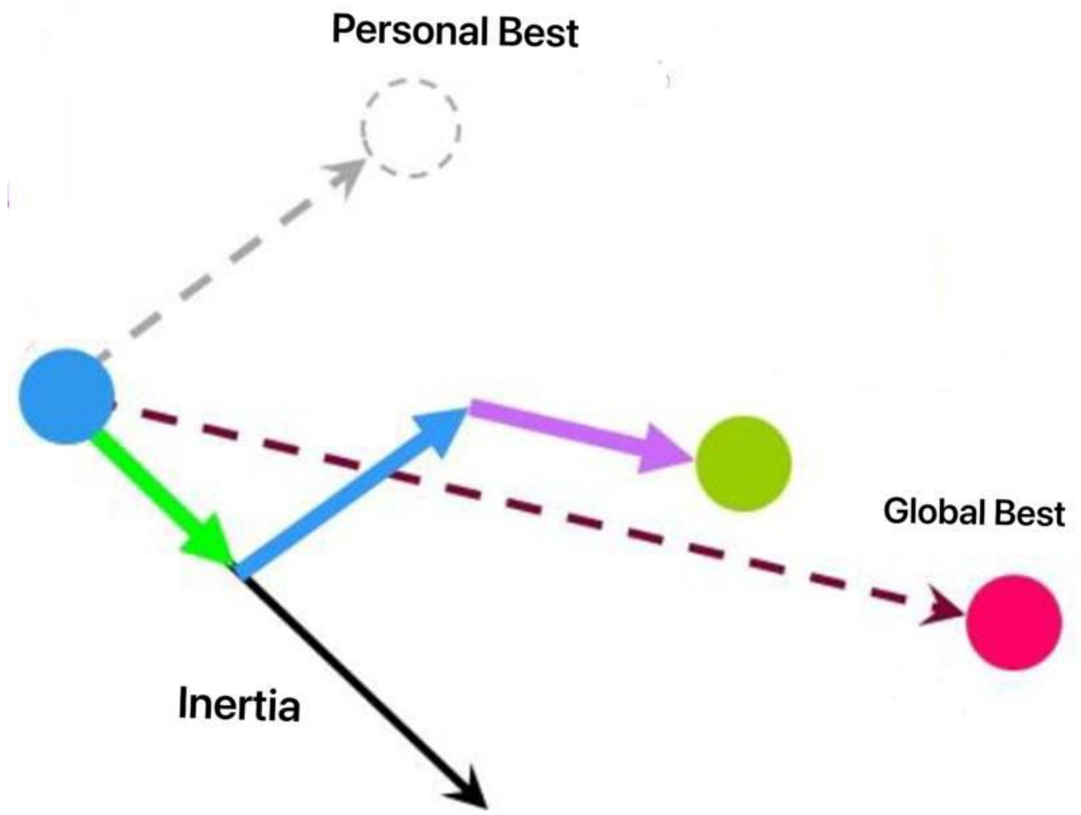
Controlling Contribution Factors and Learning Rate

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.**

W, c_1, c_2 are constants that control the learning rate relative to each factor, thus control relative importance, convergence speed and optimization accuracy.

r_1, r_2 are random values usually with a standard uniform distribution. They control exploration and exploitation within angles between global and local best.

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



2. Local Best PSO

Local PSO is just like Global PSO, except that information is now only shared among a neighborhood.

- Neighborhoods are not only defined by Euclidean distances

There are many cases where neighborhoods based on particle indices are preferred. Because:

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

- Neighborhoods overlap and this provides information sharing among them which guarantees convergence to a single point

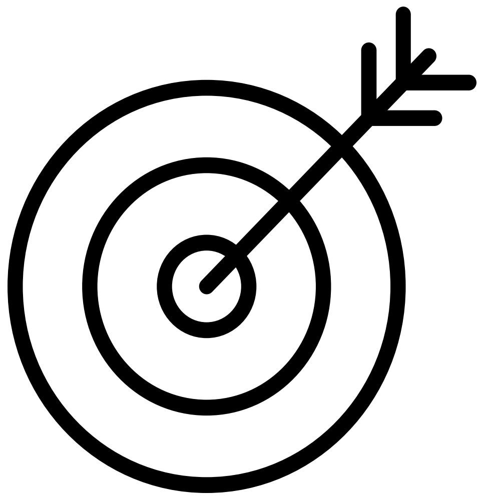
Local Best V.S Global Best

Convergence Rate

Global Best PSO has a faster convergence as information is shared directly among all particles

Exploration and Optimality

Local Best PSO finds better solutions cause the particles can escape local minima easier



Binary PSO

Used for problems where some (or all) parameters in the parameter space acquire only binary values

Probability of a bit of the position vector being 1:

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

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

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

Where π is an arbitrary pdf (usually a sigmoid)

Algorithm Aspects

Initialization

Particles are usually evenly distributed across the parameter space to ensure all areas are explored.

Termination Criteria

Termination can be according to the step size, number of iterations, minimum swarm radius, etc.

Function Evaluation

Each function evaluation needs computation, and brings power and time complexity

Chapter 3.

Implementation of PSO in Antenna Engineering

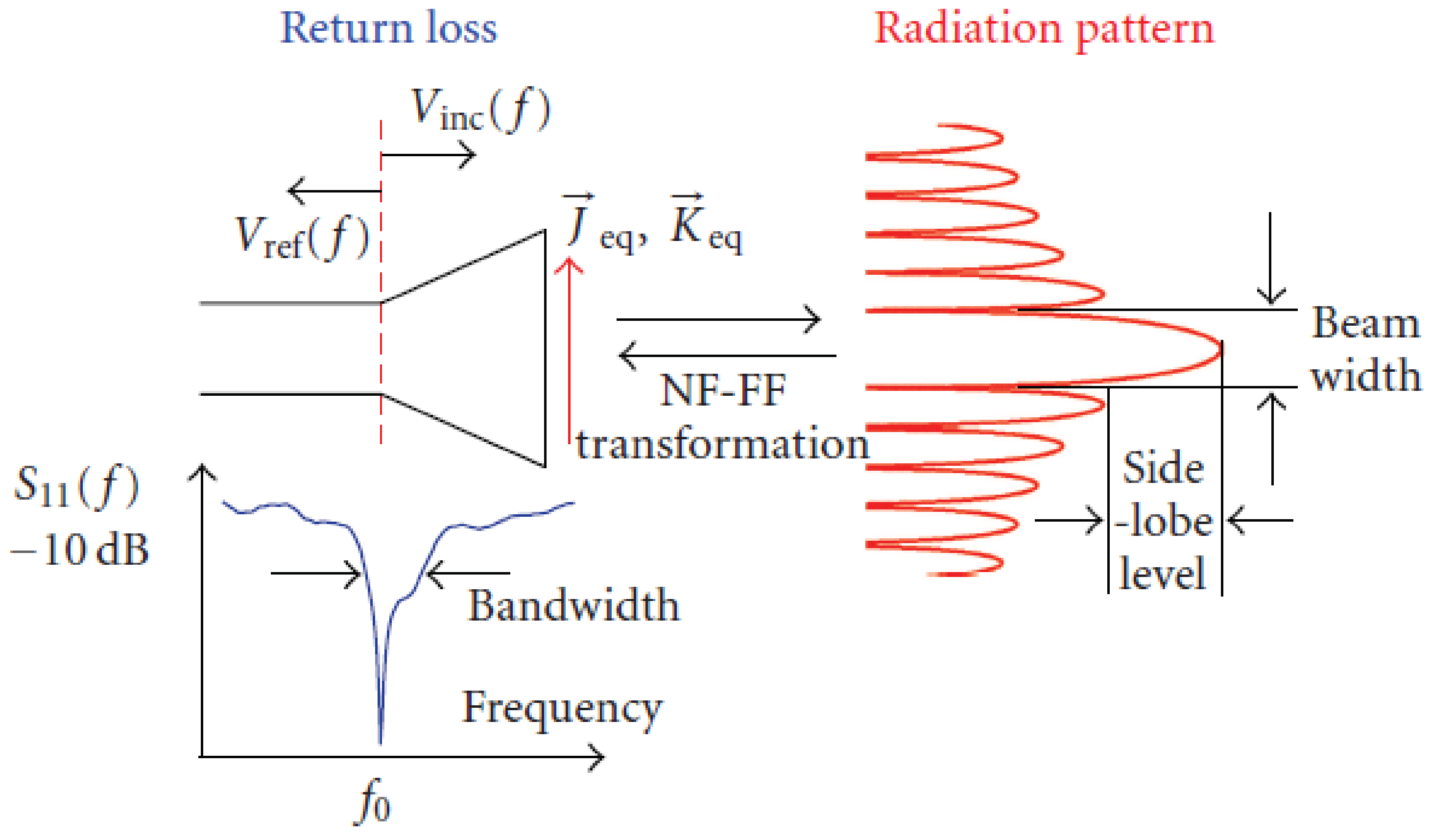
Optimization Problems in Antenna Engineering

1. Minimizing Return Loss (S_{11}) within operation frequency

$$S_{11}(f) = 20\log_{10}\frac{V_{\text{inc}}(f)}{V_{\text{ref}}(f)}\ (\text{dB}),$$

Maximizing Bandwidth:

$$BW = f_h - f_l = (f_{max} - f_{min})\ (\forall f \mid S_{11}^{f} < -10\ dB)$$



2. Approaching Desired Radiation Pattern (Beam Width, SLL, etc.)

Evaluation of Cost Functions

Maxwell Equations regarding boundary conditions should be solved

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

Next we calculate cost functions which directly relate to electromagnetic fields

Particles in the Parameter Space

What is the parameter space in Antenna Design Optimization ?

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

Each dimension of the parameter space can correspond to a <u>discrete</u> or <u>continuous</u> variable.

Design Problems based on Prior Knowledge on Geometry

Basic Antenna Design known by

designer's **prior knowledge**

Fine-Tuning Geometrical Parameters

Continuous Optimization

Classic PSO

Operating scheme is **relatively unknown**

Design space is discretized in to **pixels**!

Topology is explored by a **binary string**

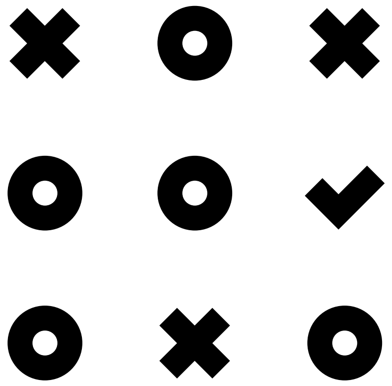
Binary PSO

Hybrid PSO

How to set weighting coefficients?

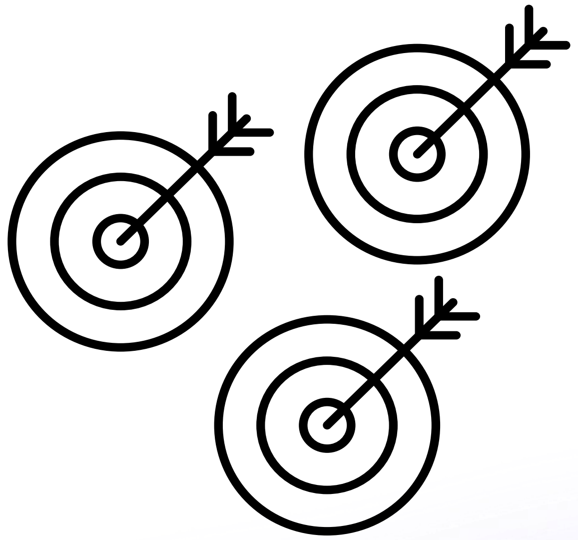
Trial and Error

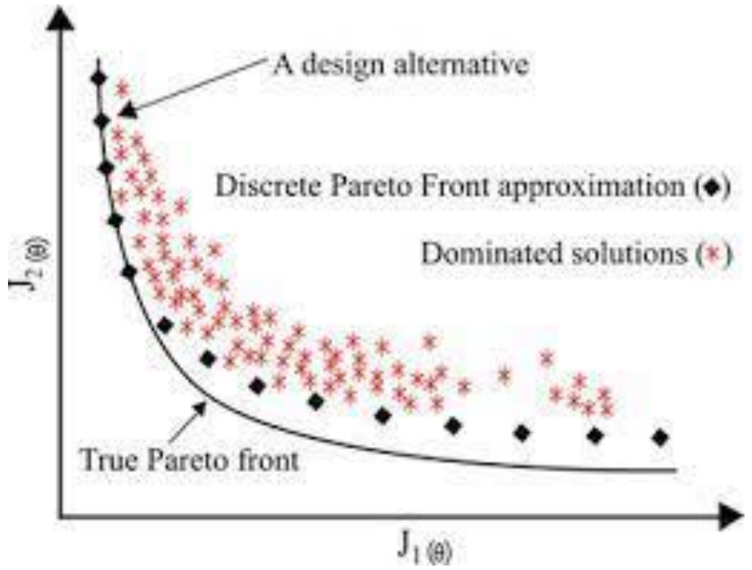
Carefully selected over trial and error



MO-PSO

Efficient way of exploiting trade-offs in multiple objective problems



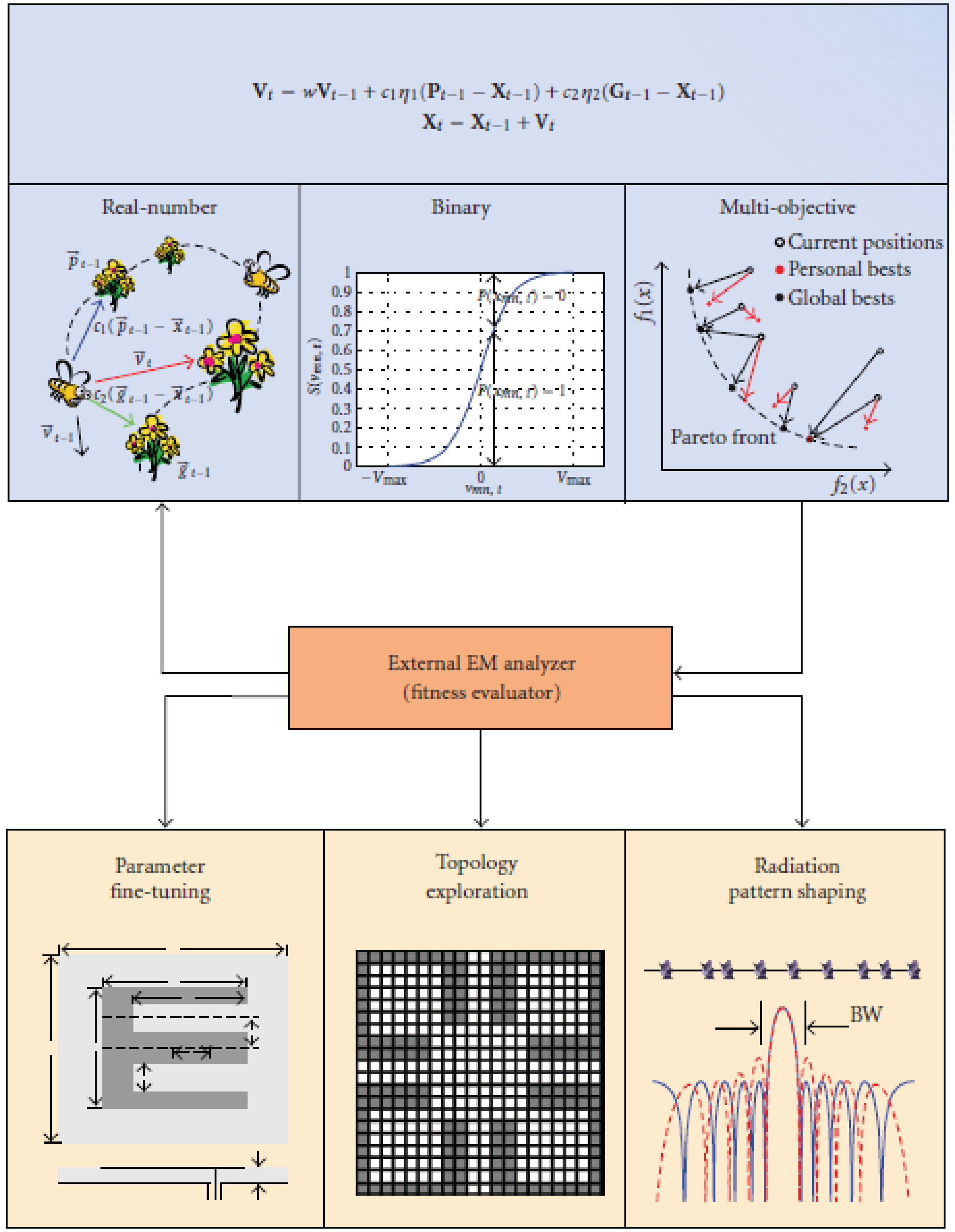


Pareto Front

A set of Non-dominated designs, where no objective can be improved without sacrificing the other

Implementing a PSO Engine

Algorithm type is picked according to **type** of **objective** we are dealing with



An **EM analyzer** acts as an **interface** and **evaluates** the **fitness function**

Chapter 4.

Examples and Applications

Dual Band E-Shaped Patch Antenna

<u>Optimization Parameters</u>

Patch Length (L)

Patch Width (W)

Slot Length (L_S)

Slot Width (W_S)

Slot Position (P_S)

Feed Position (x)

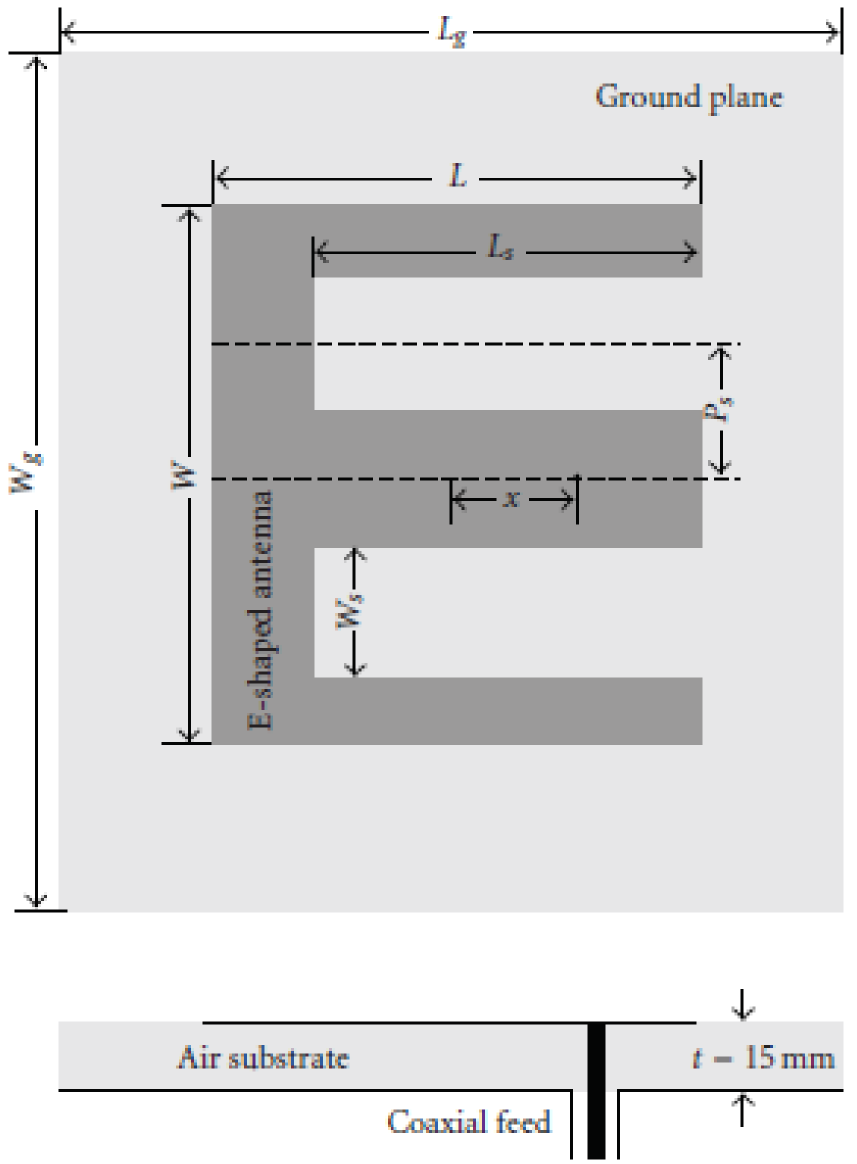


Figure 3: The topology of an E-shaped patch antenna. Each candidate design is represented by six geometrical parameters.

<u>Optimization Objectives</u>

Used as an antenna in BS for DCS, WLAN Applications

Design resonant frequencies at 1.8 GHz, 2.4Ghz

Dual Band E-Shaped Patch Antenna

Optimization Constraints
(Parameter Range)
(unit: mm)

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

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:

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

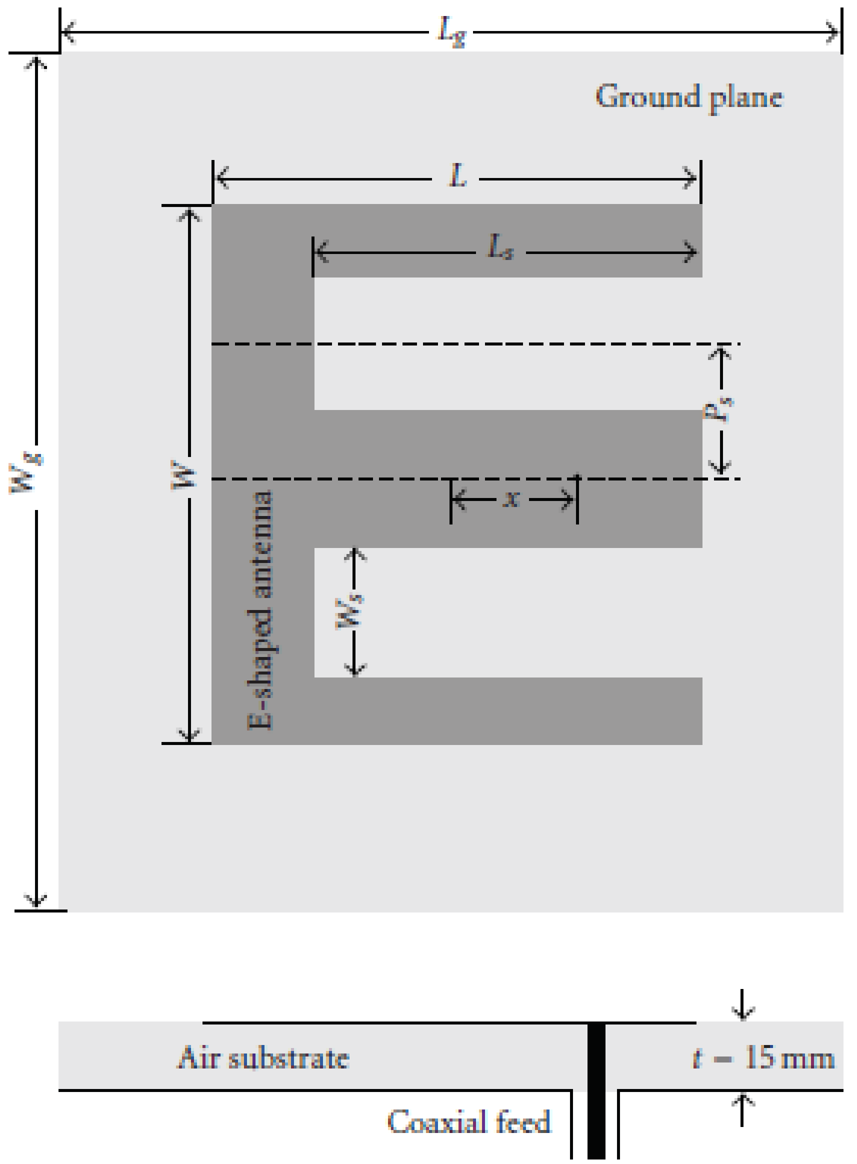


FIGURE 3: The topology of an E-shaped patch antenna. Each candidate design is represented by six geometrical parameters.

Cost Function

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

Dual Band E-Shaped Patch Antenna - Results

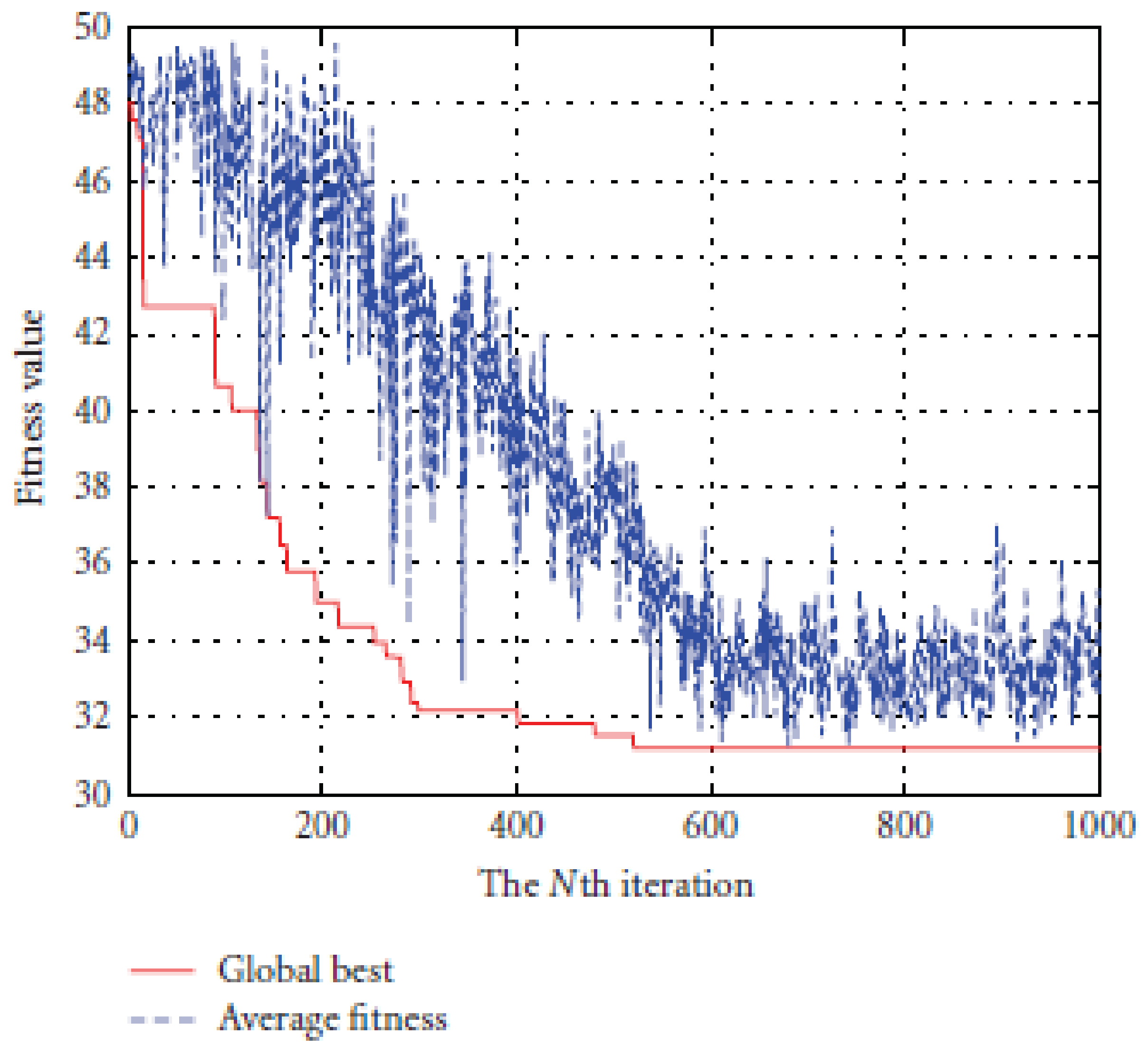


Figure 4: Convergence curves of the RPSO optimization by using a 10-agent swarm for 1000 iterations and applying the fitness function defined in (6).

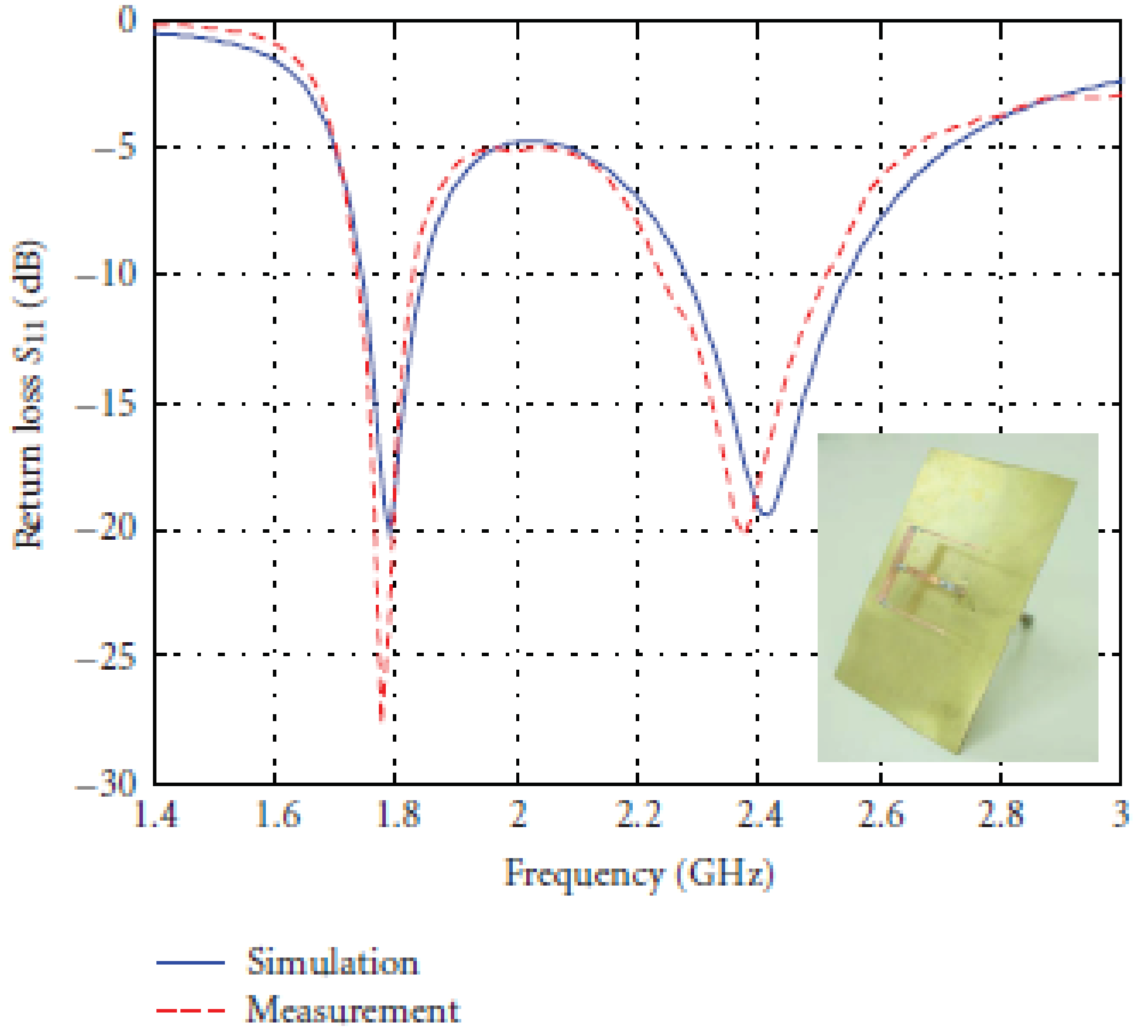


Figure 5: Simulated and measured S_{11} curves of the optimal dual-band antenna, which is prototyped and shown by the inset. Measurement results show a −15 dB return loss at both 1.8 GHz and 2.4 GHz.

Thanks for your attention !

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