METAHEURÍSTICAS

TEMA 5. METAHEURÍSTICAS BASADAS EN POBLACIONES

1. INTRODUCCIÓN A LA COMPUTACIÓN EVOLUTIVA
2. ALGORITMOS GENÉTICOS
3. ALGORITMOS EVOLUTIVOS PARA OPTIMIZACIÓN CONTINUA
4. EVOLUCIÓN DIFERENCIAL
5. PROGRAMACIÓN GENÉTICA
6. CONCLUSIONES

BIBLIOGRAFÍA
Bioinspired real parameter optimization: Where we are and what’s Next?

Francisco Herrera
Research Group on Soft Computing and Information Intelligent Systems (SCI²S)
http://sci2s.ugr.es
Dept. of Computer Science and A.I.
University of Granada, Spain

Email: herrera@decsai.ugr.es
http://decsai.ugr.es/~herrera
We focus our attention on the problem of finding the global optimum of a function that is characterized by:

- Real variables
- Multiple minima
- Non-differentiable
- Non-linear

It has many local minima and it is highly multimodal.
I. Bioinspired Parameter Optimization: Introduction
II. Pioneer and outstanding work
III. Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark
IV. Large Scale Global Optimization
V. Real-world Numerical Optimization Problems
VI. CEC2013 and CEC2014: Competition on Real-Parameter Single Objective Optimization
VII. Non Rigorous Experiments: Local vs Global Comparison
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Bioinspired Parameter Optimization: Introduction

First Approach:
Evolutionary Algorithms...

- Are function optimizers
- Inspired by natural evolution
- Population of individuals
- Are robust, hence preferred for real world problems
- Have little theory to explain how and why they work
- They come with various flavours
Bioinspired Parameter Optimization: Introduction

First Approach:
Evolutionary Algorithms...
Bioinspired Parameter Optimization: Introduction

First Approach:
Evolutionary Algorithms...
Bioinspired Parameter Optimization: Introduction

Evolutionary Algorithms don’t have this problem!!!
The idea of using simulated evolution to solve engineering and design problems have been around since the 1950’s (Fogel, 2000).

- Bremermann, 1962
- Box, 1957
- Friedberg, 1958

However, it wasn’t until the early 1960’s that we began to see three influential forms of EC emerge (Back et al, 1997):

- Evolutionary Programming (Lawrence Fogel, 1962),
- Genetic Algorithms (Holland, 1962)
- Evolution Strategies (Rechenberg, 1965 & Schwefel, 1968),
• The designers of each of the EC techniques saw that their particular problems could be solved via simulated evolution.

  – Fogel was concerned with solving programs evolution.

  – **Rechenberg & Schwefel were concerned with solving parameter optimization problems.**

  – Holland was concerned with developing robust adaptive systems.
Problem Motivation

- There are a lot of applications where a scientist/engineer has to optimize a non-linear, non-differentiable function that has multiple minima.
- An example of such an application is found in the field of neural networks where one has to optimize the topology and weights of a neural network to solve a mapping problem.
- Neural networks have been extensively used in the literature to solve classification problems, regression problems, prediction problems.
Bioinspired Parameter Optimization: Introduction

Most Popular Real-Parameter Bioinspired Algorithms

- Real-coded (parameter) genetic algorithm (RCGAs)
- Evolution strategies (ES)
- Particle swarm optimization (PSO)
- Differential evolution (DE)
- Real coding memetic algorithms (RCMA)
- Ant Colony Optimization (ACO) – A few proposals
Bioinspired Parameter Optimization: Introduction

Other Real-Parameter Bioinspired Algorithms

- Bacterial foraging optimization
- Cuckoo Search algorithms
- Frog-leaping algorithm
- Glowworm Swarm optimization
- Shark Smell Optimization (November 2014, online)

The most recent one: A new metaheuristic algorithm based Shark Smell Optimization. Complexity, 2015, in press (Wiley)
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Pioneers and outstanding work

Binary Coding

CROSSOVER is the fundamental mechanism of genetic rearrangement for both real organisms and genetic algorithms. Chromosomes line up and then swap the portions of their genetic code beyond the crossover point.
Pioneers and outstanding work

**Binary GAs in Continuous Search Space**

**Difficulties with binary-coded EAs**

- Binary GAs make the search space discrete
- Hamming cliffs: (10000)'s neighbor (01111)
  - Gray coding isn't the solution
- Arbitrary precision impossible due to fixed-length coding
- Search restricted with variable boundaries
- Not all Holland's schemata are important
  - (1****) more important than (****1)

**Solution:** Redesign crossover which gives more importance to meaningful schemata in real space
Pioneers and outstanding work

Real Coding Genetic Algorithms

- Decision variables are coded directly, instead of using binary strings
- **Recombination** and **mutation** need structural changes

\[ \Rightarrow ? \]

Recombination \quad Mutation \quad \left( x_1 x_2 \ldots \ldots \ldots x_n \right) \Rightarrow ?

- **Selection operator remains the same**
- **Simple exchanges are not adequate**
Problems with real crossover: Neighbourhood and Crossover

**Crossover idea:** combining parents genotypes to get children genotypes “somewhere in between” them

Interpretation & Generalization

Traditional **mutation & crossover** have a natural interpretation in the neighbourhood structure in terms of closeness and betweenness
Pioneers and outstanding work

Problems with real crossover: Neighbourhood and Crossover

Crossover idea:

(Real Coded Genetic Algorithms first generation)

Bioinspired Parameter Optimization
Second Generation
Pioneers and outstanding work

First Real Coding proposal: Linear/Arithmetical crossover

- **Linear Crossover**
  - From 2 parent points, 3 new points are generated:
    - $(1/2)p_1 + (1/2)p_2$, $(3/2)p_1 - (1/2)p_2$, $(-1/2)p_1 + (3/2)p_2$
    - $(1/2)p_1 + (1/2)p_2$ is the midpoint of $p_1$ and $p_2$
    - The others are on the line determined by $p_1$ and $p_2$
  - The best 2 of the 3 points are sent to the next generation
  - Disadvantage - Highly disrupted schemata. It is not compatible with the schema theorem described in the next slide.

**Extended models:** Arithmetical crossover (Michalewicz, 1992), Max-Min Arithmetic operator (Herrera, Lozano, Verdegay, 1995)
Pioneers and outstanding work

**Variable-wise recombination: Blend Crossover (BLX-α)**

![Diagram of Blend Crossover](attachment:image.png)

- Exploration: $c_{\text{min}} - \alpha \cdot I$ to $I$
- Exploitation: $c_{\text{max}} + \alpha \cdot I$

- Uniform probability distribution within a bound controlled by $\alpha$
- Diversity in children proportional to that in parents
- The search is too wide if parents are distant
Pioneers and outstanding work

**Variable-wise recombination of Parents (RCGA first generation)**

- Use a probability distribution to create offspring
- Different implementations since 1991:
  - Blend crossover (BLX-\(\alpha\)), 1993
  - Simulated binary crossover (SBX-\(\beta\)), 1995
  - Fuzzy recombination (FR-d), 1995
  - Fuzzy connectives based operator (FCB), 1994
- **Main feature:** Difference between parents used to create children
- Provides self-adaptive property

Pioneers and outstanding work

**Taxonomy of Crossover operators**

**Discrete crossover**

**Aggregation based Crossover**

**Neighborhood based Crossover**

Vector-Wise Recombination Operators

- Variable-wise recombination cannot capture nonlinear interactions

- **Alternative**: Recombine parents as vectors *(RCGA second generation)*
  - Parent-centric recombination (PCX)
  - Unimodal normally-distributed crossover (UNDX)
  - Simplex crossover (SPX)

- Difference between parents is used to create offspring solutions *(some models in this special issue)*.
Bioinspired Parameter Optimization

Second Generation

New algorithms: DE, PSO, CMA-ES

Real Coding problems are now similar to classical benchmarks: TSP, …
The PSO (Kennedy and Eberhart (1995) starts from an initial population of solutions (particles) for the optimization problem. It finds new solutions by co-jointly exploring the space and exploiting the information provided by already found, good solutions.

Particle Swarm Optimization

Particles fly through the search space (biological inspiration)

Particle Swarm Optimization

- Kennedy and Eberhart, 1995
- Particles fly through the search space
- Velocity dynamically adjusted

\[ x_i = x_i + v_i \]

\[ v_i = v_i + c_1 \text{rand}((p_{i,\text{best}} - x_i) + c_2 \text{rand}((p_{g} - x_i)) \]

- \( p_{i} \): best position of i-th particle
- \( p_{g} \): position of best particle so far
  - 1\text{st} term: momentum part (history)
  - 2\text{nd} term: cognitive part (private thinking)
  - 3\text{rd} term: social part (collaboration)

- \( c_1, c_2 \in [0,2] \)
The DE approach (Storn and Price (1997)) starts from an initial population of solutions that are mutated and crossed over to eventually obtain better solutions for the optimization problem at hand.

Differential Evolution

1. Start with a pool of random solutions
2. Create a child $v$
3. $x_k$ and $v$ are recombined with $p$
4. Keep better of $y$ and $x^{(k)}$
   - Difference of parents in creating a child is important
   - A number of modifications exist

\[ v = x^{(1)} + \lambda (x^{(2)} - x^{(3)}) \]

\[ y_i = \begin{cases} v_i, & \text{with a prob. } p \\ x_i^{(k)}, & \text{else} \end{cases} \]

Vector-Wise Recombination
1. **EVOLUCIÓN DIFERENCIAL**

- **Inicialización:**
  Una población $P_{x,0}$ de $N_p$ vectores de parámetros D-dimensionales $x_{i,0}=[x_{1,i,0}, \ldots, x_{D,i,0}]$, $i=1, \ldots, N_p$ se genera aleatoriamente dentro de unos límites inferiores y superiores previos $b_L=[b_{1,L}, \ldots, b_{D,L}]$ y $b_U=[b_{1,U}, \ldots, b_{D,U}]$.

  **Ejemplo:** el valor inicial (en la generación $g=0$) del $j$-ésimo parámetro del $i$-ésimo vector se genera por: $x_{j,i,0}=\text{rand}_j[0, 1] \cdot (b_{j,U}-b_{j,L}) + b_{j,L}$, $j=1, \ldots, D$, $i=1, \ldots, N_p$.

- **Generación de un vector de prueba:**
  En la generación $g$-ésima, una población $P_{u,g}$ consistente de $N_p$ vectores D-dimensionales $v_{i,g}=[v_{1,i,g}, \ldots, v_{D,i,g}]$ a través de operadores de mutación y recombinación aplicados a la población actual $P_{x,g}$.

  **Mutación Diferencial:** con respecto a cada vector $x_{i,g}$ en la población actual, llamado vector objetivo, se genera un vector mutado $v_{i,g}$ añadiendo un vector diferencia, escalado y aleatoriamente muestreado, a un vector base aleatoriamente seleccionado de la población actual.
1. EVOLUCIÓN DIFERENCIAL

Imagen de la Evolución Diferencial clásica
1. EVOLUCIÓN DIFERENCIAL

Ejemplo: en la generación g-ésima, el i-ésimo vector mutado $v_{i,g}$ con respecto al i-ésimo vector objetivo $x_{i,g}$ en la población actual se genera mediante

$$V_{i,g} = x_{r0,g} + F \cdot (x_{r1,g} - x_{r2,g}), \ i \neq r0 \neq r1 \neq r2.$$ 

El factor de escalado de la mutación $F \in [0,1]$
1. **Evolución Difencial**

**Ejemplo:** en la generación $g$-ésima, el $i$-ésimo vector mutado $v_{i,g}$ con respecto al $i$-ésimo vector objetivo $x_{i,g}$ en la población actual se genera mediante

$$V_{i,g} = x_{r0,g} + F \cdot (x_{r1,g} - x_{r2,g}), \text{ } i \neq r0 \neq r1 \neq r2.$$ 

El factor de escalado de la mutación $F \in [0,1]$
1. **EVOLUCIÓN DIFERENCIAL**

**Ejemplo:** en la generación g-ésima, el i-ésimo vector mutado $v_{i,g}$ con respecto al i-ésimo vector objetivo $x_{i,g}$ en la población actual se genera mediante

$$V_{i,g} = x_{r0,g} + F \cdot (x_{r1,g} - x_{r2,g}) \text{, } i \neq r0 \neq r1 \neq r2.$$  

El factor de escalado de la mutación $F \in [0,1]$. 
1. **Evolución Diferencial**

• **Recombinación Discreta:**  
Con respecto a cada vector objetivo \( x_{i,g} \) en la población actual, un nuevo vector \( u_{i,g} \) se genera cruzando el vector objetivo \( x_{i,g} \) con el correspondiente vector mutado \( v_{i,g} \) bajo un ratio predefinido de cruce \( Cr \in [0, 1] \).

**Ejemplo:** en la generación \( g \)-ésima, el \( i \)-ésimo vector \( u_{i,g} \) con respecto al \( i \)-ésimo vector objetivo \( x_{i,g} \) en la población actual se genera mediante:

\[
  u_{j,i,g} = \begin{cases} 
    v_{j,i,g} & \text{if } \text{rand}[0,1] \leq Cr \text{ or } j=j_{\text{rand}} \\
    x_{j,i,g} & \text{otherwise}
  \end{cases}
\]

• **Reemplazamiento:**  
Si el vector \( u_{i,g} \) tiene mejor valor de la función objetivo que su correspondiente vector objetivo \( x_{i,g} \), sustituye el vector objetivo en la generación \((g+1)\); si esto no ocurre, el vector objetivo permanece en la generación \((g+1)\).
1. **EVOLUCIÓN DIFERENCIAL**
1. EVOLUCIÓN DIFERENCIAL
1. EVOLUCIÓN DIFERENCIAL

Procedimiento Básico – Evolución Diferencial

```plaintext
Procedure DE{
  t = 0;
  Initialize Pop(t); /* of |Pop(t)| Individuals */
  Evaluate Pop(t);
  While (Not Done)
    {for i = 1 to |Pop(t)| do
      {parent1, parent2, parent3} = Select_3_Parents(Pop(t));
      thisGene = random_int(|Pop(t)|);
      for k = 1 to n do /* n genes per Individual */
        if (random < p) /*P is crossover constant in [0,1]*/
          Offspring_{ik} = parent1_{ik} + \gamma(parent2_{ik} - parent3_{ik});
        else
          Offspring_{ik} = Individual_{ik} in Pop(t);
        end /* for k */
      Evaluate(Offspring_i);
    end /* for i */
    Pop(t+1) = {j | Offspring_j is_better_than Individual_j} \cup
              {k | Individual_k is_better_than Offspring_k};
    t = t + 1;}
```

CÓDIGO: http://www.icsi.berkeley.edu/~storn/code.html
1. **EVLUCIÓN DIFERENCIAL**

- Es un método simple y efectivo (con complejidad algorítmica lineal).

Algunos aspectos importantes:
- **Población inicial**: Es muy importante la diversidad de la población en ED puesto que la búsqueda se orienta por diferencias entre vectores.
- **Estrategia de reparación**: En ocasiones, por el uso de los operadores de variación, es necesario utilizar estrategias para reparar. Algunas opciones:
  - Estrategias extremas:
    - Se fija el valor a un límite -> decrementar la diversidad
    - Se reinicializa a un valor aleatoria (es extrema en términos de mantenimiento de diversidad)
  - Estrategias intermedias, p.e. Poner el valor “inválido” a un valor intermedio entre su valor inicial y el valor “inválido”
2. VARIANTES DE LA EVOLUCIÓN DIFERENCIAL

• Mutación diferencial:

  • Vector de una diferencia: \( F \cdot (x_{r1} - x_{r2}) \)
  
  • Vector de dos diferencias: \( F \cdot (x_{r1} - x_{r2}) + F \cdot (x_{r3} - x_{r4}) \)
  
  • Factor de escalado de mutación F

• Rol crucial: balance exploración y explotación.

**DE/rand/1:**

\[
V_{i,G} = X_{r1,G} + F \cdot \left( X_{r2,G} - X_{r3,G} \right)
\]

**DE/best/1:**

\[
V_{i,G} = X_{best,G} + F \cdot \left( X_{r1,G} - X_{r2,G} \right)
\]

**DE/current-to-best/1:**

\[
V_{i,G} = X_{i,G} + F \cdot \left( X_{best,G} - X_{i,G} \right) + F \cdot \left( X_{r1,G} - X_{r2,G} \right)
\]

**DE/rand/2:**

\[
V_{i,G} = X_{r1,G} + F \cdot \left( X_{r2,G} - X_{r3,G} + X_{r4,G} - X_{r5,G} \right)
\]

**DE/best/2:**

\[
V_{i,G} = X_{best,G} + F \cdot \left( X_{r1,G} - X_{r2,G} + X_{r3,G} - X_{r4,G} \right)
\]
2. VARIANTES DE LA EVOLUCIÓN DIFERENCIAL

- Recombinación
  - Recombinación discreta (cruce) (variante rotacional)
    - Un punto y multipunto
    - Exponencial
    - Binomial (uniforme)
  - Recombinación aritmética
    - Recombinación lineal (invariante rotacional)
    - Recombinación intermedia (variante rotacional)
    - Recombinación intermedia extendida (variante rotacional)
Evolution Strategies

Pioneers and outstanding work

Rechenberg & Schwefel (1964) were concerned with solving parameter optimization problems. Autoadaptation of parameters.

Mut: $I \xrightarrow{} I$

$\text{Mut} (x) = x' = (x_1 + z_1, \ldots, x_n + z_n)$

$z_i \sim N_i(0,\sigma'^2)$

Pioneers and outstanding work

State of the art of the ES second generation: **CMA-ES**
Evolution Strategy with Covariance Matrix Adaptation (Hansen & Ostermeier, 1996)

- Selection-mutation ES is run for \( n \) iterations
- Successful steps are recorded
- They are analyzed to find uncorrelated basis directions and strengths
- Required \( O(n^3) \) computations to solve an eigenvalue problem
- Rotation invariant

Nikolaus Hansen
www.lri.fr/~hansen/

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IX. Final Comments
The study was made with dimensions $D = 10$, $D = 30$, $D = 50$.
The maximum number of fitness evaluations is $10,000 \cdot D$.
Each run stops when the maximal number of evaluations is achieved.

### Unimodal Functions
Success Performance Indices

<table>
<thead>
<tr>
<th>6 functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Sphere</td>
</tr>
<tr>
<td>2 Schwefel 1.2</td>
</tr>
<tr>
<td>3 Ellipsoid Condition 10^6</td>
</tr>
<tr>
<td>4 Schwefel 1.2 with Noise</td>
</tr>
<tr>
<td>5 Schwefel 2.6 on Bounds</td>
</tr>
<tr>
<td>6 Rosenbrock</td>
</tr>
</tbody>
</table>

### Multimodal Functions
Solved in at least one run

<table>
<thead>
<tr>
<th>6 functions</th>
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<tr>
<td>7 Griewank out Bounds</td>
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<tr>
<td>9 Rastrigin Separable</td>
</tr>
<tr>
<td>10 Rastrigin Rotated</td>
</tr>
<tr>
<td>11 Weierstrass</td>
</tr>
<tr>
<td>12 Schwefel 2.13</td>
</tr>
<tr>
<td>15 Hybrid Separable</td>
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</tbody>
</table>

### Multimodal Functions
Never solved

<table>
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<th>13 functions</th>
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<tbody>
<tr>
<td>8 Ackley Condition 10^2</td>
</tr>
<tr>
<td>13 Expanded 6&amp;7</td>
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<tr>
<td>14 Expanded Schaffer F6</td>
</tr>
<tr>
<td>16 Hybrid Rotated</td>
</tr>
<tr>
<td>17 Hybrid with Noise</td>
</tr>
<tr>
<td>18 Hybrid F18</td>
</tr>
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<td>19 Hybrid Narrow</td>
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<tr>
<td>20 Hybrid on Bounds</td>
</tr>
<tr>
<td>21 Hybrid F21</td>
</tr>
<tr>
<td>22 Hybrid High Condition</td>
</tr>
<tr>
<td>23 Hybrid Non-Continuous</td>
</tr>
<tr>
<td>24 Hybrid F24</td>
</tr>
<tr>
<td>25 Hybrid out</td>
</tr>
</tbody>
</table>
Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark

Algorithms involved in the comparison: (11 algorithms)

- **BLX-GL50** (Garcia-Martinez & Lozano, 2005): Hybrid Real-Coded Genetic Algorithms with Female and Male Differentiation
- **BLX-MA** (Molina et al., 2005): Adaptive Local Search Parameters for Real-Coded Memetic Algorithms
- **CoEVO** (Posik, 2005): Mutation Step Co-evolution
- **DE** (Ronkkonen et al., 2005): Differential Evolution
- **DMS-L-PSO**: Dynamic Multi-Swarm Particle Swarm Swarm Optimizer with Local Search
- **EDA** (Yuan & Gallagher, 2005): Estimation of Distribution Algorithm
- **G-CMA-ES** (Auger & Hansen, 2005): A restart Covariance Matrix Adaptation Evolution Strategy with increasing population size
- **K-PCX** (Sinha et al., 2005): A Population-based, Steady-State real-parameter optimization algorithm with parent-centric recombination operator, a polynomial mutation operator and a niched selection operation.
- **L-CMA-ES** (Auger & Hansen, 2005): A restart local search Covariance Matrix Adaptation Evolution Strategy
- **L-SaDE** (Qin & Suganathan, 2005): Self-adaptive Differential Evolution algorithm with Local Search
- **SPC-PNX** (Ballester et al., 2005): A steady-state real-parameter GA with PNX crossover operator
Two good algorithms with good ranking and similar statistical behaviour:

http://math.lanl.gov/~vrugt/software/

**AMALGAM - SO:** A Multi ALgorithm Genetically Adaptive Method for Single Objective Optimization. This method simultaneously merges the strengths of the Covariance Matrix Adaptation (CMA) evolution strategy, Genetic Algorithm (GA) and Particle Swarm Optimizer (PSO) for population evolution and implements a self-adaptive learning strategy to automatically tune the number of offspring these three individual algorithms are allowed to contribute during each generation.
Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark

Two good algorithms with good ranking and similar statistical behaviour:


Figure 3: Example of LS chain. $p_{i+1}$ is the final parameter value reached by the LS algorithm when it started with a value of $p_i$. $p_0$ is the default value for the strategy parameter.

MA-CMA-Chains: Local search adaptation
Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark

Two good algorithms with good ranking and similar statistical behaviour:


*Extension: Region based MA-LSCh-CMA*


![Diagram showing region based niches and classical niches]

<table>
<thead>
<tr>
<th>Dim</th>
<th>$R^+$</th>
<th>$R^-$</th>
<th>$p$-value</th>
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<td>10</td>
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<td>854</td>
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</tr>
</tbody>
</table>
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IX. Final Comments
Nowadays, the ability to tackle high-dimensional problems is crucial to many real problems (bio-computing, data mining, etc.), arising high-dimensional optimization problems as a very interesting field of research.

The ability of being scalable for high-dimensional problems becomes an essential requirement for modern optimization algorithm approaches.

G-CMA-ES presents good results with a low/medium number of variables but its drawback is associated to the scalability – More than 100 variables
Special Session & Competition on Large Scale Global Optimization at CEC 2008.

Workshop for Evolutionary Algorithms and other Metaheuristics for Continuous Optimization Problems - A Scalability Test at ISDA 2009.

Special Session & Competition on Large Scale Global Optimization at CEC 2010.

Special Session & Competition on Large Scale Global Optimization at CEC 2012.

Special Session & Competition on Large Scale Global Optimization at CEC 2013.
A set of 19 scalable function optimization problems were provided:


- **5 Shifted Functions**: Schwefel’s Problem 2.22 (F7), Schwefel’s Problem 1.2 (F8), Extended f10 (F9), Bohachevsky (F10), and Schaffer (F11). (Description) (Source code).

- **8 Hybrid Composition Functions** (F12-F19*): They are non-separable functions built by combining two functions belonging to the set of functions F1-F11 (Description) (Source code).

The study was made with dimensions $D = 50, D = 100, D = 200, D = 500,$ and $D = 1,000$. The maximum number of fitness evaluations is $5,000 \cdot D$. Each run stops when the maximal number of evaluations is achieved.
Large Scale Global Optimization

Special Issue of Soft Computing: Scalability of Evolutionary Algorithms and other Metaheuristics for Large Scale Continuous Optimization Problems Volume 15, Number 11, 2011 (7 DE approaches)

P01 - SOUPDE  Shuffle Or Update Parallel Differential Evolution for Large Scale Optimization

P02 - DE-D^40+M^m  Role Differentiation and Malleable Mating for Differential Evolution: An Analysis on Large Scale Optimisation

P03 - GODE  Enhanced Opposition-Based Differential Evolution for Solving High-Dimensional Continuous Optimization Problems

P04 - GaDE  Scalability of Generalized Adaptive Differential Evolution for Large-Scale Continuous Optimization


P06 - SaDE-MMTS  Self-adaptive Differential Evolution with Multi-trajectory Search for Large Scale Optimization

P07 - MOS  A MOS-based Dynamic Memetic Differential Evolution Algorithm for Continuous Optimization A Scalability Test (best results)

P08 - MA-SSW-Chains  Memetic Algorithms Based on Local Search Chains for Large Scale Continuous Optimisation Problems: MA-SSW-Chains

P09 - RPSO-vm  Restart Particle Swarm Optimization with Velocity Modulation: A Scalability Test

P10 - Tuned IPSOLS  An Incremental Particle Swarm for Large-Scale Optimization Problems: An Example of Tuning-in-the-loop (Re)Design of Optimization Algorithms

P11 - multi-scale PSO  Multi-Scale Particle Swarm Optimization Algorithm

P12 - EvoPROpt  Path Relinking for Large Scale Global Optimization

P13 - EM323  EM323 : A Line Search based algorithm for solving high-dimensional continuous non-linear optimization problems

P14 – VXQR  VXQR: Derivative-free unconstrained optimization based on QR factorizations
IEEE CEC 2012 Special Session
MOS – version
JDelscop

IEEE CEC 2013 Special Session
MOS – version
CECC-G
CC-CMA-ES
Real-world Numerical Optimization Problems


4. Special Sessions and Workshops: Problem definitions and contributions (pdf files) http://sci2s.ugr.es/EAMHCO/#SS

1. Parameter Estimation for Frequency-Modulated (FM) Sound Waves
2. Lennard-Jones Potential Problem
3. The Bifunctional Catalyst Blend Optimal Control Problem
4. Optimal Control of a Non-Linear Stirred Tank Reactor
5. Tersoff Potential Function Minimization Problem
7. Transmission Network Expansion Planning (TNEP) Problem
8. Large Scale Transmission Pricing Problem
9. Circular Antenna Array Design Problem
10. Dynamic Economic Dispatch (DED) Problem
11. Static Economic Load Dispatch (ELD) Problem
12. Hydrothermal Scheduling Problem
13. Messenger: Spacecraft Trajectory Optimization Problem
14. Cassini 2: Spacecraft Trajectory Optimization Problem
Real-world Numerical Optimization Problems


Algorithm: **GA-MPC**

**GA with a New Multi-Parent Crossover** for Solving IEEE-CEC2011 Competition Problems

*Saber M. Elsayed; Ruhul A. Sarker; Daryl L. Essam*


**STEP 4:** For each three consecutive individuals, if \( u \in [0,1] < cr \)

i) Rank these three individuals from \( f(x_i) \leq f(x_{i+1}) \leq f(x_{i+2}) \)

ii) If one of the selected individuals is the same to another, then replace one of them with a random individual from the selection pool.

iii) Calculate \( \beta = N(\mu, \sigma) \)

iv) Generate three offspring \((a_i)\):

\[
\begin{align*}
o_1 &= x_1 + \beta \times (x_2 - x_3) \\
o_2 &= x_2 + \beta \times (x_3 - x_1) \\
o_3 &= x_3 + \beta \times (x_1 - x_2)
\end{align*}
\]
The algorithm with best values is GA-MPC, in the following Wilcoxon's test we compare this one with the other algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>GA-MPC value</th>
<th>Other value</th>
<th>Critical value</th>
<th>p-value</th>
<th>5% error</th>
<th>Sig. differences?</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDASA</td>
<td>242.5</td>
<td>10.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>CDE-LS</td>
<td>239</td>
<td>14</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>DE-ACr</td>
<td>158.5</td>
<td>94.5</td>
<td>65</td>
<td></td>
<td></td>
<td>No</td>
</tr>
<tr>
<td>DE-RCH</td>
<td>242.5</td>
<td>10.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>EA-DE-MA</td>
<td>235.5</td>
<td>17.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>ED-DE</td>
<td>230.5</td>
<td>22.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>Elite GA</td>
<td>229.5</td>
<td>23.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>EPSDE</td>
<td>235</td>
<td>18</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>IADE</td>
<td>222.5</td>
<td>30.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>SACWIDE</td>
<td>224.5</td>
<td>28.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>SAMODE</td>
<td>202</td>
<td>51</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td>SAPMCSBX</td>
<td>242.5</td>
<td>10.5</td>
<td>65</td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
</tbody>
</table>

Algorithm: **GA-MPC**: GA with a New Multi-Parent Crossover for Solving IEEE-CEC2011 Competition Problems

*Saber M. Elsayed; Ruhul A. Sarker; Daryl L. Essam*

I. Evolutionary Parameter Optimization: Introduction
II. Pioneer and outstanding work
III. Milestone: CEC’2005 Real Parameter Optimization Session and Benchmark
IV. Large Scale Global Optimization
V. Real-world Numerical Optimization Problems
VI. CEC2013 and CEC2014: Competition on Real-Parameter Single Objective Optimization
VII. Non Rigorous Experiments: Local vs Global Comparison
VIII. Current Trends
IX. Final Comments
Special Session & Competition on Real-Parameter Single Objective Optimization at CEC-2013, Cancun, Mexico 21-23 June 2013.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Algorithm Name</th>
<th>Mean Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NEIPOPaCMA</td>
<td>0.27589</td>
</tr>
<tr>
<td>2</td>
<td>lcaemils</td>
<td>0.28289</td>
</tr>
<tr>
<td>3</td>
<td>DRMA-LSCh-CMA</td>
<td>0.30472</td>
</tr>
<tr>
<td>4</td>
<td>SHADE</td>
<td>0.32800</td>
</tr>
<tr>
<td>5</td>
<td>NIPOPaCMA</td>
<td>0.34873</td>
</tr>
<tr>
<td>6</td>
<td>mnaio</td>
<td>0.36127</td>
</tr>
<tr>
<td>7</td>
<td>SHADE</td>
<td>0.45583</td>
</tr>
<tr>
<td>8</td>
<td>TLEBDDE</td>
<td>0.47042</td>
</tr>
<tr>
<td>9</td>
<td>DfDfLS</td>
<td>0.47222</td>
</tr>
<tr>
<td>10</td>
<td>bbeefl</td>
<td>0.47687</td>
</tr>
<tr>
<td>11</td>
<td>SPSRDEEMS</td>
<td>0.49421</td>
</tr>
<tr>
<td>12</td>
<td>CMAES-RIS</td>
<td>0.50515</td>
</tr>
<tr>
<td>13</td>
<td>SPSAABC</td>
<td>0.51956</td>
</tr>
<tr>
<td>14</td>
<td>janda</td>
<td>0.52960</td>
</tr>
<tr>
<td>15</td>
<td>DE_APC</td>
<td>0.57617</td>
</tr>
<tr>
<td>16</td>
<td>fl-Pso</td>
<td>0.58058</td>
</tr>
<tr>
<td>17</td>
<td>TPC-GA</td>
<td>0.61008</td>
</tr>
<tr>
<td>18</td>
<td>PVADE</td>
<td>0.63422</td>
</tr>
<tr>
<td>19</td>
<td>CDAAS</td>
<td>0.68859</td>
</tr>
<tr>
<td>20</td>
<td>SPS2011</td>
<td>0.75352</td>
</tr>
<tr>
<td>21</td>
<td>PLES</td>
<td>0.83349</td>
</tr>
</tbody>
</table>

Table 1: The Table gives the mean aggregated rank of all the 21 algorithms ($N = 21$) across all problems and all dimensions from the CEC 2013 Special Session & Competition on Real-Parameter Single Objective Optimization after the maximum available number of function evaluations was used.

Winners extend CMAES

Table 2: Given is for each of the top three performing algorithms iCMAES-ILS, NBIP-OP-ACMA-ES, and DRMA-LSCh-CMA the sum of the ranks with respect to the average error values that are measured for each of the 28 CEC 2013 benchmark functions. The average error values correspond to the errors measured at the maximum number of function evaluations. Given are also the results of a Friedman test at the significance level \( \alpha = 0.05 \). \( \Delta R \) are the minimum significant difference 22.07 for all dimensions, Inf for dimension 10, 12.64 for dimension 30 and 12.96 for dimension 50, respectively. The numbers in parenthesis are the difference of the sum of ranks relative to the best algorithm. Algorithms that are significantly different from the best algorithm are highlighted.

<table>
<thead>
<tr>
<th>All Dims</th>
<th>Algorithms</th>
<th>Sum Rank</th>
<th>( \Delta R )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>iCMAES-ILS</td>
<td>148.0</td>
<td>(0)</td>
</tr>
<tr>
<td></td>
<td>NBIP-OP-ACMA-ES</td>
<td>160.5</td>
<td>(12.5)</td>
</tr>
<tr>
<td></td>
<td>DRMA-LSCh-CMA</td>
<td>195.5</td>
<td>(47.5)</td>
</tr>
<tr>
<td>Dim=10</td>
<td>Algorithms</td>
<td>Sum Rank</td>
<td>( \Delta R )</td>
</tr>
<tr>
<td></td>
<td>NBIP-OP-ACMA-ES</td>
<td>51.5</td>
<td>(0)</td>
</tr>
<tr>
<td></td>
<td>iCMAES-ILS</td>
<td>54.0</td>
<td>(2.5)</td>
</tr>
<tr>
<td></td>
<td>DRMA-LSCh-CMA</td>
<td>62.5</td>
<td>(11.0)</td>
</tr>
<tr>
<td>Dim=30</td>
<td>Algorithms</td>
<td>Sum Rank</td>
<td>( \Delta R )</td>
</tr>
<tr>
<td></td>
<td>iCMAES-ILS</td>
<td>46.5</td>
<td>(0)</td>
</tr>
<tr>
<td></td>
<td>NBIP-OP-ACMA-ES</td>
<td>56.5</td>
<td>(10.0)</td>
</tr>
<tr>
<td></td>
<td>DRMA-LSCh-CMA</td>
<td>65.0</td>
<td>(18.5)</td>
</tr>
<tr>
<td>Dim=50</td>
<td>Algorithms</td>
<td>Sum Rank</td>
<td>( \Delta R )</td>
</tr>
<tr>
<td></td>
<td>iCMAES-ILS</td>
<td>47.5</td>
<td>(0)</td>
</tr>
<tr>
<td></td>
<td>NBIP-OP-ACMA-ES</td>
<td>52.5</td>
<td>(5.0)</td>
</tr>
<tr>
<td></td>
<td>DRMA-LSCh-CMA</td>
<td>68.0</td>
<td>(20.5)</td>
</tr>
</tbody>
</table>
Winners extend CMAES

http://www.ntu.edu.sg/home/epnsugan/index_files/cec-benchmarking.htm


• Benchmark Results for a Simple Hybrid Algorithm on the CEC 2013 Benchmark Set for Real parameter Optimization [#1566] . . Tianjun Liao and Thomas Stuetzle Universite Libre de Bruxelles (ULB), IRIDIA, Belgium (Codes-Results available, as ICMAES-ILS)

• CMA-ES with Restarts for Solving CEC 2013 Benchmark Problems [#1318] . Ilya Loshchilov Ecole Polytechnique Federale de Lausanne, Laboratory of Intelligent Systems, Switzerland (Codes-Results available, as NBIPOPaCMA)

• Dynamically updated Region Based Memetic Algorithm for the 2013 CEC Special Session and Competition on Real Parameter Single Objective Optimization [#1617] . . Benjamin Lacroix, Daniel Molina and Francisco Herrera Universidad de Granada, Spain; Universidad de Cadiz, Spain (Codes-Results available, as DRMA-LSch-CMA)
There are again two MAs among the three winner algorithms: GaAPADE [1], the first winner, a hybridization of an GA, an DE and an Evolutionary Strategy; L-SHADE [2], a hybridization of SHADE with LS and a reducing population (SHADE without LS got the fourth place in CEC’2013, clearly the LS improves the results).

MVMO [3] was the only non-MA among the winners in CEC’2014.


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IX. Final Comments
It is usual to find a paper with a novel proposal:

“Advanced xxx algorithm”

For example: Advanced PSO, advanced DE ....

Authors compare the new proposal “Advanced xxx algorithm” with the basic “xxx algorithm” or recent “xxx algorithms” that are far from the state of the art.

The proposal “Advanced xxx algorithm” is better than previous ones (of course) and authors claim on the “high quality of the proposal”

Does authors publish a paper with a good algorithm?
Examples for comparison:


Non Rigorous Experiments:

Local vs Global Comparison

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Algorithm 2</th>
<th>$R^+$</th>
<th>$R^-$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frankenstein PSO</td>
<td></td>
<td>278.0</td>
<td>22.0</td>
<td>6.39E-5</td>
</tr>
<tr>
<td>OLPSO Global</td>
<td></td>
<td>310.0</td>
<td>15.0</td>
<td>8.166E-6</td>
</tr>
<tr>
<td>SADE</td>
<td></td>
<td>263.0</td>
<td>37.0</td>
<td>6.498E-4</td>
</tr>
<tr>
<td>DEGL</td>
<td></td>
<td>325.0</td>
<td>0.0</td>
<td>5.960E-8</td>
</tr>
<tr>
<td>JADE</td>
<td></td>
<td>298.0</td>
<td>27.0</td>
<td>7.498E-5</td>
</tr>
</tbody>
</table>

Table 1: Results obtained by the Wilcoxon test for algorithm G-CMA-ES ($D=10$)

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Algorithm 2</th>
<th>$R^+$</th>
<th>$R^-$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frankenstein PSO</td>
<td></td>
<td>286.5</td>
<td>38.5</td>
<td>4.030E-4</td>
</tr>
<tr>
<td>OLPSO Global</td>
<td></td>
<td>325.0</td>
<td>0.0</td>
<td>5.960E-8</td>
</tr>
<tr>
<td>SADE</td>
<td></td>
<td>217.0</td>
<td>83.0</td>
<td>0.0564</td>
</tr>
<tr>
<td>DEGL</td>
<td></td>
<td>277.0</td>
<td>48.0</td>
<td>0.0013</td>
</tr>
<tr>
<td>JADE</td>
<td></td>
<td>216.5</td>
<td>108.5</td>
<td>0.1524</td>
</tr>
</tbody>
</table>

Table 2: Results obtained by the Wilcoxon test for algorithm G-CMA-ES ($D=30$)

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Algorithm 2</th>
<th>$R^+$</th>
<th>$R^-$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frankenstein PSO</td>
<td></td>
<td>276.0</td>
<td>24.0</td>
<td>9.084E-5</td>
</tr>
<tr>
<td>OLPSO Global</td>
<td></td>
<td>281.0</td>
<td>44.0</td>
<td>8.082E-4</td>
</tr>
<tr>
<td>SADE</td>
<td></td>
<td>205.0</td>
<td>120.0</td>
<td>0.2457</td>
</tr>
<tr>
<td>DEGL</td>
<td></td>
<td>276.0</td>
<td>49.0</td>
<td>0.0015</td>
</tr>
<tr>
<td>JADE</td>
<td></td>
<td>217.0</td>
<td>108.0</td>
<td>0.148</td>
</tr>
</tbody>
</table>

Table 3: Results obtained by the Wilcoxon test for algorithm G-CMA-ES ($D=50$)
Non Rigorous Experiments:
Local vs Global Comparison

It is usual to find a paper with a novel proposal:

“Advanced xxx algorithm”

For example: Advanced PSO, advanced DE ....

Authors compare the new proposal “Advanced xxx algorithm” with the basic “xxx algorithm” or recent “xxx algorithms” that are far from the state of the art.

The proposal “Advanced xxx algorithm” is better than previous ones (of course) and authors claim on the “high quality of the proposal”

Does authors publish a paper with a good algorithm?
Non Rigorous Experiments:

Local vs Global Comparison

It is usual to find a paper with a novel proposal:

“Advanced xxx algorithm”

For example: Advanced PSO, advanced DE, …

Authors compare the new proposal “Advanced xxx algorithm” with the basic “xxx algorithm” or “recent xxx algorithms” that are far from the state of the art.

The proposal “Advanced xxx algorithm” is better than previous ones and authors claim on the “high quality of the proposal”.

From the local point of view is !!! (Good???)… But the proposal “Advanced xxx algorithm” may be far from the state of the art: CMAES extensions or recent ones
The two following kind of studies are important:

A) To propose new advances inside of techniques (DE, PSO, …), but authors must try to reach the state of the art.

B) New optimization frameworks, as a first idea on a new research branch, are welcome: (third generation?)

Artificial Bee Colony Optimization

Variable mesh optimization
Non Rigorous Experiments: 
Local vs Global Comparison

B) New optimization frameworks, as a first idea on a new research branch, are welcome:

Shark smell optimization

Now it is necessary to advance in the development of new/novel proposals inside of these frameworks, making them competitive with the state of the art.
Non Rigorous Experiments: (Go back on RMA analysis)
Local vs Global Comparison

*Extension: Region based MA-LSCh-CMA (CEC2005 Benchmark)*


MDE_pBX is a state-of-the-art differential evolution (DE). 3SOME is an example from the MC family.

<table>
<thead>
<tr>
<th>Dim</th>
<th>RMA-LSCh-CMA vs</th>
<th>R+</th>
<th>R−</th>
<th>p - value</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>3SOME</td>
<td>291.5</td>
<td>10</td>
<td>5.13E-6</td>
</tr>
<tr>
<td>10</td>
<td>MDE_pBX</td>
<td>195.5</td>
<td>108</td>
<td>0.230</td>
</tr>
<tr>
<td>10</td>
<td>IPOP-CMA-ES</td>
<td>94.5</td>
<td>209</td>
<td>0.117</td>
</tr>
<tr>
<td>30</td>
<td>3SOME</td>
<td>299.5</td>
<td>25.5</td>
<td>5.88E-5</td>
</tr>
<tr>
<td>30</td>
<td>MDE_pBX</td>
<td>257.5</td>
<td>67.5</td>
<td>0.01</td>
</tr>
<tr>
<td>30</td>
<td>IPOP-CMA-ES</td>
<td>162.5</td>
<td>162.5</td>
<td>1</td>
</tr>
<tr>
<td>50</td>
<td>3SOME</td>
<td>232.5</td>
<td>42.5</td>
<td>6.73E-4</td>
</tr>
<tr>
<td>50</td>
<td>MDE_pBX</td>
<td>299.5</td>
<td>25.5</td>
<td>5.88E-5</td>
</tr>
<tr>
<td>50</td>
<td>IPOP-CMA-ES</td>
<td>212</td>
<td>113</td>
<td>0.191</td>
</tr>
</tbody>
</table>

Non Rigorous Experiments: (Go back on RMA analysis)

Local vs Global Comparison

Extension: Region based MA-LSCh-CMA (SOCO 2011 Benchmark, higher dimension than CEC2005)


**Table 10:** Wilcoxon signed ranks test results between RMA-LSCh-CMA ($R_+$) reference algorithms ($R_-$) on the SOCO’2011 benchmark in dimension 100

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$R_+$</th>
<th>$R_-$</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA-LSCh-CMA</td>
<td>119.5</td>
<td>70.5</td>
<td>0.324</td>
</tr>
<tr>
<td>3SOME</td>
<td>79</td>
<td>92</td>
<td>0.777</td>
</tr>
<tr>
<td>MDE_pBX</td>
<td>180</td>
<td>10</td>
<td>1.64E-4</td>
</tr>
<tr>
<td>IPOP-CMAES</td>
<td>153.5</td>
<td>36.5</td>
<td>0.017</td>
</tr>
</tbody>
</table>


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IX. Final Comments
There are different areas of research that focus the attention of researchers in “bioinspired parameter optimization”:

• **The algorithms’ scalability: High dimensional problems**


MOS algorithm and variants is the best one.

• **Automatic Tuning and Self-Adaptation of Algorithmic Parameters (Iterated Race and extensions)**

What’s Next?

There are different areas of research that focus the attention of researchers in “bioinspired parameter optimization”:

- **Expensive optimization problems**
  - Approximate fitness models
  - Surrogate models
  - ...
  - New bioinspired algorithms must be design.

- **Synergy with Cloud Computing**

Cloud computing is an emerging computing infrastructure that provides flexible and on-demand access to a large pool of computational resources.

The marriage of cloud computing with bioinspired algorithms is just at the infant stage.
What’s Next?

There are different areas of research that focus the attention of researchers in “bioinspired parameter optimization”:

- **New frameworks for Evolutionary parameter optimization** and the development of advanced approaches to compete with the state of the art.

- **Memetic Algorithms as the extension of hybrid approaches** (new frameworks and local search).

  **Recent high quality methods are MAs:** MA-CMA-Chains, GaAPADE, MOS, ....
What’s Next?

Final questions to discuss in “Bioinspired parameter optimization”:

1. Whether it is important that algorithms are nature-based or not.

   Yes, they are good models, high quality models. BUT, we must compete against the state of the art.

2. The discussion between designing bioinspired algorithms for one specific problem and designing them for a benchmark of problems (See IEEE CEC 2011 session).

   The influence of the Non-free lunch theory.

3. New hybrid metaheuristics. The importance of a good trade-off between exploration/exploitation.
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Many real-world problems may be formulated as optimization problems of parameters with variables in continuous domains (parameter optimization problems).

The development of high quality bioinspired algorithms (improving known or developing new algorithms) allows us to tackle a large number of real-world applications.

It is very important to understand stochastic search in continuous and high-dimensional search spaces to advance in the topic.
Bioinspired real parameter optimization: Where we are and what’s Next?

Thanks !!!