Universidad de Granada

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Algoritmos Evolutivos y Bioinspirados

Manuel Lozano

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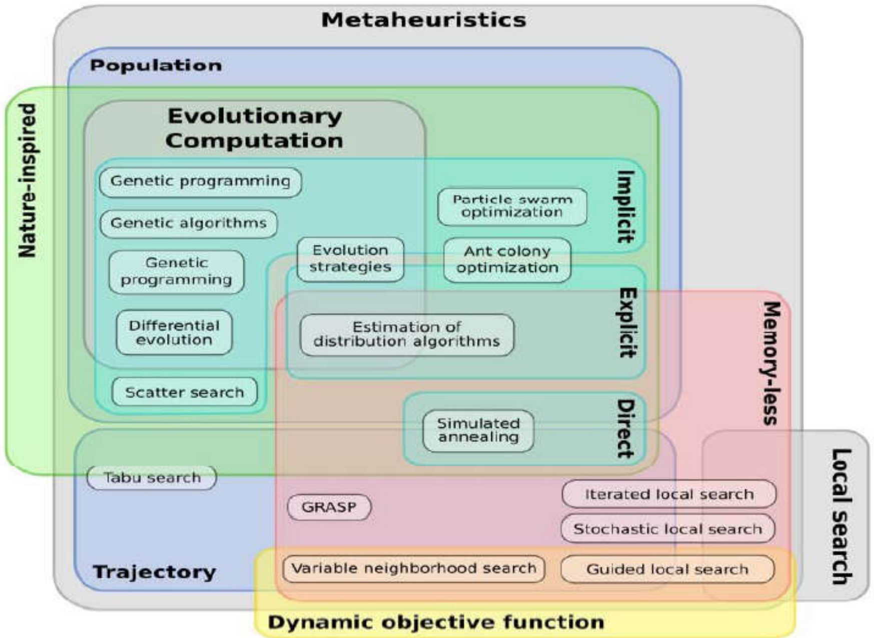
Técnicas de Soft Computing
para
Aprendizaje y Optimización

DECSAI

Departamento de Ciencias de la
Computación e Inteligencia Artificial

Metaheurísticas

- Simulated annealing (SA)
- Tabu search (TS)
- Evolutionary algorithms (EAs)
- Particle swarm optimization (PSO)
- Ant colony optimization (ACO)
- Estimation of distribution algorithms (EDAs)
- Scatter search
- Path relinking
- Greedy randomized adaptive search procedure (GRASP)
- Iterated local search (ILS)
- Guided local search
- Variable neighborhood search (VNS)



Metaheurísticas:

Intuición (Inspiración) + Aleatoriedad

“Adiestrar Aleatoriedad”

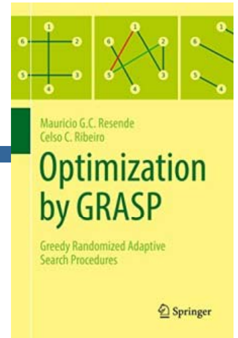
Clasificación de las MHs

- **Basadas en métodos constructivos: GRASP, IG, Optimización Basada en Colonias de Hormigas.**

Semi-Greedy Heuristics

- A semi-greedy heuristic tries to get around convergence to non-global local minima.
- repeat until solution is constructed
  - For each candidate element
    - apply a greedy function to element
  - Rank all elements according to their greedy function values
  - Place well-ranked elements in a restricted candidate list (RCL)
  - Select an element from the RCL at random & add it to the solution

Greedy Randomized Adaptive Search Procedures



A Basic GRASP

- GRASP tries to capture good features of greedy & random constructions.
- iteratively
  - samples solution space using a greedy probabilistic bias to construct a feasible solution (semi-greedy construction)
  - applies local search to attempt to improve upon the constructed solution
- keeps track of the best solution found

GRASP (for maximization)

bias towards greediness

good diverse solutions

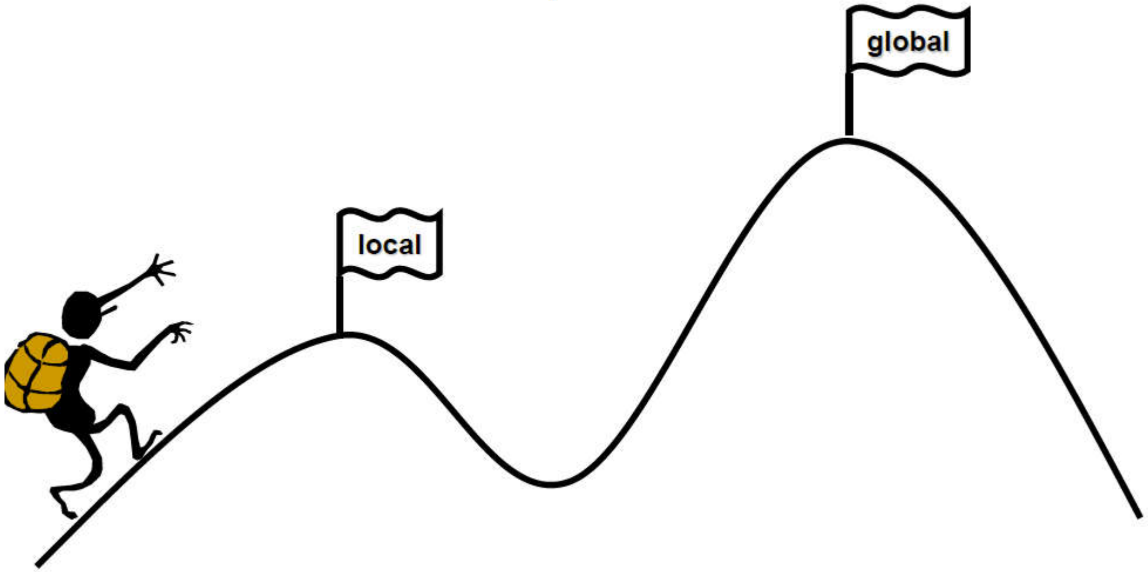
```
best_obj = 0;
repeat many times{
    x = semi-greedy_construction( );
    x = local_search(x);
    if ( obj_function(x) > best_obj ){
        x* = x;
        best_obj = obj_function(x);
    }
}
```

Iterated Greedy Algorithm

```
procedure IteratedGreedy
{
    X_0 = GenerateInitialSolution;
    X = LocalSearch(X_0);                    % optional
    repeat
        X_p = Destruction (X);
        X_c = Construction (X_p);
        X* = LocalSearch (X_c);              % optional
        X = AcceptanceCriterion (X, X*);
    until termination condition met
}
```

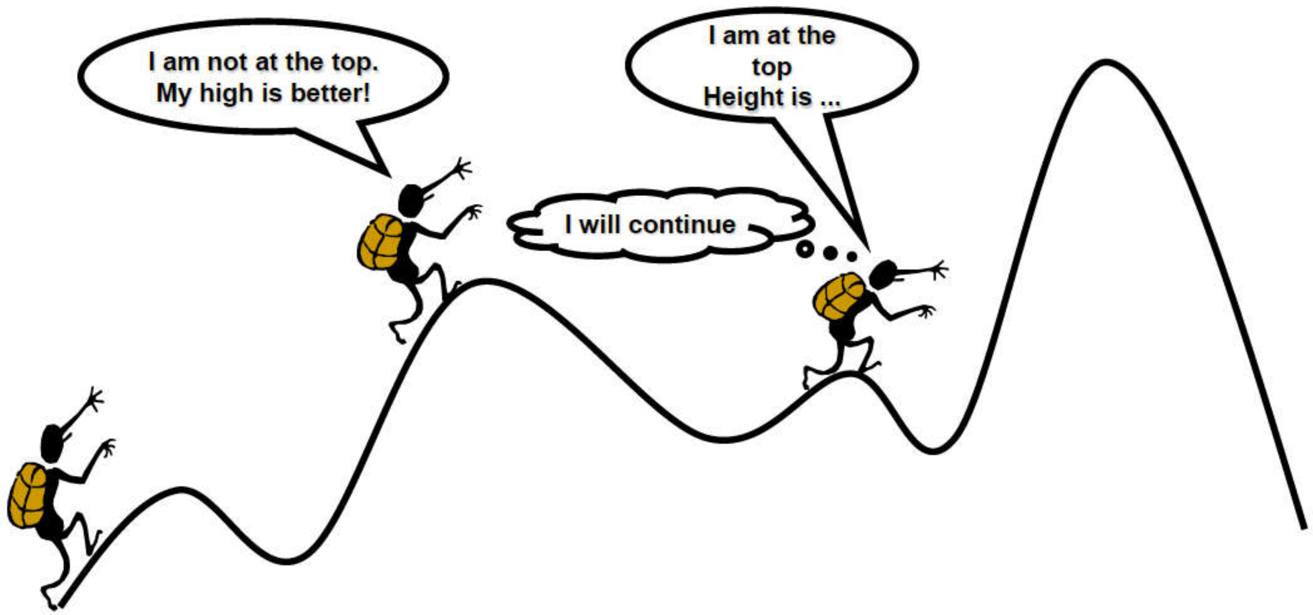
Clasificación de las MHs

- **Basadas en trayectorias** (la heurística subordinada es un **algoritmo de búsqueda local** que sigue una trayectoria en el espacio de búsqueda): Búsqueda Local, Enfriamiento Simulado, Búsqueda Tabú, BL Iterativa, …



Clasificación de las MHs

- **Basadas en poblaciones** (el proceso considera múltiples puntos de búsqueda en el espacio): Algoritmos Genéticos, Scatter Search, Algoritmos Meméticos, PSO, …



Componentes de las MHs

- **Todas las MHs están compuestas por un conjunto relativamente pequeño de métodos (Gendreau and Potvin, 2003):**

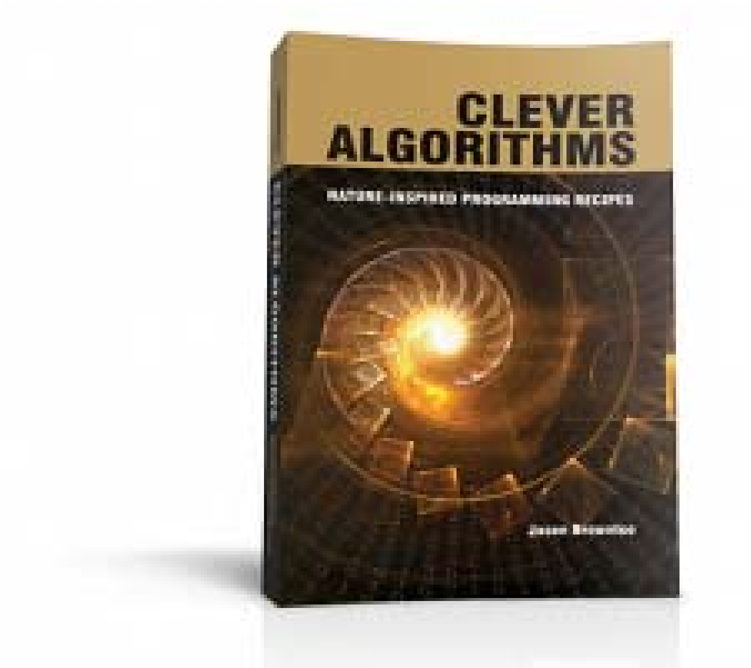
  - **Construcción.** Lo emplean todas las MHs para crear una o un conjunto de soluciones (*Greedy*).

  - **Recombinación.** Permite generar nuevas soluciones combinando soluciones actuales.

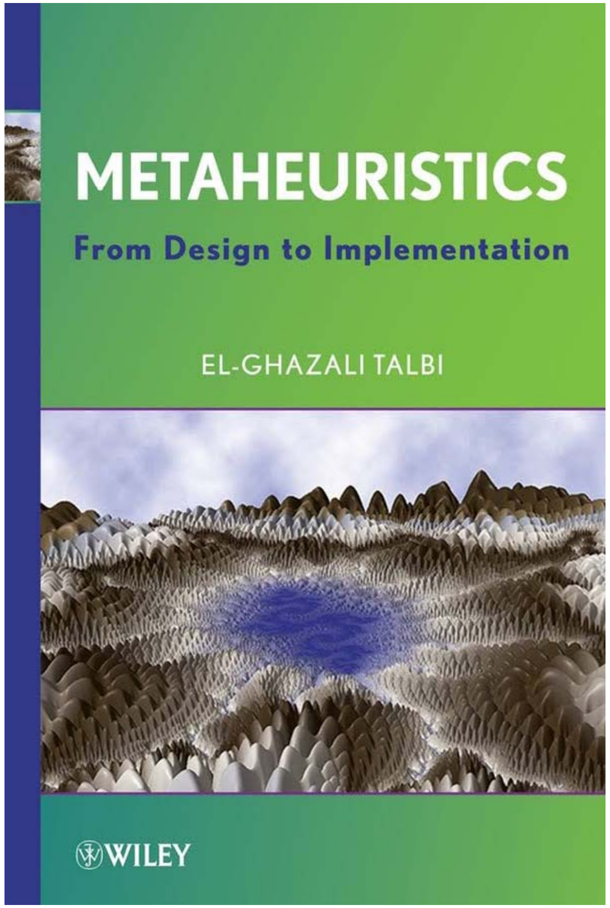
  - **Alteración Aleatoria.** Se utiliza para introducir una perturbación aleatoria que modifica una o varias soluciones actuales (*mutaciones, búsquedas locales*, *etc*).

  - **Presión Selectiva.** Favorecer a las soluciones con mejor adaptación.

Literatura Relevante



http://cleveralgorithms.com/



La naturaleza sabe optimizar

Algoritmos Bioinspirados (ABs)

- **La Computación Bioinspirada (bioinspired Algorithms/Natural Computing/biologically inspired computing)**

- **Se basa en emplear analogías con sistemas naturales o sociales para la resolución de problemas.**

- **Los algoritmos bioinspirados simulan el comportamiento de sistemas naturales para el diseño de métodos heurísticos no determinísticos de "*búsqueda*" /"aprendizaje"/"comportamiento", etc.**

- **En la actualidad los "Algoritmos Bioinspirados" son uno de los campos más prometedores de investigación en el diseño de algoritmos.**

ABs: Primera Generación

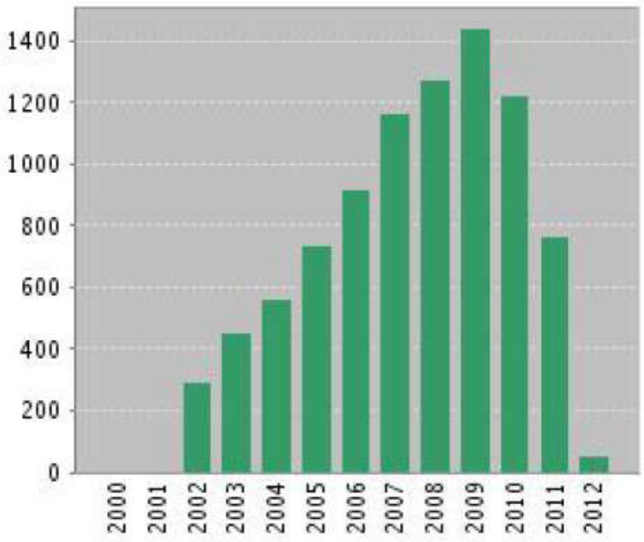
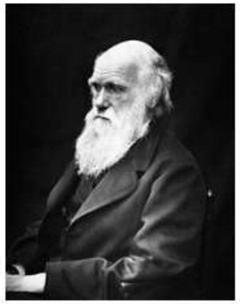


Fig. 1. *Publicaciones para EAs y ACO*

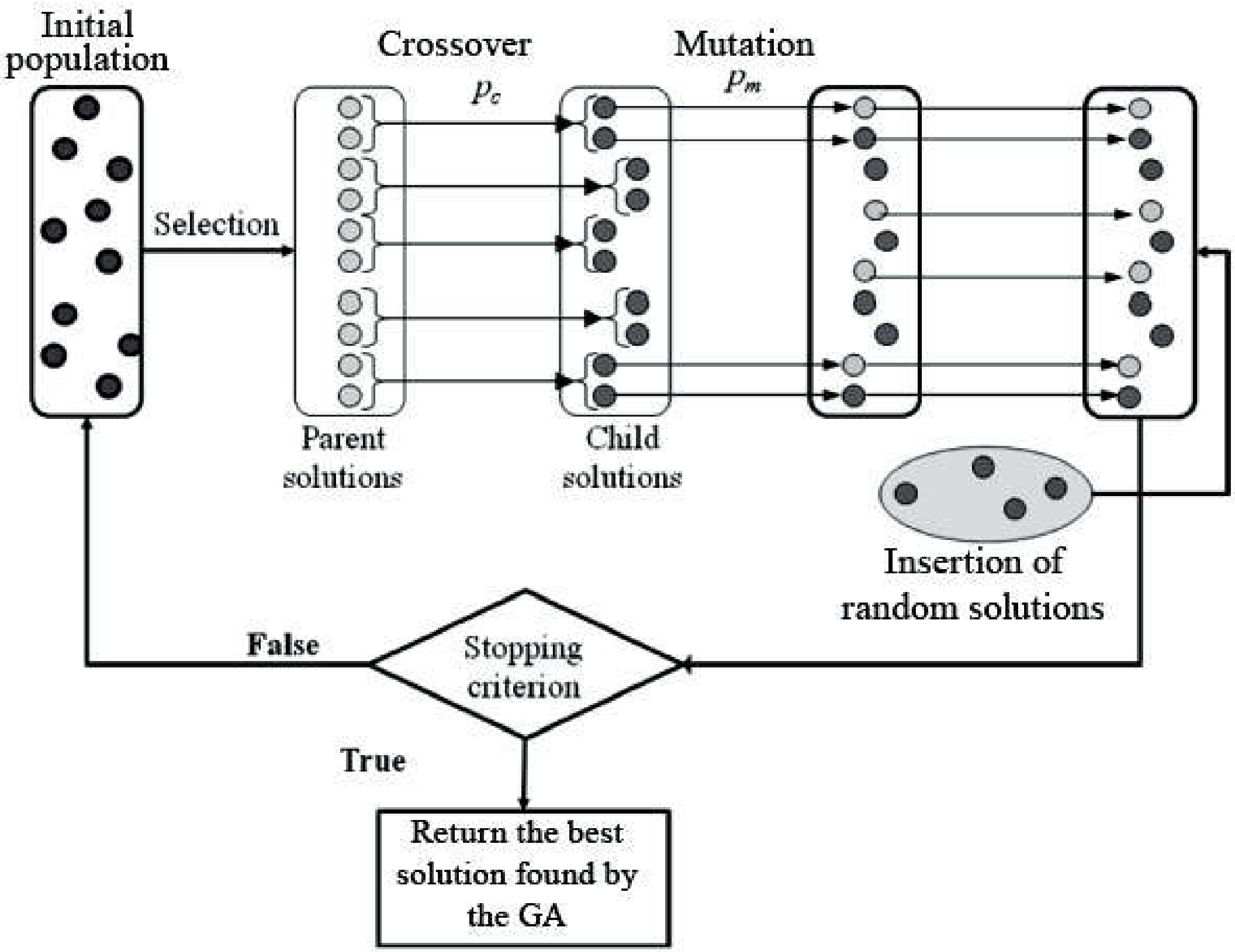


1. Algoritmos evolutivos (EAs)

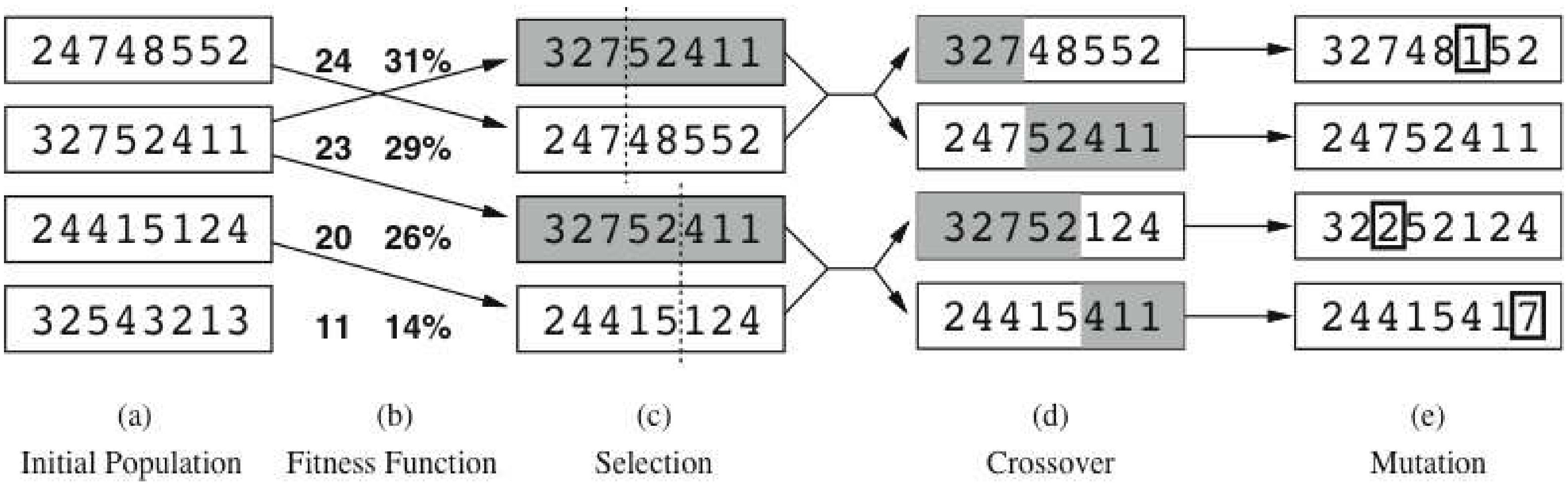
2. Algoritmos de optimización basados en colonias de hormigas (ACO)

3. Algoritmos de optimización basados en nubes de partículas (PSO)

Computación Evolutiva

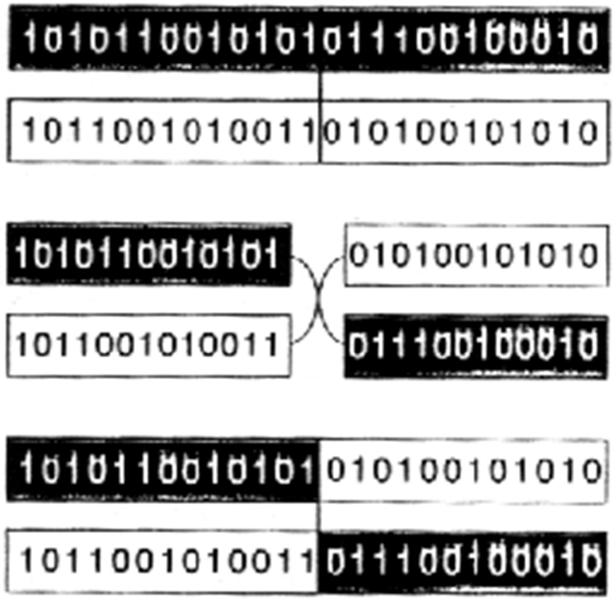


Computación Evolutiva

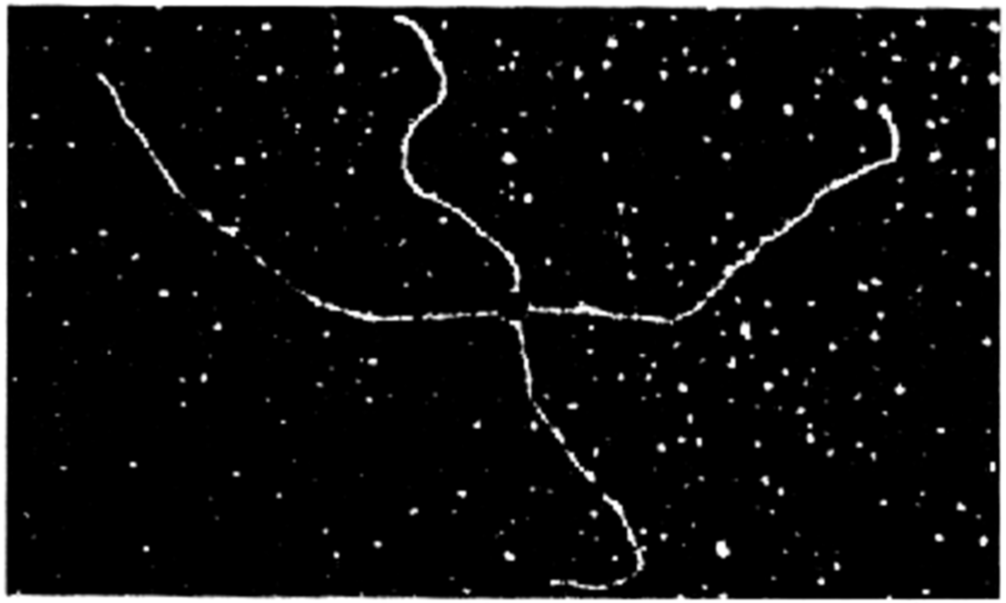


Computación Evolutiva

OPERADOR DE CRUCE



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.

ABs Basados en Inteligencia Colectiva (*Swarm Intelligence*)

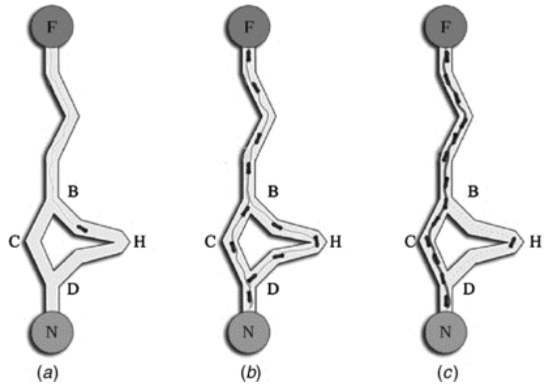
Mediante determinadas interrelaciones entre sus miembros, de la colonia emerge un comportamiento colectivo que les permite reaccionar eficientemente a situaciones ambientales problemáticas; tarea que, de forma individual, estos seres no serían capaces de acometer (**Inteligencia Colectiva** [Bon99])

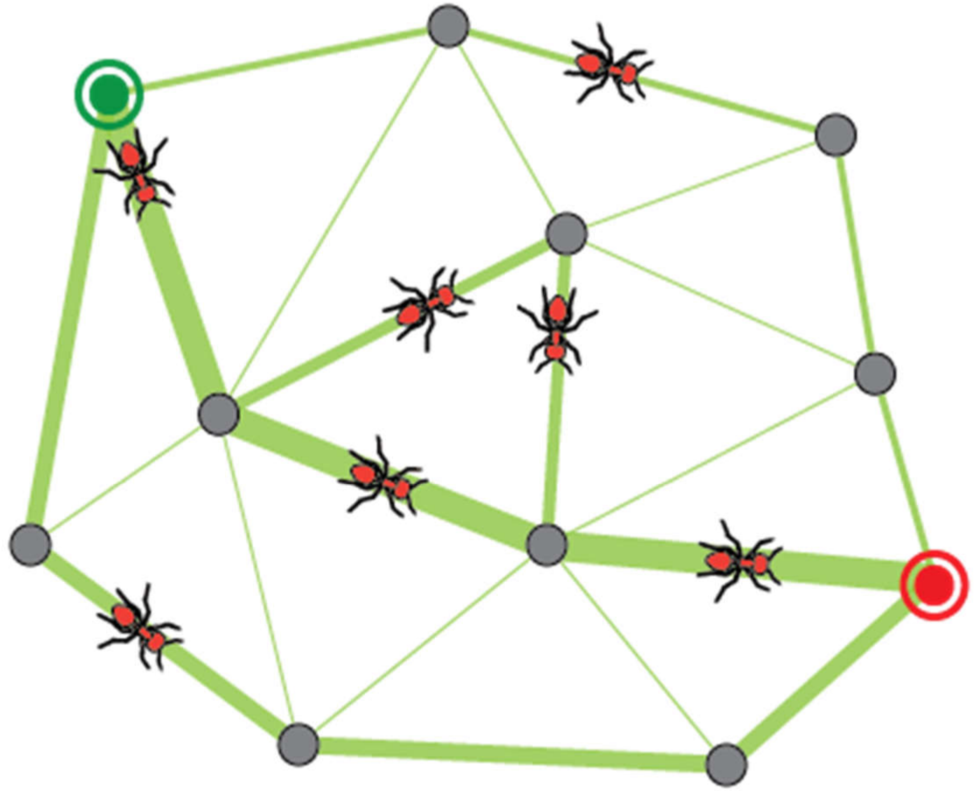
"Algoritmos o mecanismos distribuidos de resolución de problemas inspirados en el comportamiento colectivo de colonias de insectos sociales u otras sociedades de animales".

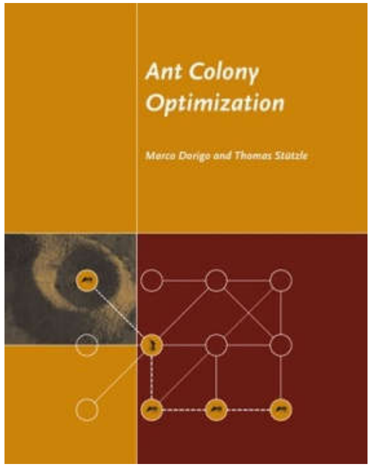
Modelos pioneros: ACO y PSO

E. Bonabeau, M. Dorigo, G. Theraulaz
Swarm Intelligence. From Nature to Artificial Systems.
Oxford University Press, 1999.

Técnicas de Optimización Basadas en Colonias de Hormigas (ACO)







M. DORIGO, T. STÜTZLE, **Ant Colony Optimization**
The MIT Press, 2004.

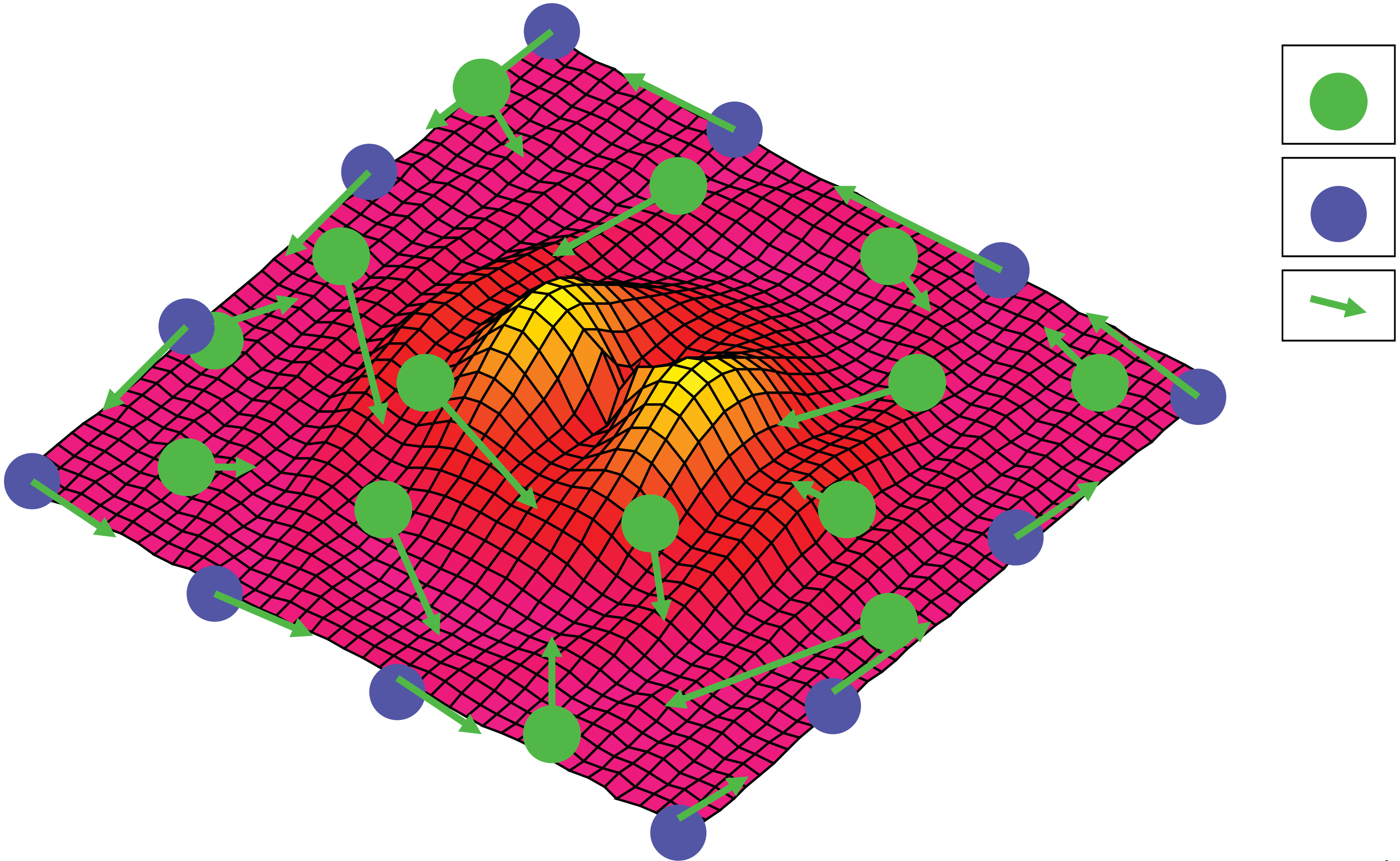
Particle Swarm Optimization

- La población se compone de varias partículas (nube de partículas = *particle swarm*) que se mueven ("vuelan") por el espacio de búsqueda durante la ejecución del algoritmo.

- Se mantiene la **posición** y **velocidad** de las partículas.

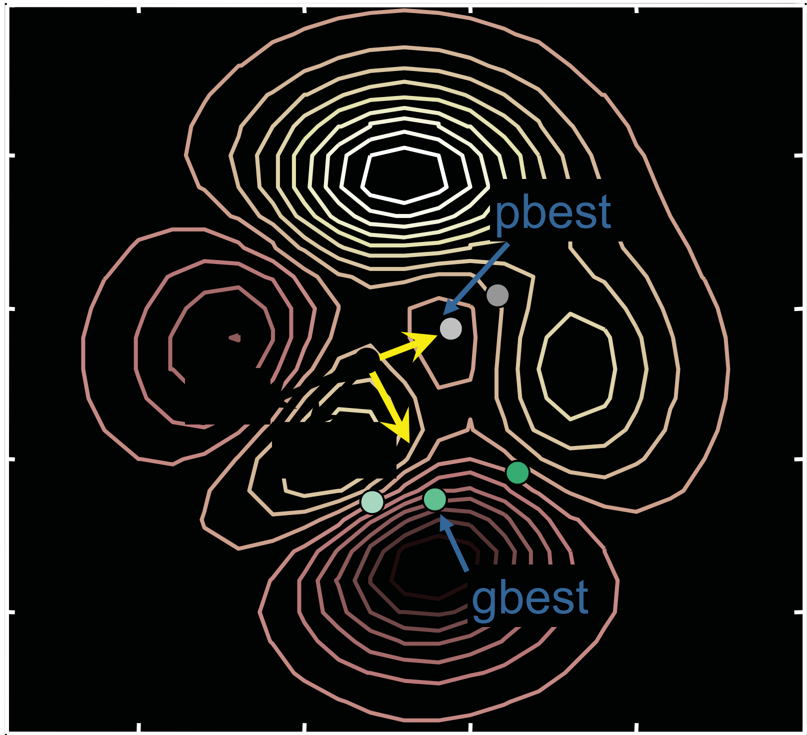
- En PSO, los individuos se comunican directa o indirectamente con otros vía las direcciones de búsqueda.

Particle Swarm Optimization



Particle Swarm Optimization

- El movimiento de cada partícula *p* depende de:
    - *Su mejor posición desde que comenzó el algoritmo (pBest),*
    - *La mejor posición de las partículas de su entorno (lBest) o de toda la nube (gBest) desde que comenzó el algoritmo.*
- En cada iteración, se cambia la ***posición*** y ***velocidad*** de las partículas para acercarlas a las posiciones *pBest* y *lBest/gBest*.



ABs: Segunda Generación

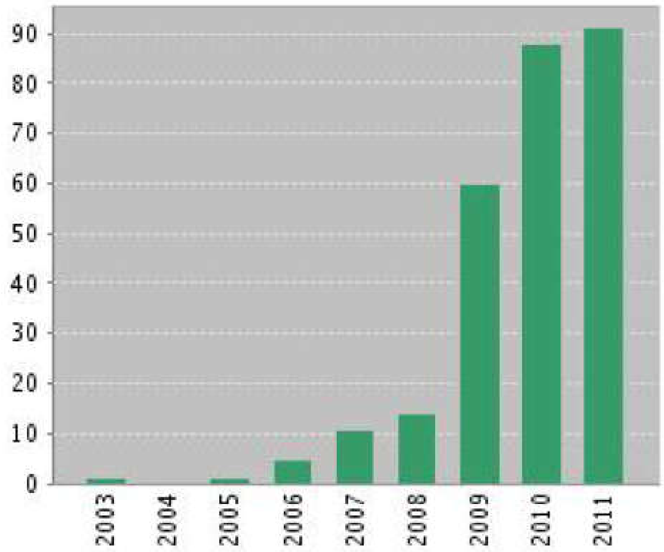


Fig. 2. *Publicaciones para ABC, BBO, BFO y AFSA*

1. ABs basados en:

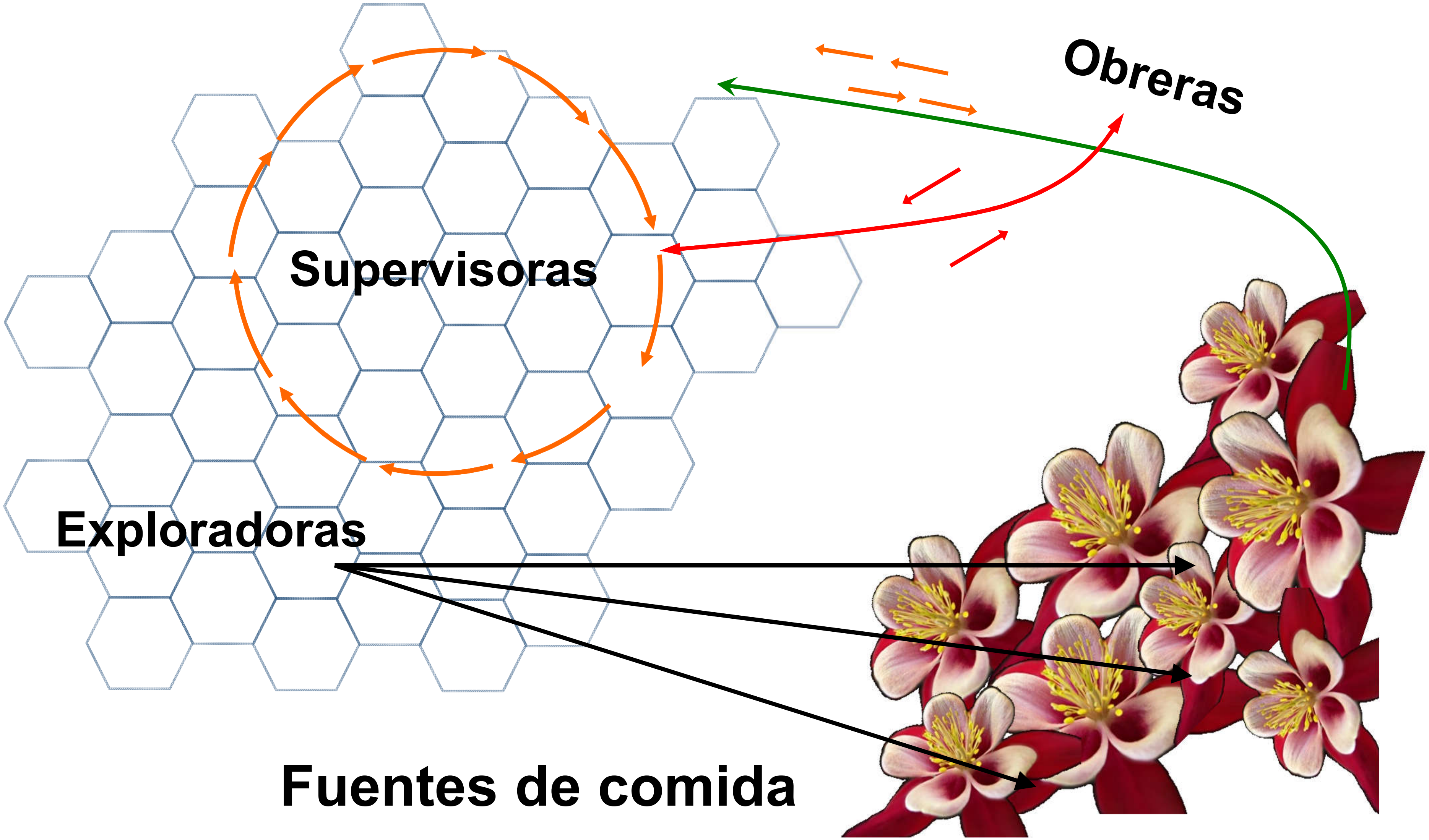
- Biogeografía (BBO)
- Colonias de abejas (ABC)
- Alimentación de las bacterias (BFO)
- Bancos de peces (AFSA)
- Sistema inmune (AIS)
- Búsqueda de comida de grupos de animales (GSO)
- Pájaro cuco (COA)
- Mosquitos (MOX)
- Mala hierba invasiva (IWO)
- Luciérnaga (FA)
- Enjambres de luciérnagas (GWSO)

Algoritmos Bioinspirados

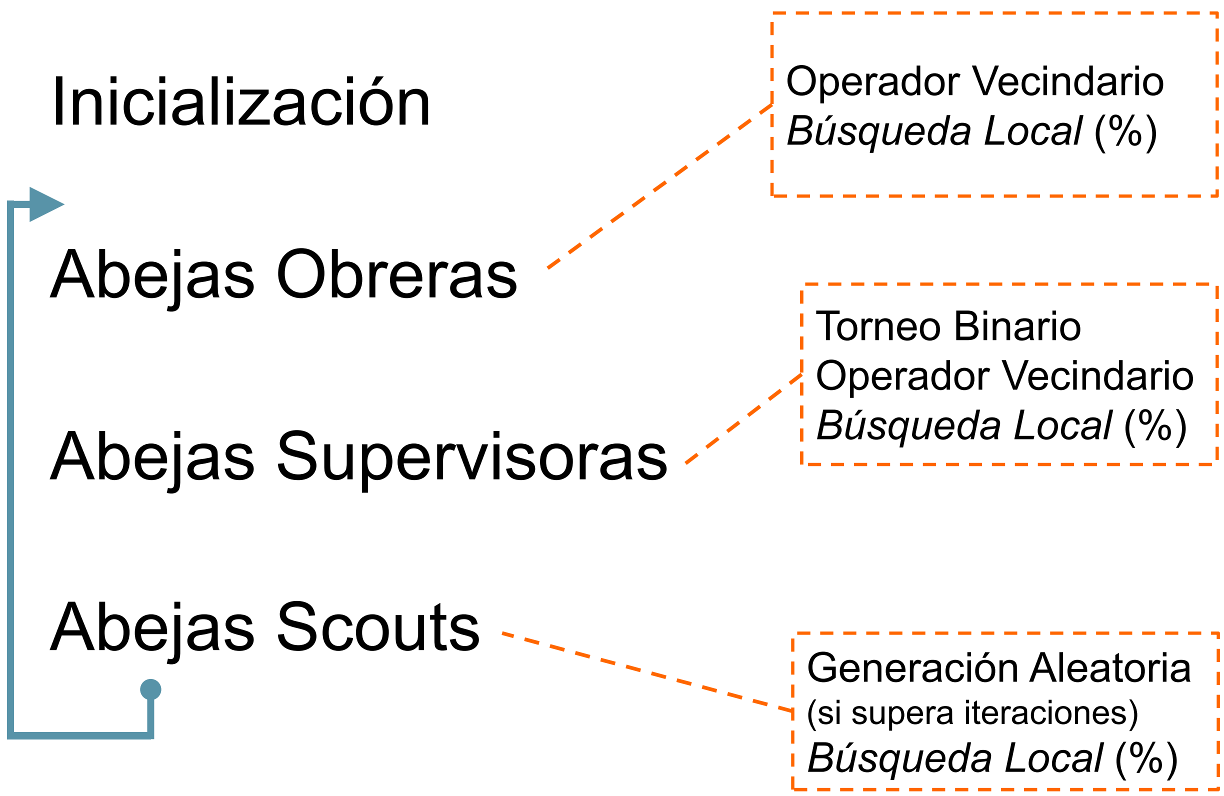
ABs	Nombre (en inglés)	ISI	SCOPUS
EAs	*Evolutionary Algorithms*	6.949	25.740
PSO	*Particle Swarm Optimization*	9.533	16.484
ACO	*Ant Colony Optimization*	2.757	4.347
ABC	*Artificial Bee Colony*	153	369
BFO	*Bacterial Foraging Optimization*	73	146
BBO	*Biogeography-based Optimization*	45	95
AFSA	*Artificial Fish School Algorithm*	7	37
AIS	*Artificial Immune System (Optimization)*	302	632
IWO	*Invasive Weed Optimization*	41	71
GSO	*Group Search Optimizer*	18	37
FA	*Firefly Algorithm*	16	39
GWSO	*Glowworm Swarm Optimization*	12	32
COA	*Cuckoo Optimization Algorithm*	1	1

Tabla. 1. *Ejemplos relevantes de algoritmos bioinspirados (Número de publicaciones)*

Algoritmo de Colonias de Abejas Artificiales



Esquema ABC


Inicialización
Abejas Obreras
Abejas Supervisoras
Abejas Scouts
Operador Vecindario
Búsqueda Local (%)
Torneo Binario
Operador Vecindario
Búsqueda Local (%)
Generación Aleatoria
(si supera iteraciones)
Búsqueda Local (%)

Aplicaciones: Organizar Hospital

Information Sciences 326 (2016) 215–226

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

An alternative artificial bee colony algorithm with destructive–constructive neighbourhood operator for the problem of composing medical crews

José A. Delgado-Osuna[a], Manuel Lozano[b], Carlos García-Martínez[c,*]

SINC – La ciencia es noticia

Las abejas ayudan a organizar el hospital

innovaspain.com – El portal líder de la innovación en español

Modelos organizativos inspirados en las colonias de abejas

Por Juan Miguel Cobos - 18 febrero, 2016

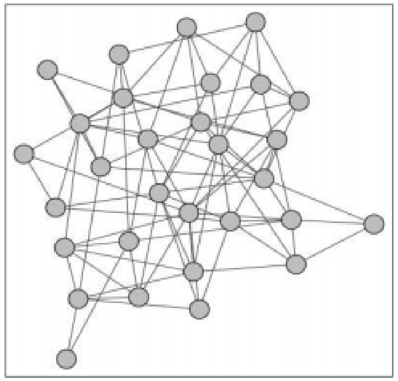
radio 5 rne

Entre paréntesis **-** Las abejas, el modelo a imitar en centros de gestión complejos – 10 Feb 2016

Aplicaciones:
Atacar Redes Criminales

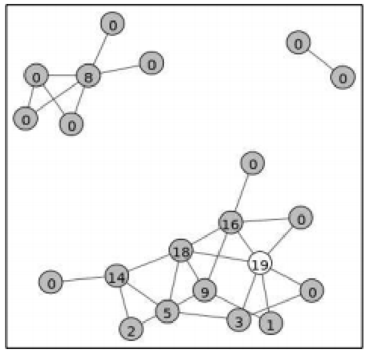
Problema de la detección de nodos críticos:

Encontrar *k* nodos críticos que al ser eliminados se produce la máxima fragmentación de la red, de acuerdo a alguna métrica predefinida.



Grafo de Entrada

ALGORITMOS BIOINSPIRADOS



Grafo Residual

Atacar Redes Criminales

Information Sciences 377 (2017) 30–50

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

ELSEVIER

Optimizing network attacks by artificial bee colony

Manuel Lozano[a], Carlos García-Martínez[b], Francisco J. Rodríguez[c,*], Humberto M. Trujillo[d]

CrossMark

LA VANGUARDIA

Patrones de conducta

Un algoritmo inspirado en las abejas ayudará a desmontar redes criminales

MAYTE RIUS

La herramienta identifica de manera automática a los actores más peligrosos dentro de un conjunto interrelacionado de individuos

rtve

Noticias | Televisión | Radio | Deportes | Infantil | A la carta | El Tiempo

Desarrollan un algoritmo, inspirado en el comportamiento de las abejas, que ayuda a desmantelar redes sociales criminales

- Identifica cuáles son los actores o nodos más peligrosos y su interconexión
- Mejoraría la toma de decisiones por parte de las fuerzas de seguridad
- Podría tener otros muchos fines, como diseñar estrategias para vacunas

23.02.2017 | actualización 18h59

Por
RTVE.es / UGR

Algoritmos Bioinspirados

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

WILEY

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. 22 (2015) 3–18
DOI: 10.1111/itor.12001

Metaheuristics—the metaphor exposed

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Swarm and Evolutionary Computation 48 (2019) 220–250

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

Bio-inspired computation: Where we stand and what's next

Javier Del Ser [a,b,c,*], Eneko Osaba [b], Daniel Molina [d], Xin-She Yang [e], Sancho Salcedo-Sanz [f], David Camacho [g], Swagatam Das [h], Ponnuthurai N. Suganthan [j], Carlos A. Coello Coello [i], Francisco Herrera [d]

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[g] *Universidad Autonoma de Madrid, 28049, Madrid, Spain*
[h] *Electronics and Communication Sciences Unit, Indian Statistical Institute, Kolkata, 700108, India*
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[j] *Nanyang Technological University, 639798, Singapore*

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Evolutionary computation
Swarm intelligence
Nature-inspired computation
Dynamic optimization
Multi-objective optimization
Many-objective optimization
Multi-modal optimization
Large-scale global optimization
Topologies
Ensembles
Hyper-heuristics
Surrogate model assisted optimization
Computationally expensive optimization
Distributed evolutionary computation
Memetic algorithms
Parameter tuning
Parameter adaptation
Benchmarks

ABSTRACT

In recent years, the research community has witnessed an explosion of literature dealing with the mimicking of behavioral patterns and social phenomena observed in nature towards efficiently solving complex computational tasks. This trend has been especially dramatic in what relates to optimization problems, mainly due to the unprecedented complexity of problem instances, arising from a diverse spectrum of domains such as transportation, logistics, energy, climate, social networks, health and industry 4.0, among many others. Notwithstanding this upsurge of activity, research in this vibrant topic should be steered towards certain areas that, despite their eventual value and impact on the field of bio-inspired computation, still remain insufficiently explored to date. The main purpose of this paper is to outline the state of the art and to identify open challenges concerning the most relevant areas within bio-inspired optimization. An analysis and discussion are also carried out over the general trajectory followed in recent years by the community working in this field, thereby highlighting the need for reaching a consensus and joining forces towards achieving valuable insights into the understanding of this family of optimization techniques.

1. Introduction

Over millions of years, Nature has evolved to give rise to intelligent behavioral characteristics and biological phenomena, where adaptability, self-learning, robustness, and efficiency enable biological agents (such as insects and birds) to undertake complex tasks. While cases exemplifying these capabilities are truly multi-fold, the most illustrative ones revolve around the social behavior of animals such as ant colonies, beehives and bird flocks, where concepts such as stigmergy and the collective swarming movement of organisms often lead to the so-called Swarm Intelligence (SI), where improved exploration mechanisms over complex search spaces can be achieved by agents obeying local rules without any central control. The overall functionalities of the swarm are much richer than the simple sum of individual actions. Similarly, other renowned examples arise from the genetic inheritance process, the immune system of the human body or the neural activity

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https://doi.org/10.1016/j.swevo.2019.04.008
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Available online 29 April 2019

Cognitive Computation
https://doi.org/10.1007/s12559-020-09730-8

Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration Versus Algorithmic Behavior, Critical Analysis Recommendations

Daniel Molina[1] · **Javier Poyatos**[1] · **Javier Del Ser**[2,3,4] · **Salvador García**[1] · **Amir Hussain**[5] · **Francisco Herrera**[1,5]

Received: 27 September 2019 / Accepted: 14 May 2020

Abstract
In recent algorithmic family simulates different biological processes observed in Nature in order to efficiently address complex optimization problems. In the last years the number of bio-inspired optimization approaches in literature has grown considerably, reaching unprecedented levels that dark the future prospects of this field of research. This paper addresses this problem by proposing two comprehensive, principle-based taxonomies that allow researchers to organize existing and future algorithmic developments into well-defined categories, considering two different criteria: the source of inspiration and the behavior of each algorithm. Using these taxonomies we review more than three hundred publications dealing with nature-inspired and bio-inspired algorithms, and proposals falling within each of these categories are examined, leading to a critical summary of design trends and similarities between them, and the identification of the most similar classical algorithm for each reviewed paper. From our analysis we conclude that a poor relationship is often found between the natural inspiration of an algorithm and its behavior. Furthermore, similarities in terms of behavior between different algorithms are greater than what is claimed in their public disclosure: specifically, we show that more than one-third of the reviewed bio-inspired solvers are versions of classical algorithms. Grounded on the conclusions of our critical analysis, we give several recommendations and points of improvement for better methodological practices in this active and growing research field.

Keywords Nature-inspired algorithms · Bio-inspired optimization · Taxonomy · Classification

Introduction

In years, a great variety of nature- and bio-inspired algorithms has been reported in the literature. This many real-world optimization problems, no exact solver can be applied to solve them at an affordable computational cost or within a reasonable time, due to their complexity or the amount of data to use. In such cases the use of traditional techniques has been widely proven to be unsuccessful, thereby calling for the consideration of alternative optimization approaches.

In this context, complexity is not unusual in Nature: a plethora of complex systems, processes and behaviors have evinced a surprising performance to efficiently address intricate optimization tasks. The most clear example can be found in the different animal species, which have developed over generations very specialized capabilities by virtue of evolutionary mechanisms. Indeed, evolution has allowed animals to adapt to harsh environments, foraging, very difficult tasks of orientation, and to resiliently withstand radical climatic changes, among other threats. Animals, when organized in independent systems, groups or swarms or colonies (systems quite complex in their own) have managed to colonize the Earth completely, and eventually achieve a global equilibrium that has permitted them to endure for thousands of years.

This renowned success of biological organisms has inspired all kinds of solvers for optimization problems, which have been so far referred to as *bio-inspired optimization algorithms*. This family of optimization methods simulate biological processes such as natural evolution, where solutions are represented by individuals that reproduce and mutate to generate new, potentially improved candidate solutions for the problem at hand.

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Extended author information available on the last page of the article.

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Software Disponible

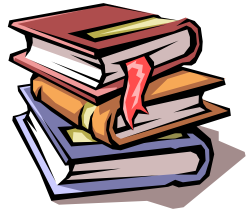
- ECJ, Java
  - Configurable con ficheros de texto.
  - Sólo requiere programar la función objetivo.
- ParaDisEO, C++
  - Paralelismo.
  - Complejo de integrar un problema.
  - Gráficas.
- Inspyred, Python
  - Muchos algoritmos.
  - Fácil de usar.
- EO, C++
  - Completo.
  - Buen documentado.
  - Antigüo, problemas.

Evolving Objects

Software Disponible específico

- Mealpy, Python
  - Muchos Bio-inspirados.
  - Continuo crecimiento.
- NiaPy, Python
  - Nature-Inspired
  - Extension.
- PyaDE, Python
  - Algoritmos DE.
  - Modelos adaptativos.
- PySwarm, Python
  - Completo.
  - Buen documentado.
  - Gráficas

Bibliografía



Revistas científicas

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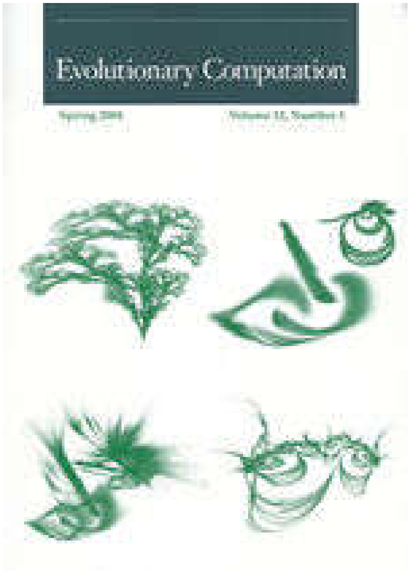
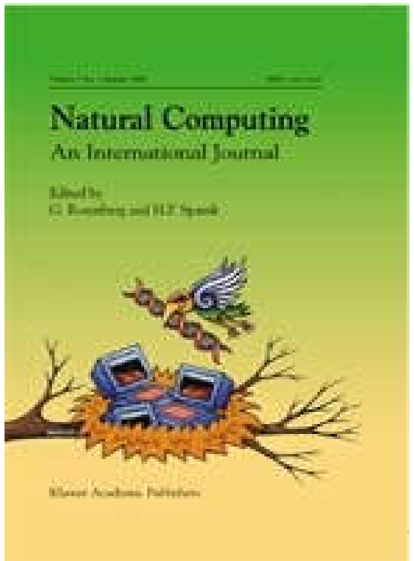
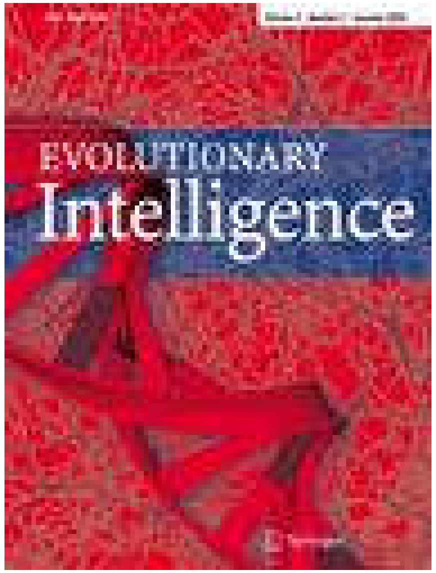




MIT Press **IEEE Press** **Springer**

Bibliografía

Revistas científicas



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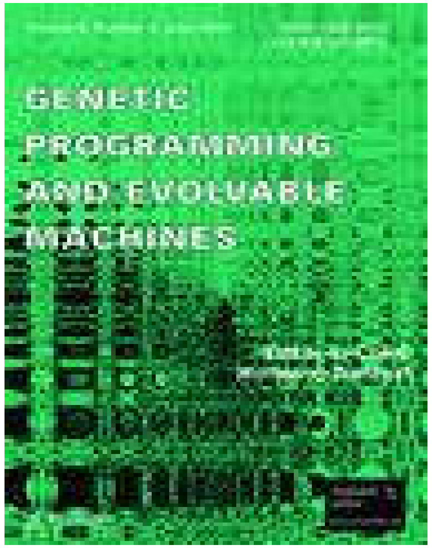

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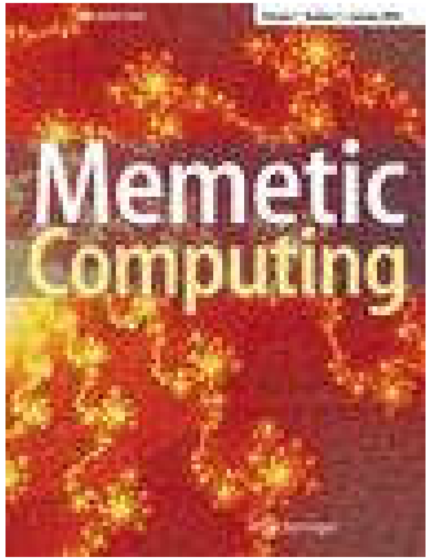

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