Emergent Optimization: Design and Applications in Telecommunications and Bioinformatics

PhD Thesis Dissertation

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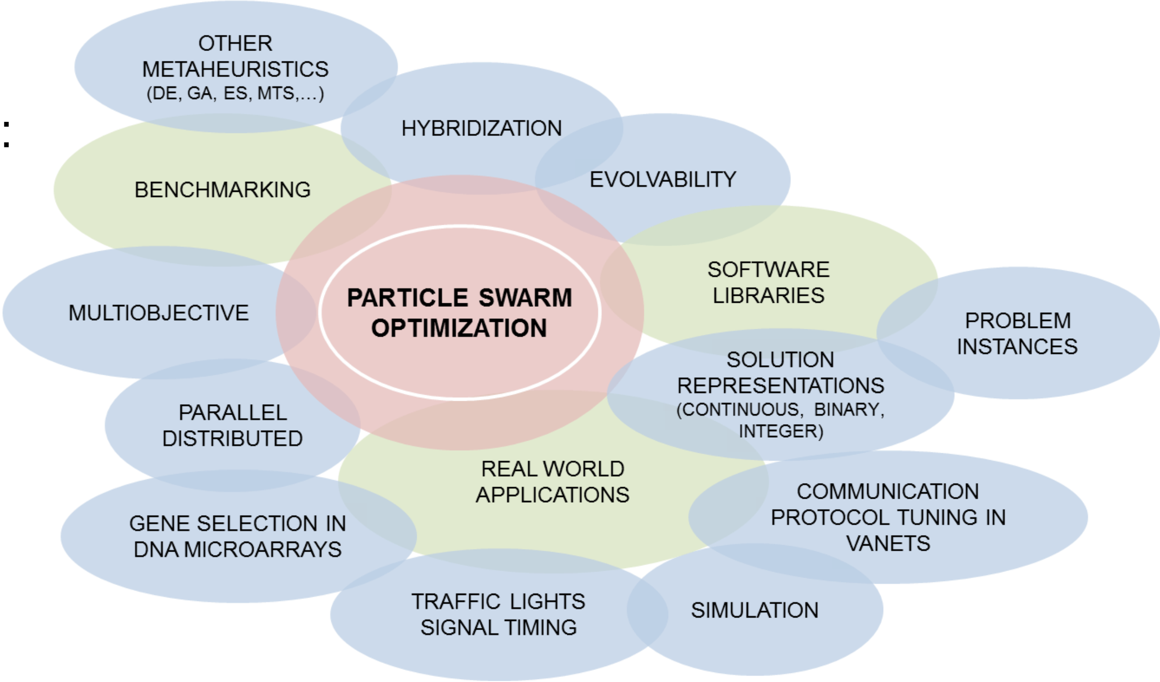
Objectives

Part I

- **Work hypothesis:**

I.H: ***Particle Swarm Optimization is a first class base-line optimizer able of the best performance in modern benchmarking, as well as in present real-world optimization problems***

- An ideal approach should have:
  - **Design and analysis** of new PSO proposals and their validation on standard **benchmarks**
  - Application to **real world problems** in different areas of engineering



Organization

Part I

Part I
- Introduction
- Fundamentals

Part II
- Design of algorithms
- Analysis of properties
- Benchmarking & validation

Part III
- Application to real world
- Algorithmic analysis
- Problem domain solution analysis

Part IV
- Conclusions
- Future Work

Design of Algorithms
- DEPSO, RPSO-vm, SMPSO
- PSO6, **PSO6-Mtsls**, PMSO

Analysis of Properties
- Scalability, Speedup,
- **Evolvability**, Performance

Benchmarks & Validation
- CEC'05, BBOB'09, DTLZ,
- **SOCO'10**, Statistical Tests

Genomic & Bioinformatic
- Gene selection in Cancer **DNA Microarrays**

Telecommu-nications
- Communication Protocol Optimization in **VANETs**

Traffic Management
- Signal Light **Timing Programs**

Part I

Introduction	Fundamentals

Optimization Problem

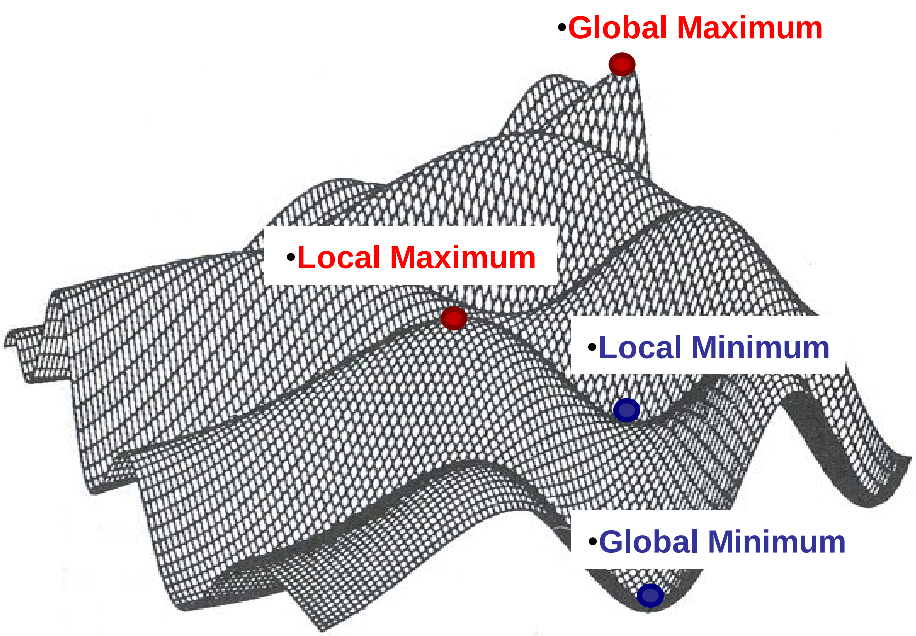
- An optimization problem can be defined as a pair: $P = (S,f)$ where:

  S is the set of possible solutions (a.k.a. solution space)

  $f: S \rightarrow \mathbf{R}$ is an objective function we wish to maximize or minimize

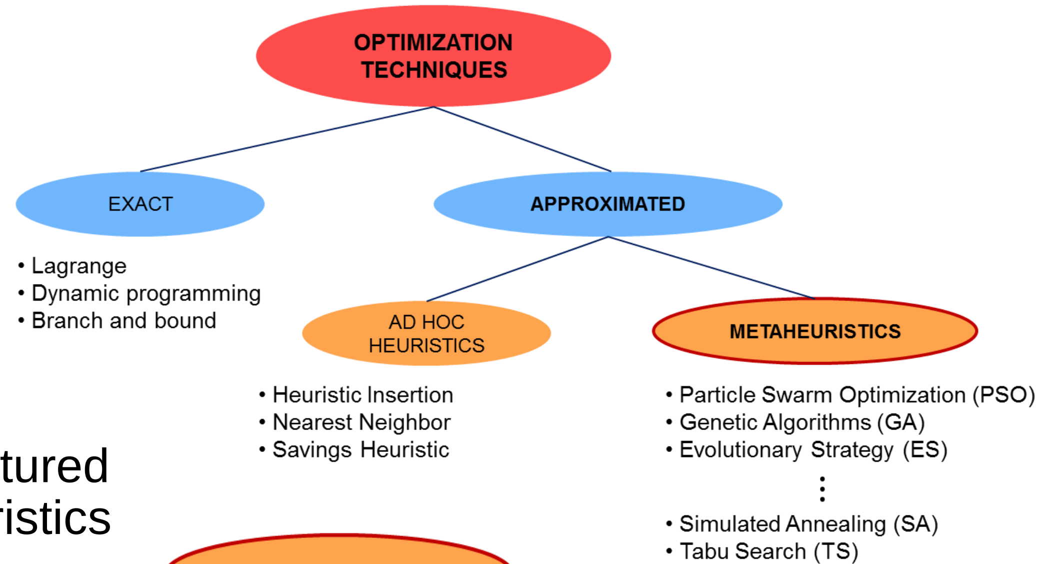
- In the case of minimization the objective is to find

$$s' \in S \mid f(s') \leq f(s), \forall s \in S$$

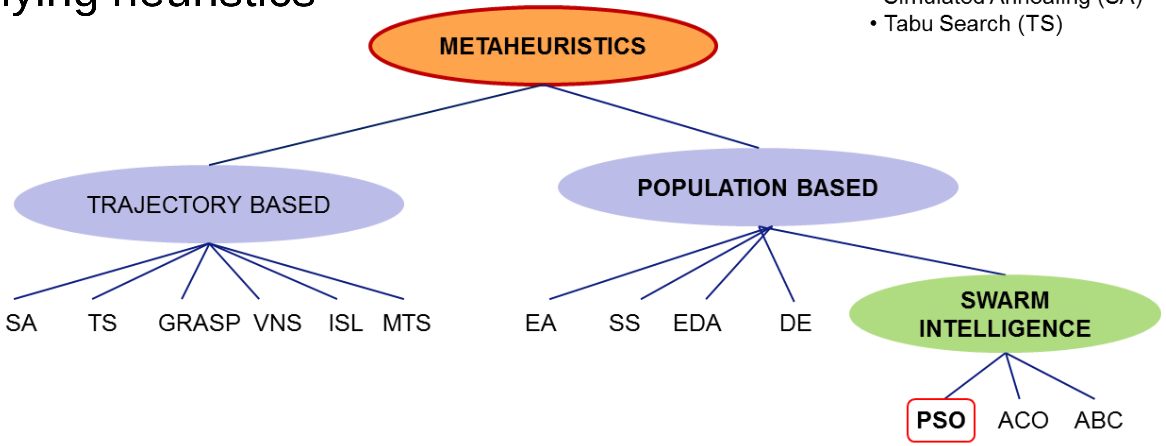


Definition and Classification

- Optimization algorithms



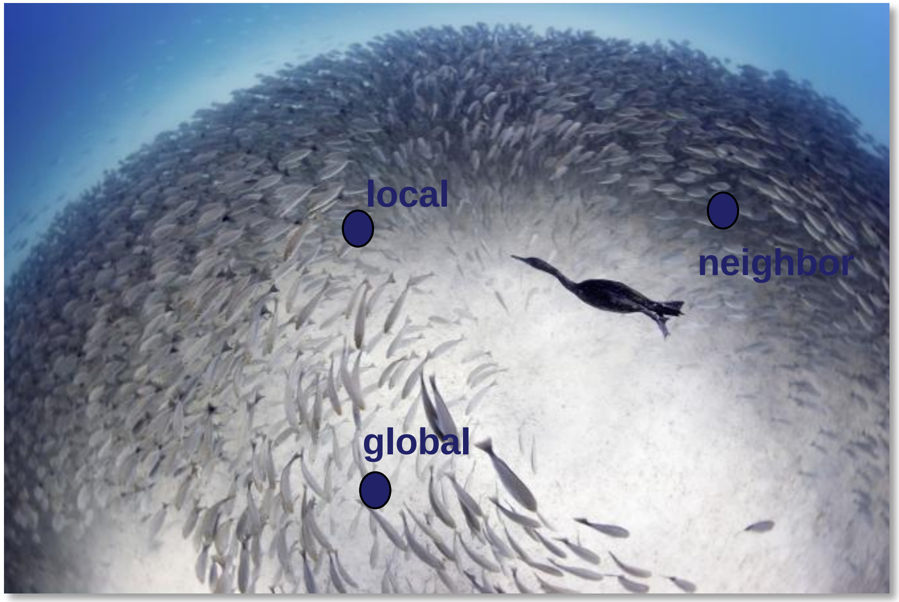
- A **metaheuristic** is a top-level structured strategy that guides underlying heuristics to solve a given problem



- **Swarm Intelligence**
  - Nature inspired techniques based on swarm dynamics and search strategies

Particle Swarm Optimization (PSO)

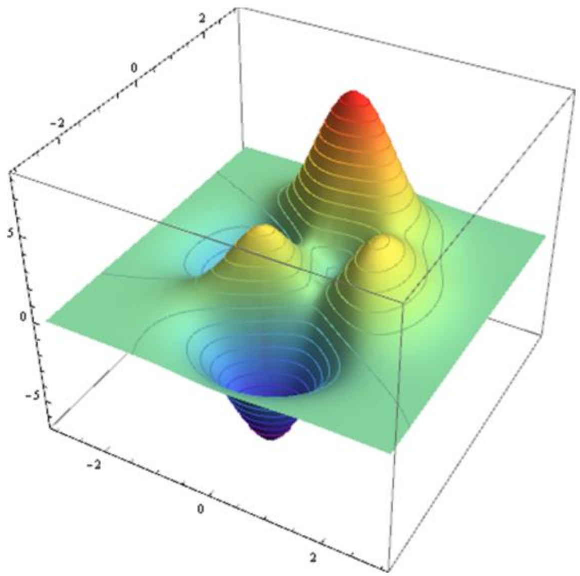
- **Features**
  - Designed in 1995 by Kennedy and Eberhart
  - Inspired on the Nature: Swarm of birds and fish schooling, modeling movements and reactions
  - Solutions are encoded as particles that
    - are moved using a velocity equation
    - the velocity depends on the position of other particles

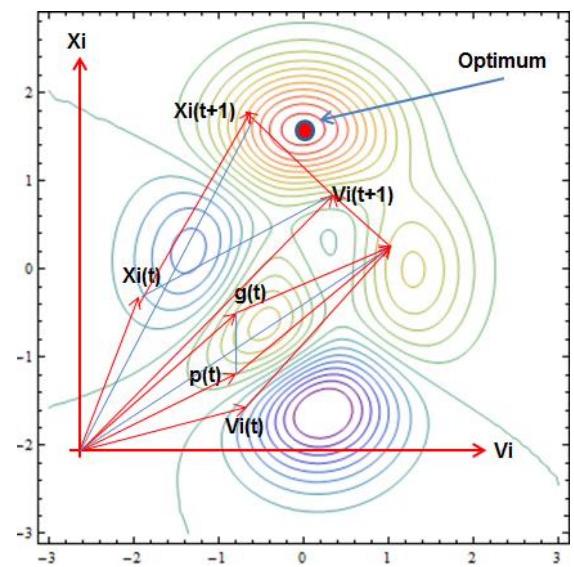


- **Popular metaheuristic nowadays**
  - Fast convergence
  - Easy to understand and implement

Particle Swarm Optimization (PSO)

- **Learning procedure**
  - Linear combination of vectors with random components





  - Movement dynamics

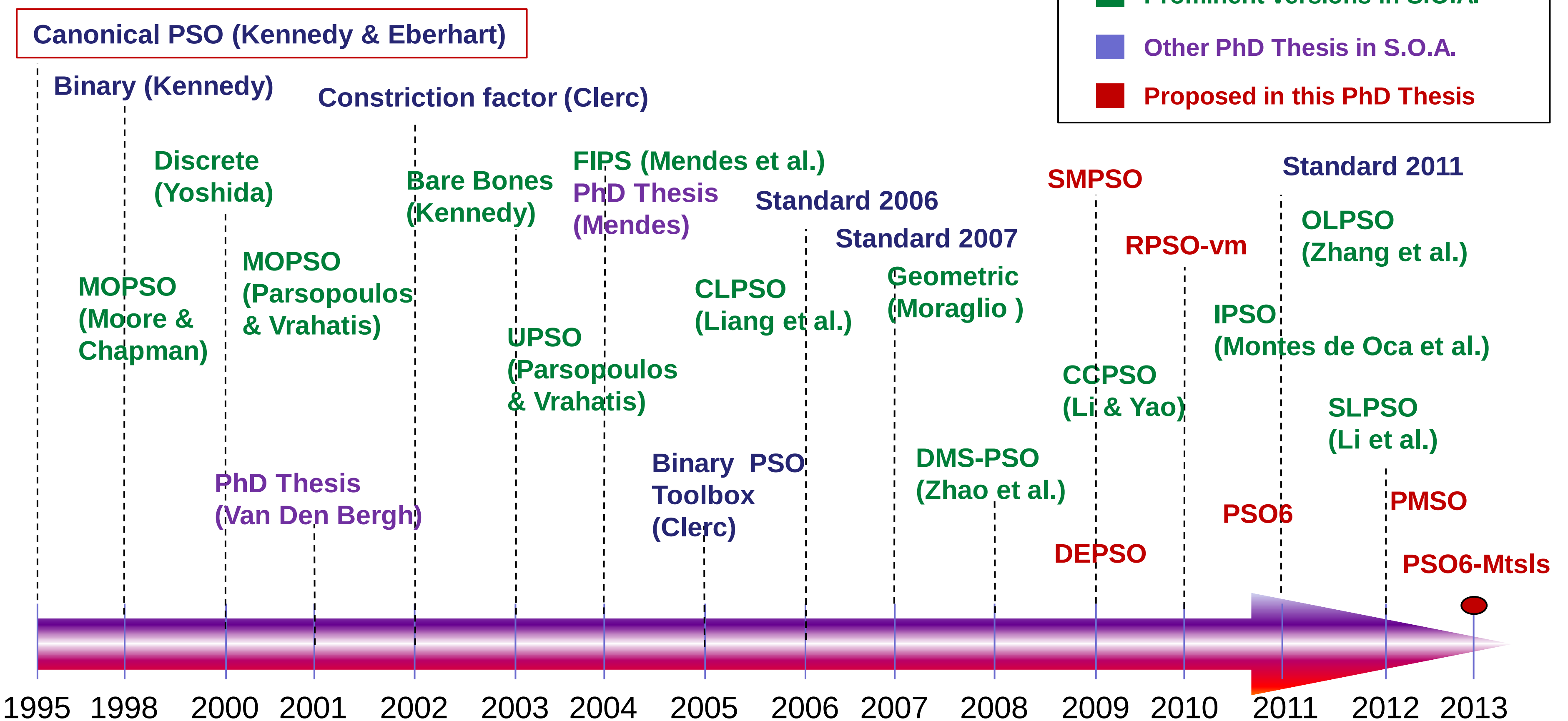
$$\vec{x}_i^{t+1} = \vec{x}_i^{t} + \vec{v}_i^{t+1}$$

$$\vec{v}_i^{t+1} = \omega \cdot v_i^t + U^t[0,\rho] \cdot \underbrace{\boxed{(\vec{p}_i^t - \vec{x}_i^t)}}_{\text{Individual factor}} + U^t[0,\rho] \cdot \underbrace{\boxed{(\vec{b}_i^t - \vec{x}_i^t)}}_{\text{Social factor}}$$

Particle Swarm Optimization (PSO)

- Major achievements in the State Of the Art (S.O.A.)

Standards
Prominent versions in S.O.A.
Other PhD Thesis in S.O.A.
Proposed in this PhD Thesis



Particle Swarm Optimization (PSO)

- From the literature we can conclude that:
  - **Benchmarking** (7 standard benchmarks)
    - CEC'05, CEC'08, SOCO'10
    - BBOB'09
    - ZDT, DTLZ, WFG
  - **Real world applications** (more than 28 domains)

    1 Communications

    …

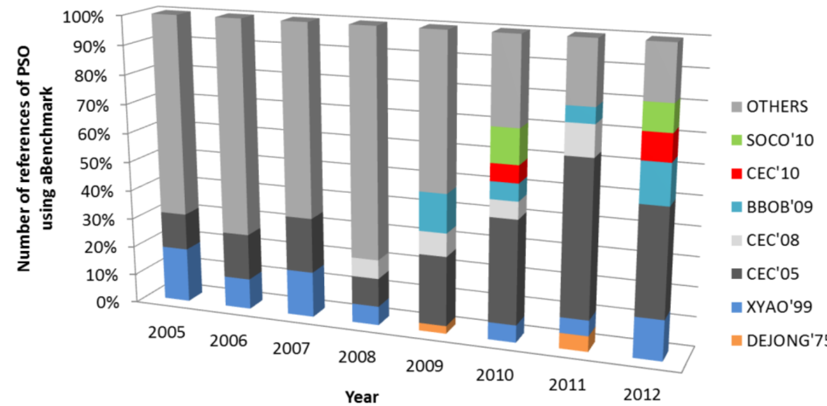
    15 Bioinformatics (Data Mining)

    18 Traffic management

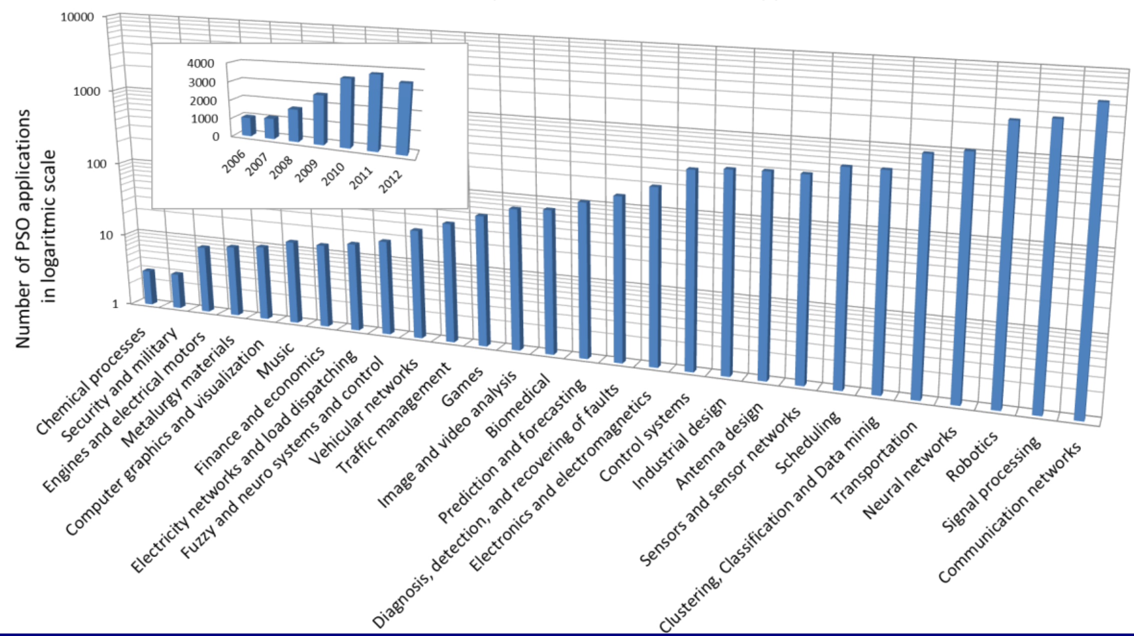
    19 Vehicular networks

    …

    28 Chemical processes

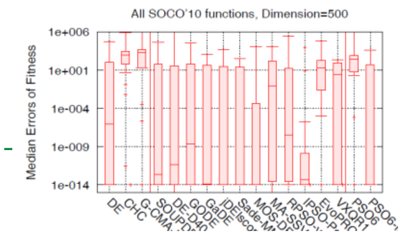


PSO publications on real world applications



Source: work done in this thesis based in more than 3000 papers, using IEEExplore, DBLP
ACM Digital Library, MIT Press…

Experimental Procedure for our Studies



Benchmarking

Given a **problem** to solve

Given an **algorithm** to evaluate

1º Select algorithms **to compare** with

2º Execute multiple **independent runs**

3º Perform **statistical** analyses

4º Analyze functions' **properties**

4º Analyze problem **domain** solutions

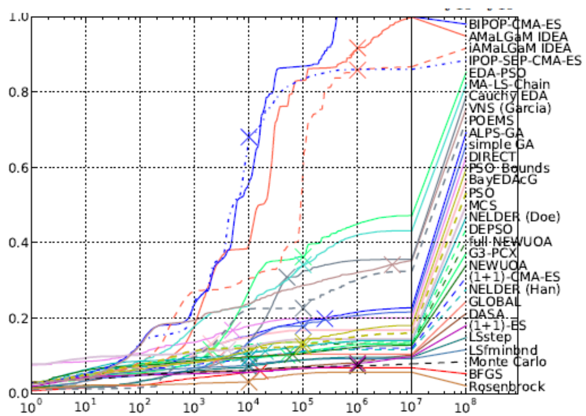
Real world applications

Reference Algorithms

Part I

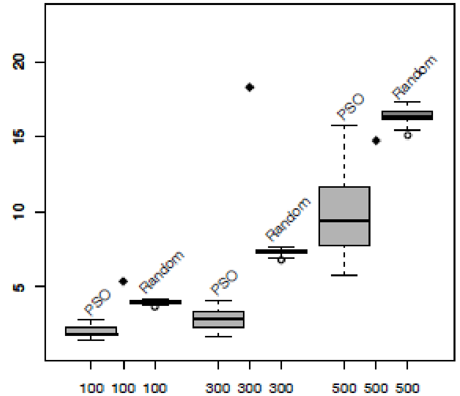
Benchmarking

- G-CMA-ES,
- DE (rand/1), CHC,K-PCX
- FIPS, FIPS-Square
- IPSO, IACO, MOS-DE, GaDE
- CLPSO
- OMOPSO, NSGA-II



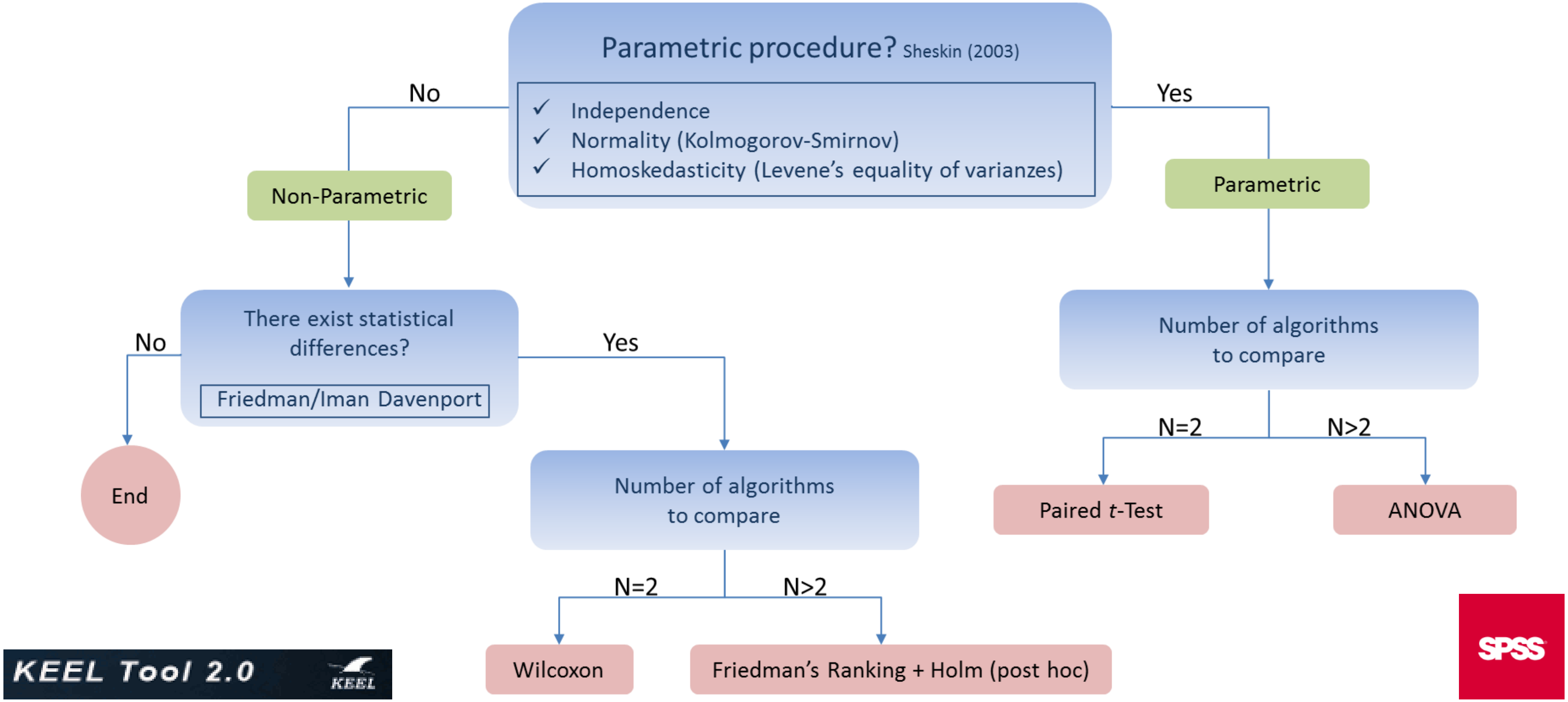
Real world applications

- PSO Standards 2006, 2007, and 2011
- DE (rand/1)
- GA, SA, ES
- Random Search
- Deterministic SGCP



Statistical Validation

- *<u>Null-hypothesis</u>: equality of distributions with a confidence level of 95% (Statistical differences can be found if tests result with p-value<0.05)*



[GMLH09] S. García, D. Molina, M. Lozano, and F. Herrera, *A study on the use of nonparametric tests for analyzing the evolutionary algorithms' behavior: a case study on the CEC'2005*, Journal of Heuristics 15 (2009), no. 6, 617–644.

Part II

Design of Algorithms	Analysis of Properties

Design Issues

- In PSO, modify the learning procedure to induce an improved performance usually means a reformulation to have a new velocity vector equation
- We have opted for several mechanisms:

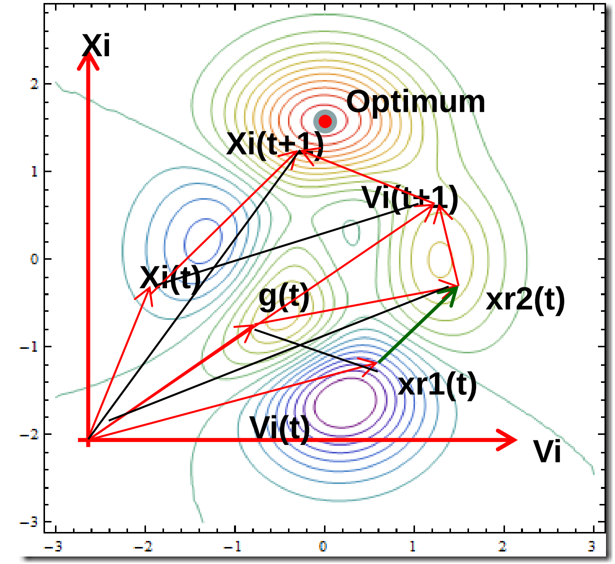
Mechanism	Description	Proposals
Hybridization	Using differential evolution operators	**DEPSO**
Velocity modulation	Constraining velocity to the search range	**RPSO-vm**
Multi-objective	Using velocity modulation and leader selection from non-dominated set	**SMPSO**
Neighborhood topology & number of informants	Discovering a quasi-optimal information scheme	**PSO6 $\pm$ 2**
Interdependency of variables	Hybridizing with local search & range decisions	**PSO6-Mtsls**
Parallel swarm	Structuring swarms in parallel	**PMSO**

Hybrid PSO with DE

- Motivation: **combining** the global structure of **PSO with differential operators of DE/rand/1** we expect to improve the performance of the resulting technique: **DEPSO**
- **Main idea** → For each particle, the velocity is updated according to two main influences: **social** and **differential variation** operators
- **New learning procedure**:

$$\vec{v}_i^{t+1} = \omega \cdot v_i^t + F \cdot \underbrace{\boxed{(\vec{x}_{r1}^t - \vec{x}_{r2}^t)}}_{\text{Differential variation}} + U^t[0,\rho] \cdot \underbrace{\boxed{(\vec{b}_i^t - \vec{x}_i^t)}}_{\text{Social factor}}$$

- Crossover and trial selection are applied as in DE

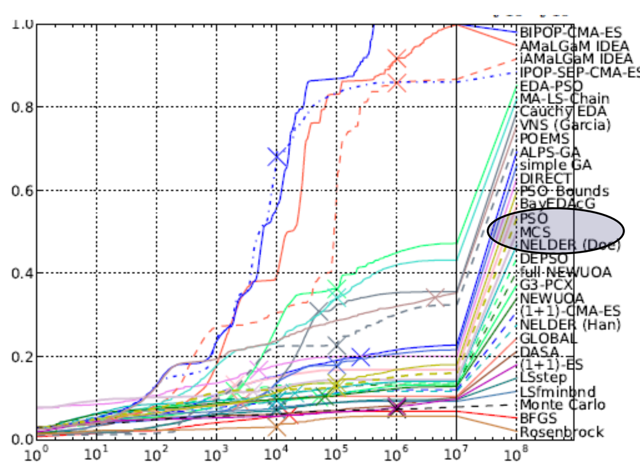


DEPSO: Extensive Experimental Framework

- **Results on MAEB’09/CEC’05**:
  - Ranked in **3th position out of 21** participants for D=10
  - Statistically similar to G-CMA-ES and to the best one: STS

[GAA09a] J. García-Nieto, J. Apolloni, and E. Alba. **Algoritmo Basado en Cúmulos de Partículas y en Evolución Diferencial para Optimización Continua**, MAEB 2009.

- **Results on BBOB’09**
  - **Noiseless:** accurate coverage for separate and weakly Structured
  - **Noisy:** accurate coverage for moderate and severe noise multimodal

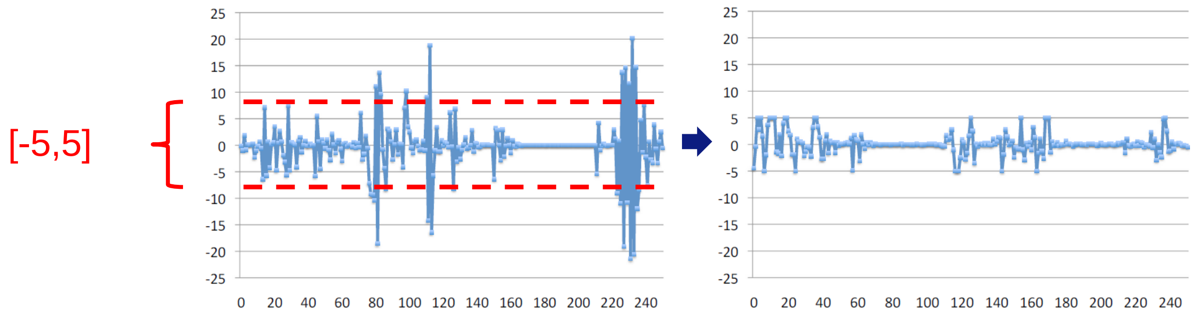


MAEB’09 D10
G-CMA-ES
GADEDIST
DEPSO
DE
MOS3
MOS1
MOS4
MOS2
DMO
K-PCX
BFPS
ACOR-SW
MALSChain-CMA-ES
ACOR
ACOR-SIMPLEX
GDGA
AEF
BLXRL
CIXL2RL
CIXL1RL
SBXRL

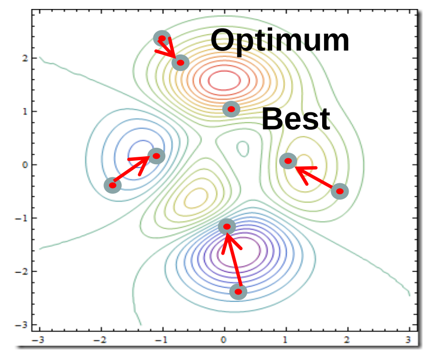
[GAA09c] J. García-Nieto, E. Alba and J. Apolloni. **Particle Swarm Hybridized with Differential Evolution: Black-Box Optimization for Noisy Functions**, GECCO 2009.

RPSO-vm for Large Scale Problems

- For certain kinds of complex problems (deceiving), the **velocity grows** and takes particles **out of the variable ranges**
- Moreover, for **large scale** problems (with a huge number of variables) this usually leads PSO to perform an **erratic behavior**
- **Velocity modulation**: to guide particles inside the problem variable's search range



- **Restarting:**
  - when **std approaches zero**
    - to avoid particles to fall into local basins of attraction
  - when the overall **fitness does not improve** for a number of steps
    - to control particles dispersion in deceiving landscapes



RPSO-vm: Scalability Test

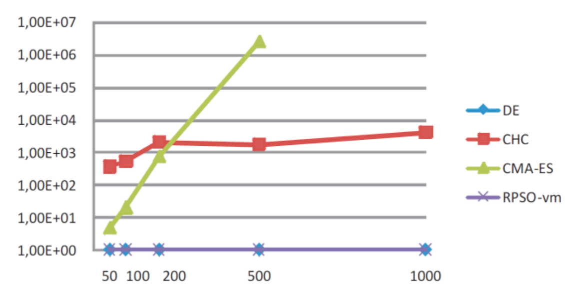
- Experiments in the scope of *Special Issue Soft Computing:* **SOCO'10**. A number of 19 functions were considered with dimensions: 50, 100, 200, 500, and 1000 variables

Ranking: RPSO-vm vs G-CMA-ES vs CHC (Control algorithm: DE)

50	100	200	500	1000	Diff?
RPSO-vm	RPSO-vm	RPSO-vm	RPSO-vm	RPSO-vm	**No**
G-CMA-ES	G-CMA-ES	G-CMA-ES	G-CMA-ES	_	**Yes**
CHC	CHC	CHC	CHC	CHC	**Yes**

- Accurate behavior on **non-separable multimodal** (f12, f14, f15, f19)

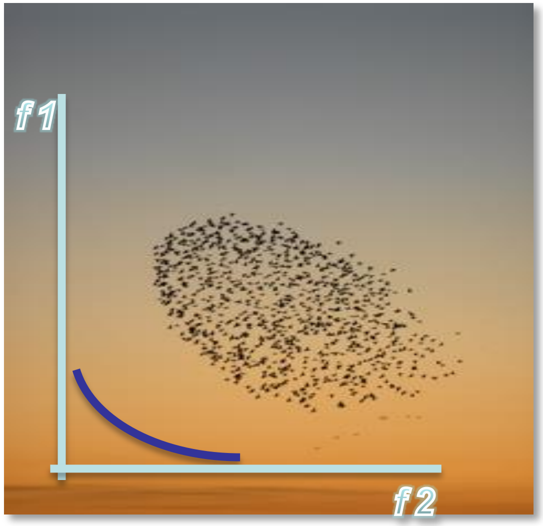
f19

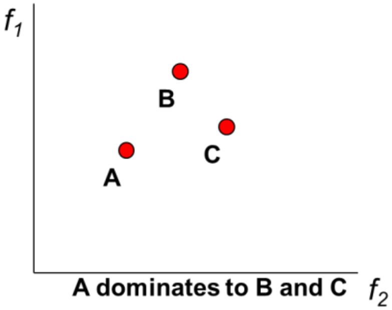


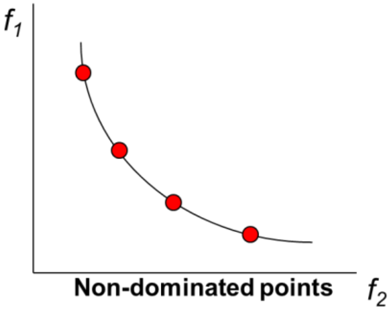
[GA11] J. García-Nieto, E. Alba. **Restart Particle Swarm Optimization with Velocity Modulation: A Scalability Test.** *Soft Computing (2011)*

Multi-Objective PSO

- **MO Problems** have more than one objective function which are in conflict with each other
  - Pareto dominance
  - The search process does not seek a single solution
  - Set of non-dominated solutions: Pareto optimal set
- In **MOPSO**, some issues have to be considered:
  - How to select a leader from the set of non-dominated solutions
  - How to keep non-dominated solutions
  - How to maintain diversity





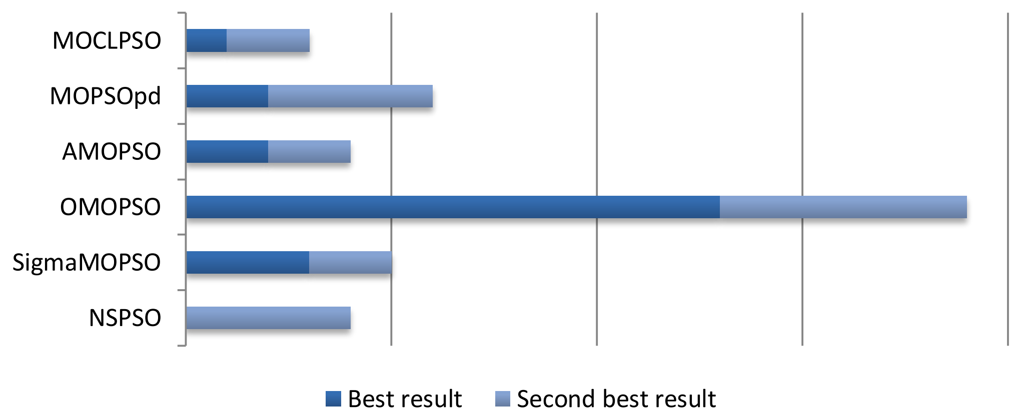


[DGNCLA09] J.J. Durillo, J. García-Nieto, A.J. Nebro, C.A. Coello Coello, F. Luna and E. Alba. **Multi-Objective Particle Swarm Optimizers: An Exprimental Comparison**, EMO 2009

Comparison of Multi-Objective PSOs

- First, we made a comparison of six representative MOPSOS in the state of the art
- On benchmarks of MO problems: ZDT. DTLZ, and WFG

MO Algorithm
MOCLPSO
MOPSOpd
AMOPSO
OMOPSO
SigmaMOPSO
NSPSO



Number of times out of the 21 evaluated problems in which the best I_{HV} value has been obtained

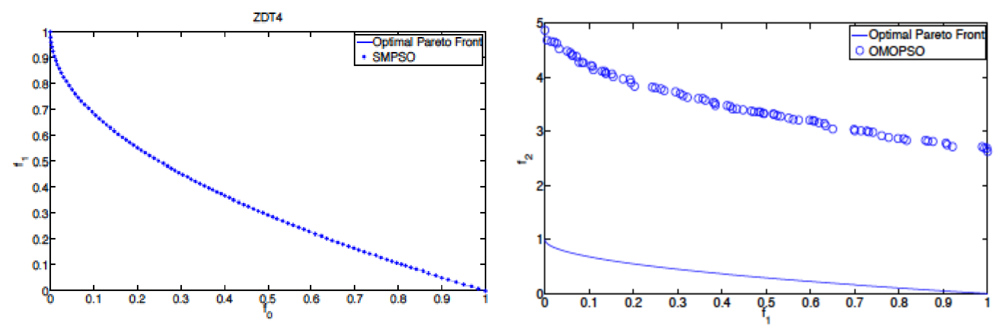
- Main drawback observed in existing techniques
  - difficulties with multi-modal problems
  - erratic movements in particles' velocity

SMPSO

- Our MO proposal: **Speed Modulation PSO**
  - OMOPSO is taken as a starting point
  - Velocity modulation mechanism (as in RPSO-vm)
  - External archive

Velocity modulation also helps for **multimodal multi-objective** problems

SMPSO vs. OMOPSO fronts on ZDT4



SMPSO vs NSGA-II vs SPEA2

	I_{e+}^1	I_{Δ}	I_{HV}
SMPSO	**18**	**17**	**13**
NSGA-II	2	0	2
SPEA2	1	3	6

Number of times out of the 21 evaluated problems in which the best value in each indicator has been obtained

SMPSO vs OMOPSO

	I_{e+}^1	I_{Δ}	I_{HV}
SMPSO	**11**	**11**	**13**
OMOPSO	10	10	8

Number of times out of the 21 evaluated problems in which the best value in each indicator has been obtained

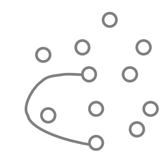
Part II

Design of Algorithms	Analysis of Properties

Quest for an Optimal Number of Informants

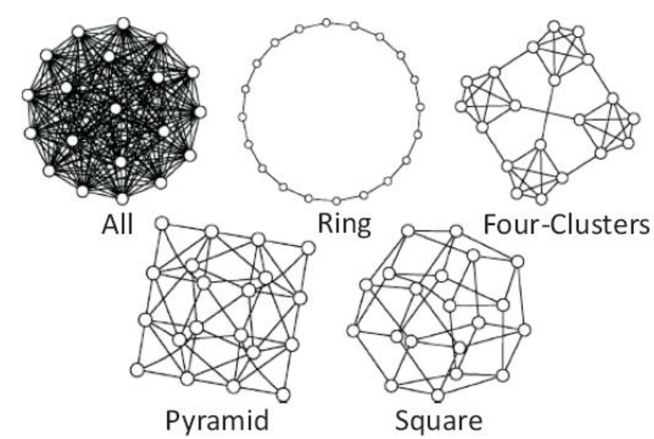
- In Canonical and Standard PSO (2006, 2007, and 2011), the calculation of a new particle's velocity is influenced by just **two informant terms**: the particle's best previous location, and the best previous location of any of its neighbors

$$\mathbf{v}_i^{t+1} = \chi\left(\mathbf{v}_i^t + U^t[0,\varphi_1]\cdot(\mathbf{p}_i^t - \mathbf{x}_i^t) + U^t[0,\varphi_2]\cdot(\mathbf{b}_i^t - \mathbf{x}_i^t)\right)$$



- Mendes et al. 2004 proposed the Fully Informed PSO (FIPS): **particle's velocity can be adjusted by any number of terms**, since important information given by other neighbors may be neglected through overemphasis on the single best neighbor

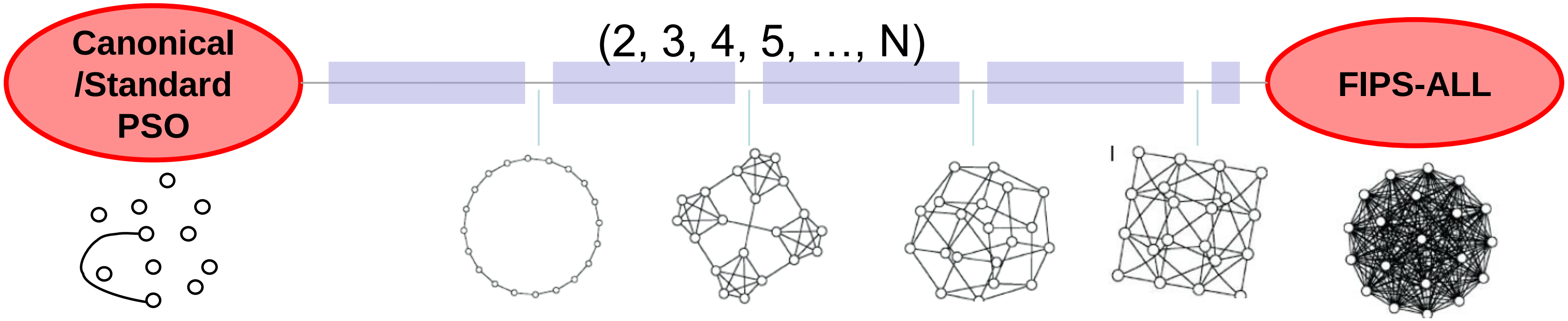
$$\mathbf{v}_i^{t+1} = \chi\left[\mathbf{v}_i^t + \sum_{j\in\mathcal{N}_i} U^t\,[0,\varphi_j]\cdot(\mathbf{p}_j^t - \mathbf{x}_i^t)\right]$$



- In FIPS, the neighborhood of informants is arranged in **structured topologies**

Quest for an Optimal Number of Informants

- Again**,** **important information may be neglected** through overemphasis, in this case, on the (ad-hoc, a priori) structured sets of neighbors



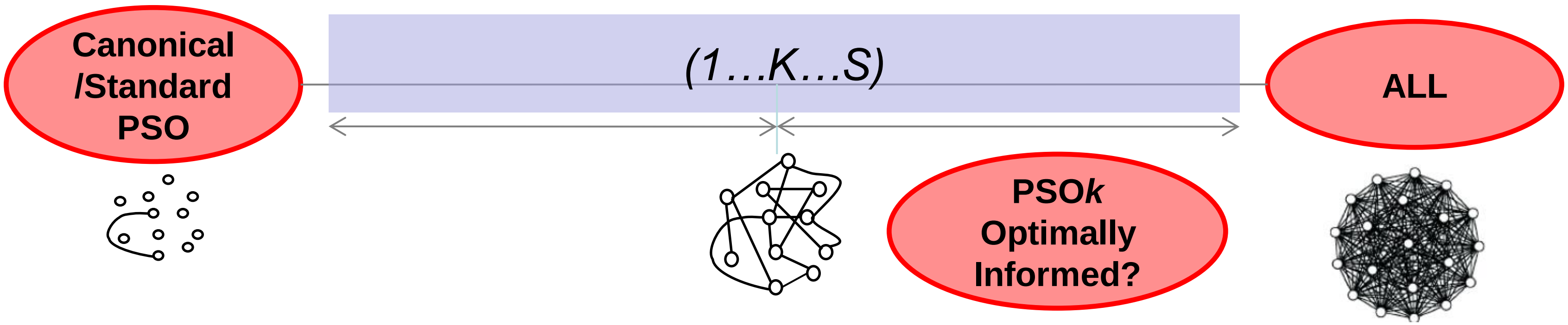
- **Motivation: generalize the number of neighbors that inform** particles, in order to discover whether there exists a quasi-optimal number of informants for a particular problem

<u>Research question:</u> certain numbers (sets) of informant neighbors may provide new essential information about the search process, hence leading the PSO to perform more accurately than existing versions

[GA11] J. García-Nieto, and E. Alba. **Empirical Computation of the Quasi-optimal Number of Informants in Particle Swarm Optimization**. GECCO'11

Quest for an Optimal Number of Informants

- Generalization of the number of informant terms from 1 to *S* (swarm size), resulting *S* different versions of PSO, each one of them with neighborhoods containing *k* informant particles (in FIPS-ALL, *S*=*k*)



- Providing each *k* neighborhood with structured topologies is impracticable (enormous number of graphs combinations)

- We simply select *k* random (uniform) neighbors in the swarm, for each particle *i* and each time step *t* (topology independent)

$$\mathcal{N}_i^t = \{n_1, \ldots, n_k\} \mid \mathcal{N}_i^t \subset S^t, \forall n_j, n_h \in \mathcal{N}_i^t, n_h \neq n_j \neq i$$

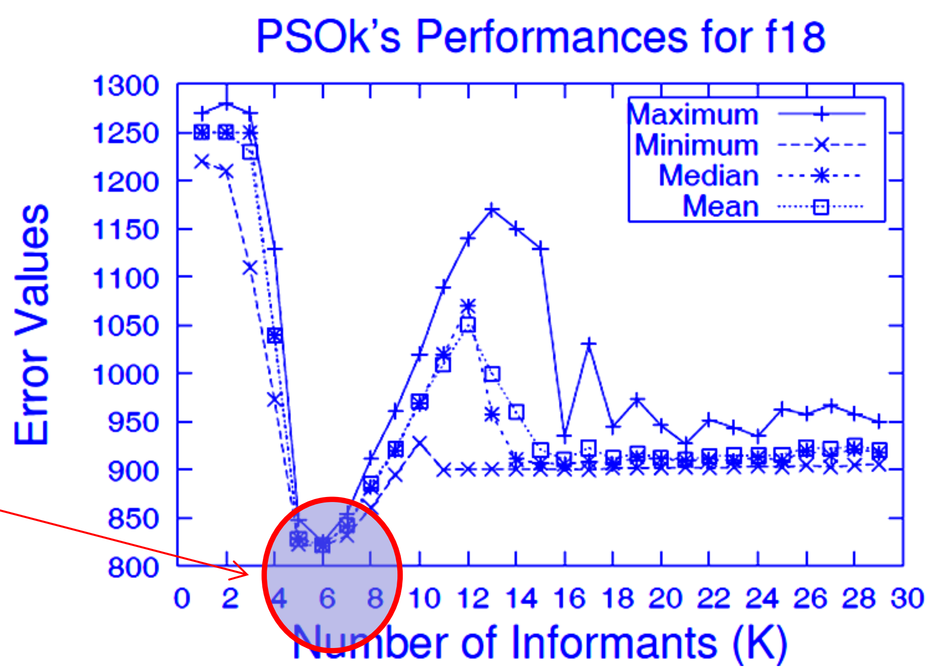
Understanding our Quest

- Experimental phase
  - 30 PSOk versions (*k*=1..30)
  - 25 Benchmark functions (CEC'2005)
  - 25 Independent runs
  - A total number of 18,750 (30x25x50) experiments
- For each problem function: the maximum, median, mean, and minimum error fitness are plotted

For each *k = {1..S}*, a different algorithm can be developed

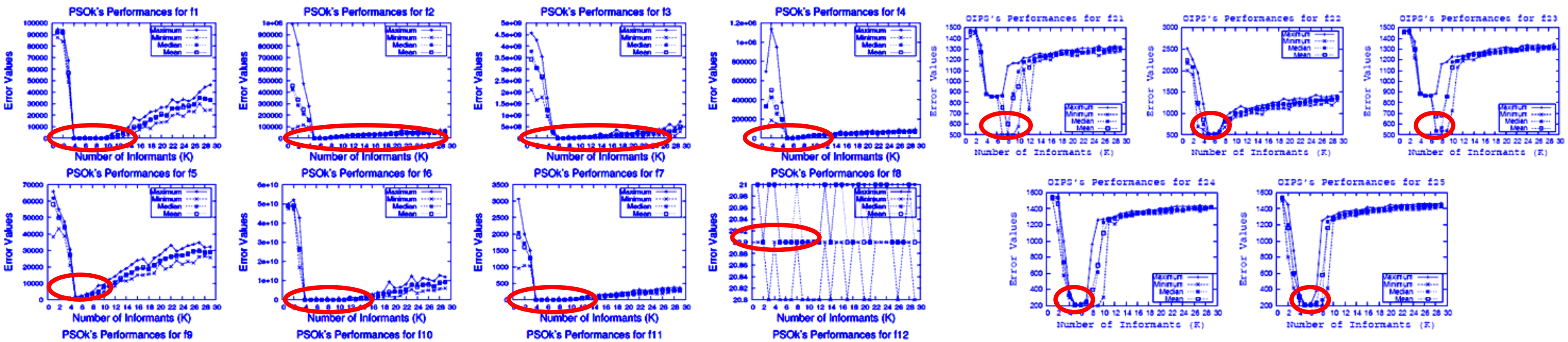
Swarm size	Ss	30
Acceleration coefficient	φ	4.1
Constriction coefficient	χ	0.7298

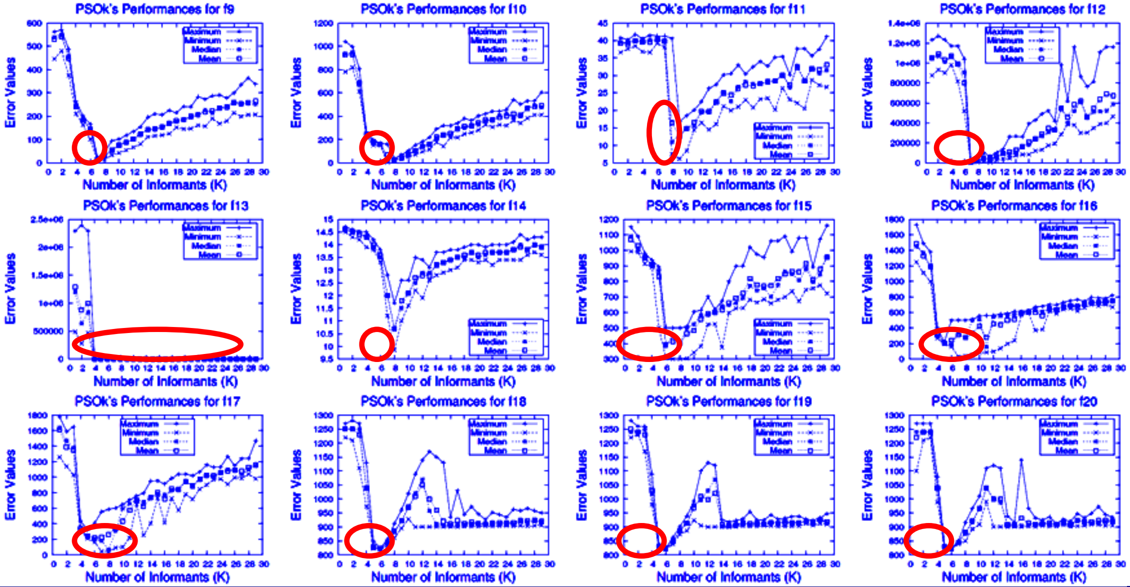
Best performing PSO*k*=6



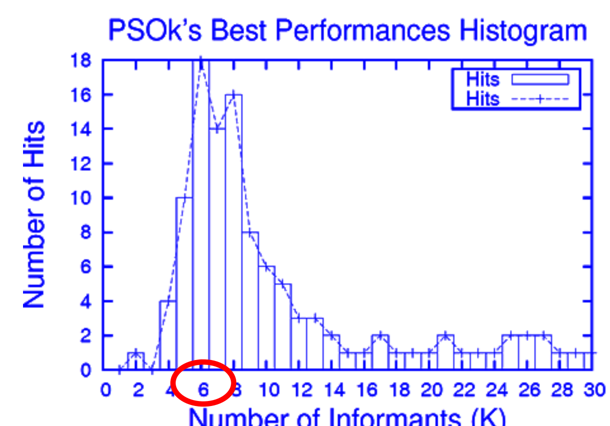
Impact of the Number of Informants

- For all the CEC'05 functions



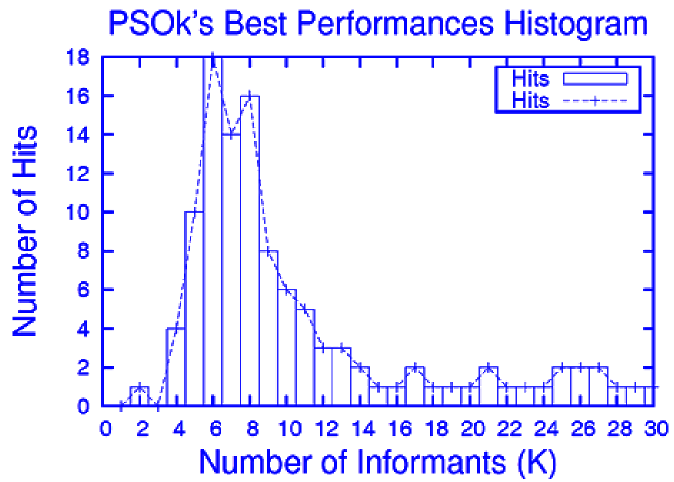


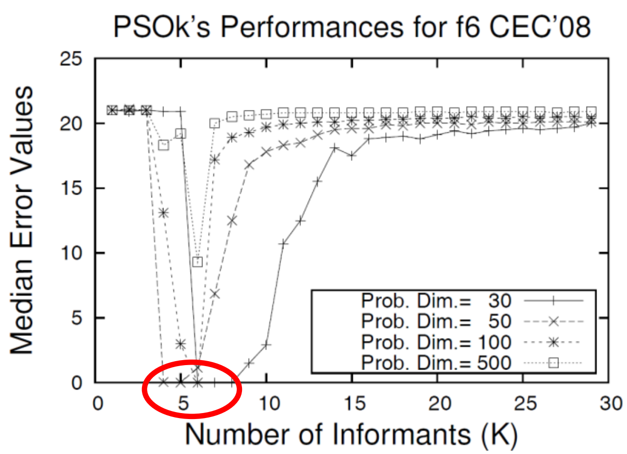
In general, changes in performance observed in PSO*k* when *k*=6±2



Impact of the Number of Informants

- Observations and implications
  - The interval between 5 and 8 informants concentrates most of successful runs
  - Combining 6 and 8 informants could be a source of new competitive algorithms
  - There are sets of functions that share similar curve shapes.
  - In fact, biased functions to the same optimum share similar curve shapes. Is it because of an unknown feature of CEC'05 functions?
  - Similar curve shapes observed for different benchmarks (CEC'08) and dimensions (30, 50, 100, and 500)





Performance Comparisons

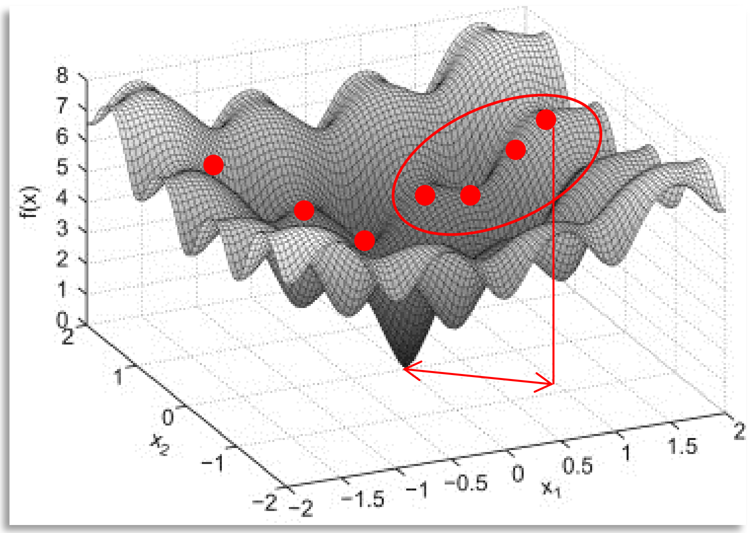
- The best PSO*k* (and its combinations) against FIPS-Usquare (the best one in Mendes et al. 2004), FIPS-ALL, and the Standard PSO 2007

Algorithm	Best performance in functions (CEC'2005)	Number of functions	Statistical Ranking (Friedman)
PSOHE{6,8}	**f1, f5, f7, f9, f18, f19, f20, f22, f24, f25**	**10**	**2.58**
PSO6	f1, f2, f3, f6, f7, f19, f20, f24, f25	9	2.86
FIPS-Usquare	f1, f3, f6, f10, f12, f13, f15, f16, f17	9	2.88
PSOU[6,8]	f1, f14, f21, f23	4	3.26
FIPS-ALL	f11	1	3.76
Standard 2007	f8	1	5.66

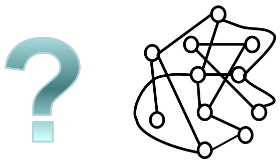
***Two new combinations of PSO6 and PSO8: PSOHE{6,8} and PSOU[6,8]**

Evolvability: A Step Beyond

- Here, we analyze the internal behavior of PSO from the point of view of the **evolvability**



- Def. **Capacity of algorithm's operators** to improve the fitness quality for a given problem
- It is also possible to distinguish **which algorithm has larger search capabilities**, and (to have an idea of) why



- Our **motivation** is to find evidences of why neighborhoods with **6±2** informant particles perform better than other combinations of informants

[GA12] J. García-Nieto, and E. Alba. **Why Six Informants Is Optimal in PSO**. ACM GECCO'12

Metrics to Measure Evolvability

- **Fitness-distance (*fitness distance correlation*) using PSO informants as neighbors**
  - Correlation: both, fitness and distance to optimum decreases

$$r_{fdc} = \frac{c_{fd}}{s_f \cdot s_d}, being \;\; c_{fd} = \frac{1}{n}\sum_{i=1}^{n}(f_i - \overline{f}) \cdot (d_i - \overline{d})$$

rfdc: interpretation
+1: convex
0: plateau
-1: deceiving

- **Fitness-fitness (*fitness cloud*)**
  - In our case: plot of fitness of a new particle that is generated from its informants, and the mean fitness of these informants

$$\{(f_1, \overline{f_1}), \ldots, (f_n, \overline{f_n})\}$$

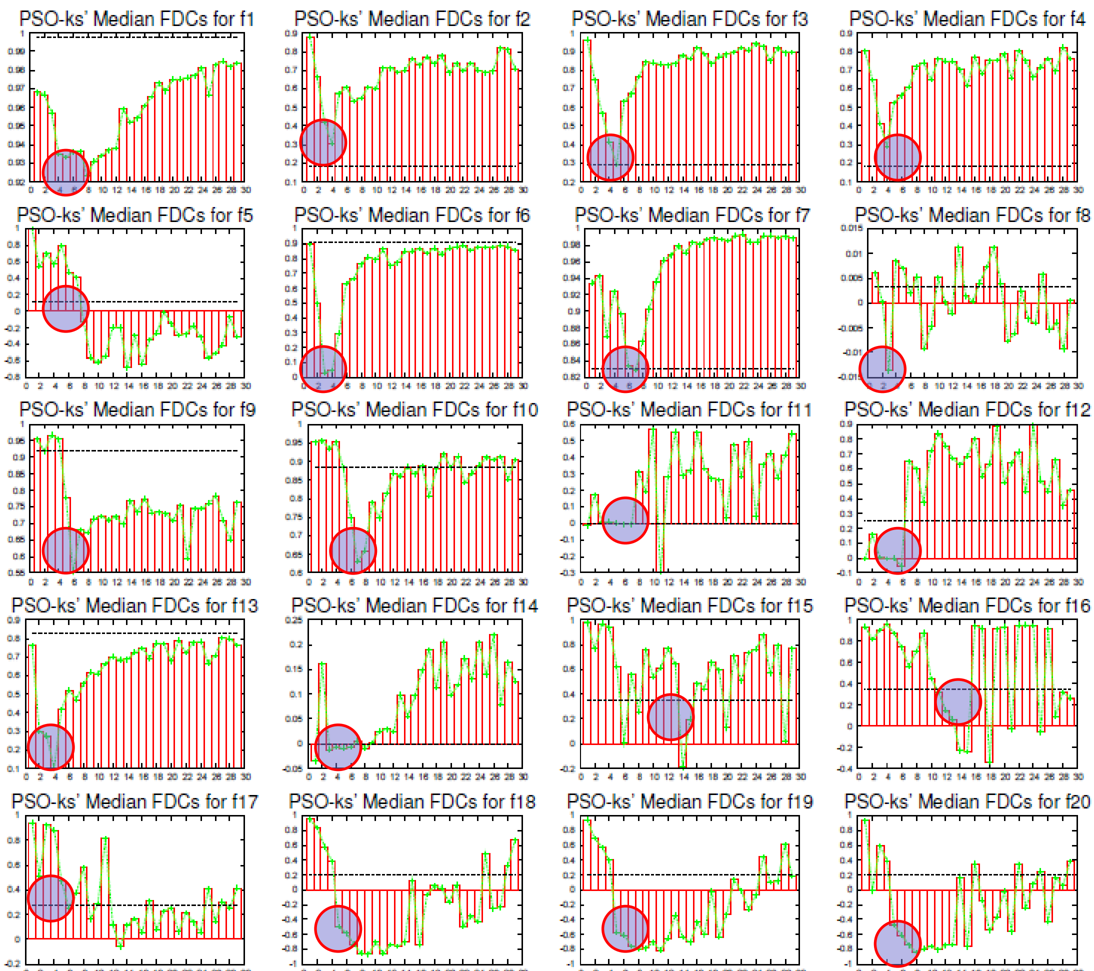
- **Escape probability**
  - Average number of steps required to scape from a local optimum

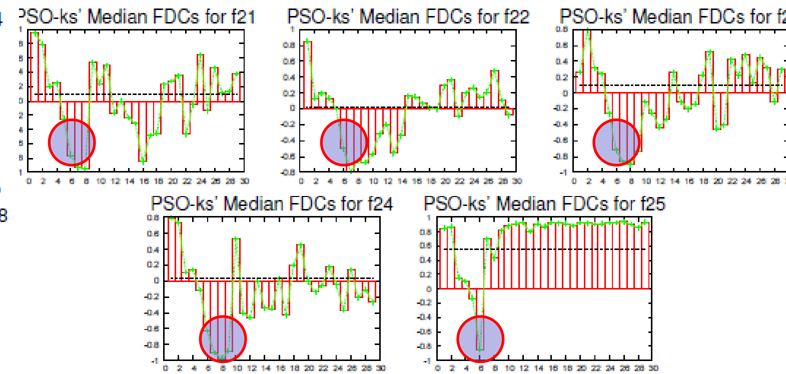
$$P(\bar{f}_i) = \frac{1}{S_i}$$

Fitness-Distance

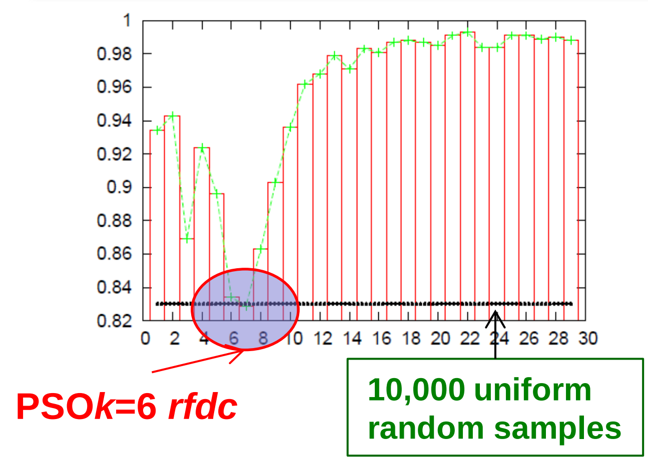
Part II

- For all the CEC'2005 functions



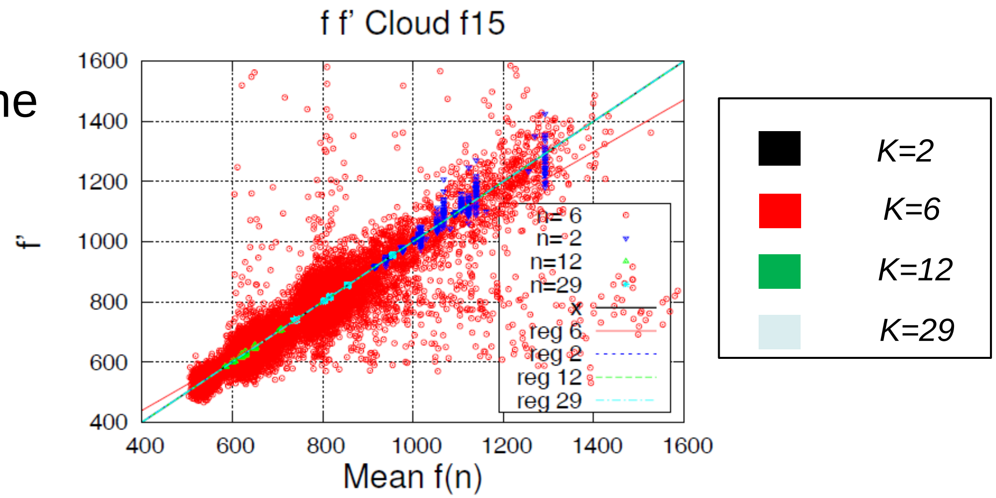


In general, changes in correlations observed in PSO*k* when *k*=6±2

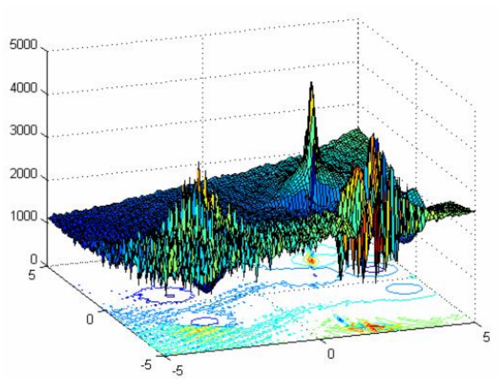


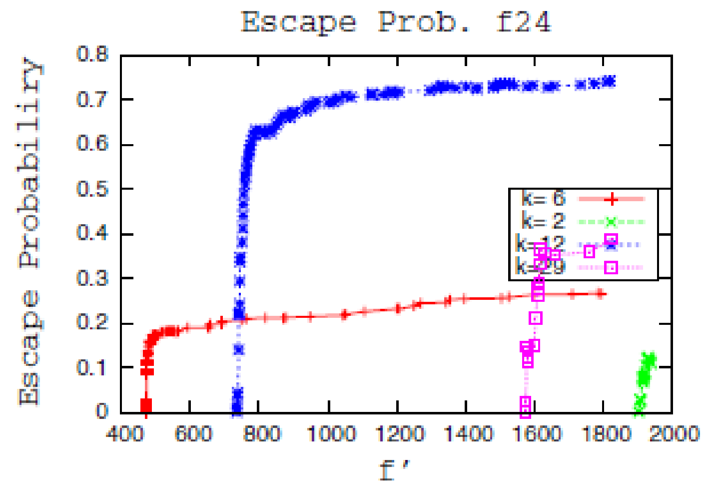
Fitness-Fitness & Escape Probability

- **Fitness-fitness**: a number of 6 informants is able to keep for longer the generation of new better particles with improving fitness: more final diverse solutions



- **Escape probability**: PSO6 generally shows a moderated *ep* progress, although reaching a deeper basin of local optimum, e.g., better fitness values

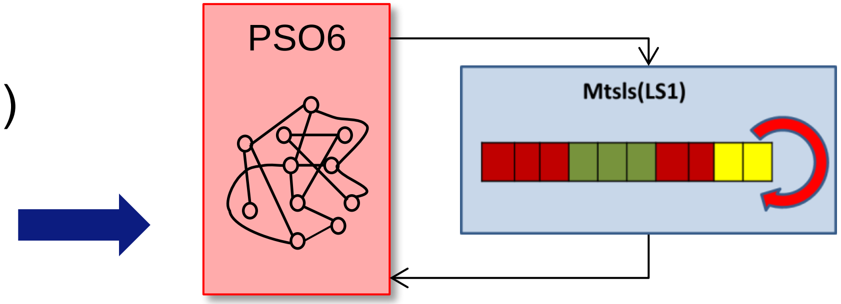




Hybrid PSO6 with Multiple Trajectory Search

- A moderate performance is still observed in PSO6 $\pm$ 2 for non-separable complex problems
  - Particles move **dimension by dimension**, which makes hard to find the problem **optimum** when variables are interdependent
- Incorporation of a local search method to our PSO6 to allow particles to explore their regional neighborhoods in the context of variations of dependent variables
- In concrete, Multiple Trajectory Search local search (best algorithm in CEC'08)

PSO6-MtsIs



[GA13] J. García-Nieto, and E. Alba. **Hybrid PSO6 for Hard Continuous Optimization**. IEEE Trans. on Sys. Man & Cyb. Part B, (2013). Under review

PSO6-Mtsls: Results

- Results on **SOCO'10**: Friedman's ranking with Holm's correction

Our proposal is in the **top of best algorithms** with statistically similar distribution of results for all dimensions: 50, 100, 200, and 500

50 -SOCO'10
jDElsop
PSO6-Mtsls
IPSO-Powell
Sade-MMTS
GaDE
SOUPE
GODE
DE-D40-Mm
RPSO-vm
DE
EvoPSOpt
PSO6
VXQR1
MA-SSV
G-CMA-ES
CHC

*Control MOS-DE

- Results on an extended benchmark: **CEC'05+SOCO'10** (40 problem functions)
  - Comparison with other techniques hybridized with **Mtsls**

Function's features	PSO6-Mtsls versus			
	G-CMA-ES	IPSO-Powell	IPSO-Mtsls	ACOr-Mtsls
Separable	(6, 1, 0)	(0, 4, 0)	(0, 3, 0)	(0, 4, 0)
Non-separable	(12, 4, 6)	(13, 9, 2)	(9, 12, 3)	(9, 12, 5)
Unimodal	(1, 2, 1)	(1, 5, 1)	(1, 5, 1)	(1, 5, 1)
Multimodal	(17, 3, 5)	(12, 8, 1)	(8, 10, 2)	(8, 11, 4)
Rotated	(7, 2, 5)	(7, 3, 0)	(7, 3, 0)	(7, 4, 0)
Non rot.	(10, 3, 1)	(6, 10, 2)	(2, 12, 3)	(2, 12, 5)
SOCO'10	(10, 3, 1)	(5, 10, 2)	(1, 12, 3)	(1, 12, 2)
CEC'05	(8, 2, 5)	(8, 3, 0)	(8, 3, 1)	(8, 4, 3)
Total	(18, 5, 6)	(13, 13, 2)	(9, 15, 3)	(9, 16, 5)

PSO6-Mtsls number of (win, draw, lose)

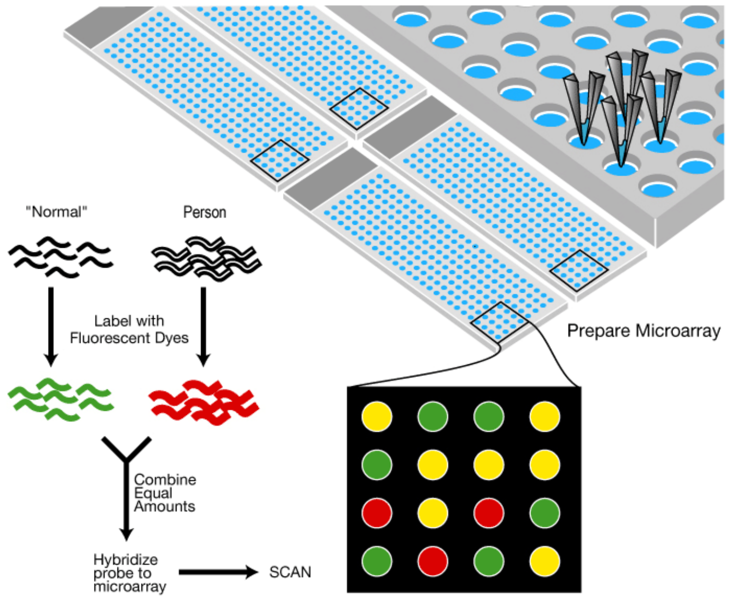
50 - CEC'05+SOCO'10	
PSO6-Mtsls	**(23/40)**
IACOr-Mtsls	**(21/40)**
IPSO-Mtsls	(18/40)
IPSO-Powell	(14/40)
G-CMA-ES	(11/40)

Part III

Real World Applications

Gene selection in DNA Microarrays

- **DNA Microarrays** allow scientists to simultaneously analyze thousands of genes, thus providing important insights about cells' functions

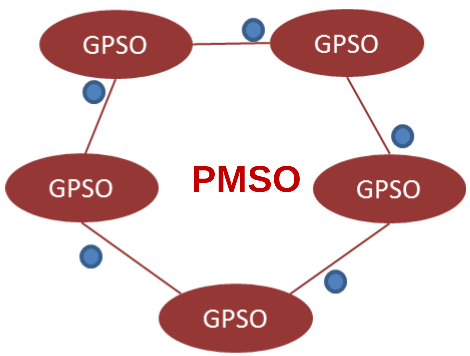


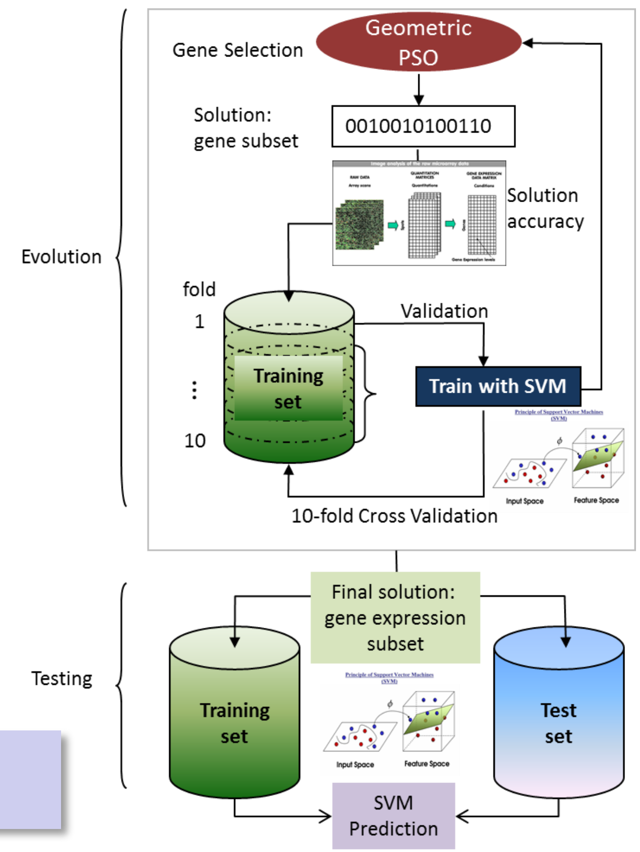
- Involving a vast amount of data
- Machine learning techniques can help us to discover subsets with high predictive power: ***classification***
- complex and costly (computationally speaking)
- An intelligent reduction pre-process is required: ***feature selection***

Objective: to discover small subsets of genes able to predict the class of an external (independent) gene sample as much as possible

Parallel Multi-Swarm Optimization

- Our proposal, **PMSO**: island model Geometric PSO for binary optimization
- **3PMBCX** particle's movement operator in GPSO is specially well adapted to feature selection (*García-Nieto et al. CEC'07*)





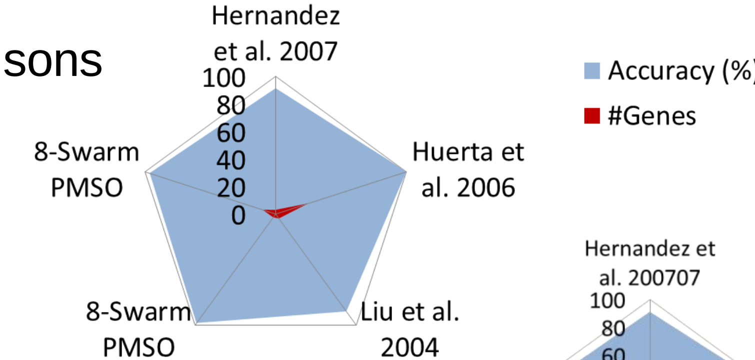
- Classification & validation: SVM with 10-fold cross-validation
- Final validation with external test set

[GA12] J. García-Nieto, and E. Alba. **Parallel Multi-Swarm Optimizer for Gene Selection in DNA Microarray**. Applied Intelligence (2012)

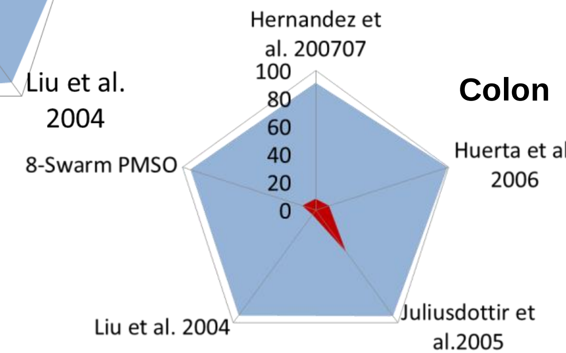
Results

- PMSO: **performance** results & comparisons
  - On four real datasets:
    - AML-ALL Leukemia
    - Colon
    - Lymphoma
    - Lung

Kent Ridge Bio-medical Dataset



AML-ALL Leukemia



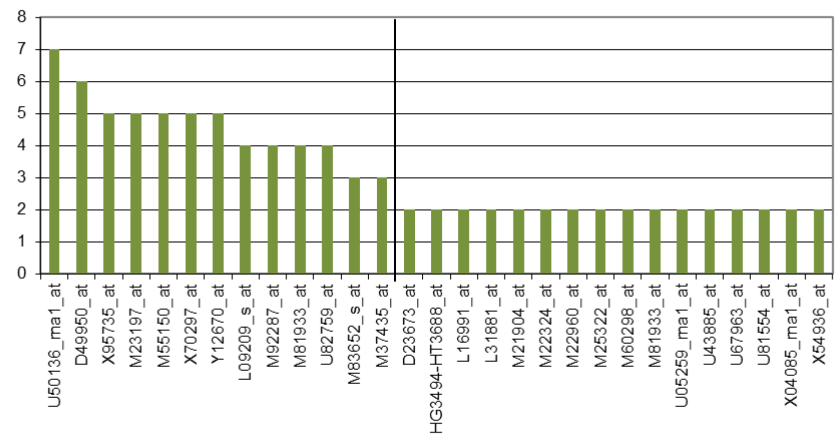
Colon

Island Config.
8-Swarms
4-Swarms
2-Swarms
1-Swarm

8-Swarms PMSO: best configuration in terms of **accuracy** and **speed-up**

- **Biological validation**: most frequently selected genes by PMSO also suggested by the reference literature:

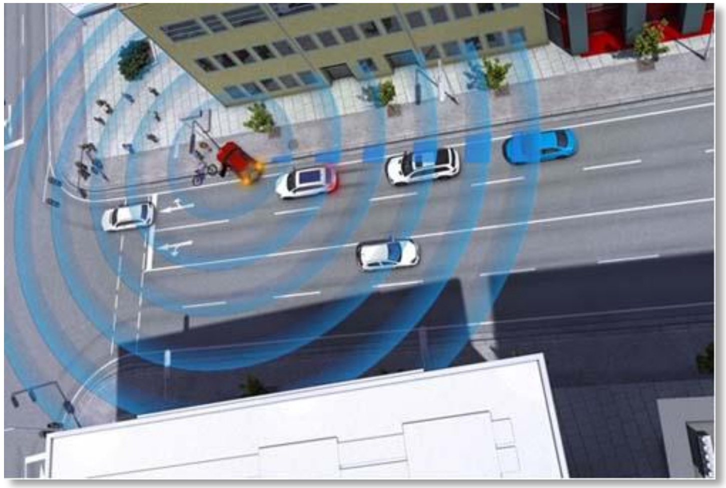
  Science (Golub et al. 1999) for Leukemia
  Nature (Alizadeh et al. 2000) for Lymphoma



Protocol Configuration in VANETs

- **Vehicular Ad Hoc Networks (VANETs)** are composed of a set of communicating vehicles (nodes) equipped with devices which are able to spontaneously interconnect to each other without any pre-existing infrastructure

- VANETs implications:
  - no service provider
  - limited coverage
  - high dynamism
  - non structured topology



- VANETs applications:
  - safety
  - traffic management
  - defense
  - transportation

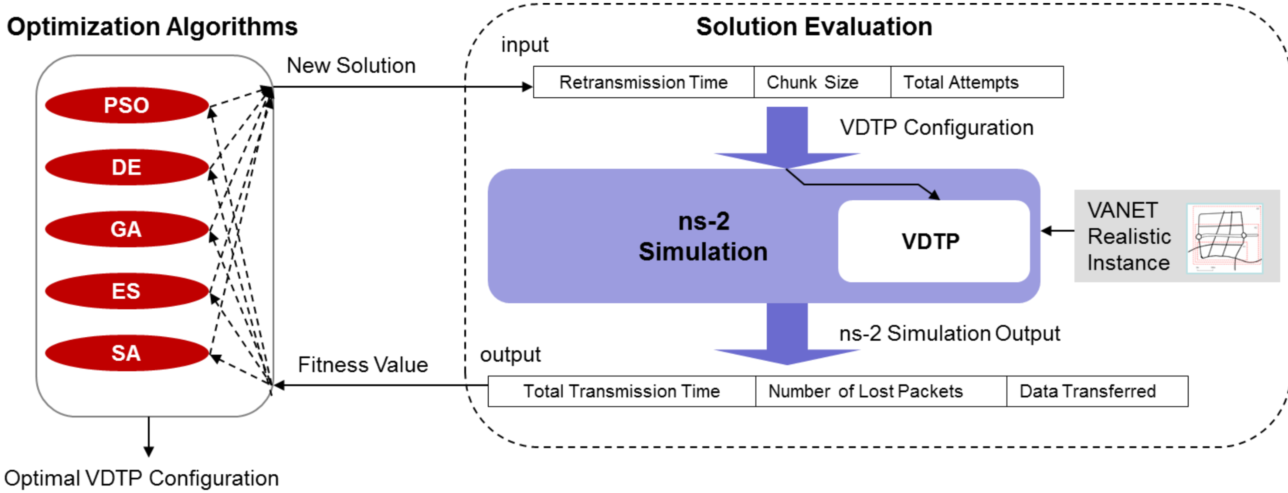
Objective: to find optimized sets of parameters to fine-tune communication protocols in VANETs

- In our case, **VDTP** application protocol in the scope of the CARLINK-CELTIC European project

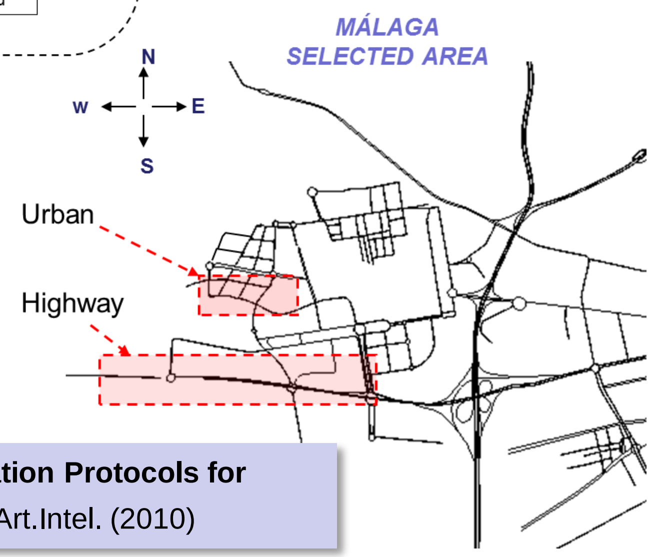
CARLINK CELTIC Telecommunication Solutions

Protocol Configuration in VANETs

- Optimization strategy: PSO for off-line simulation (*Ns-2*)



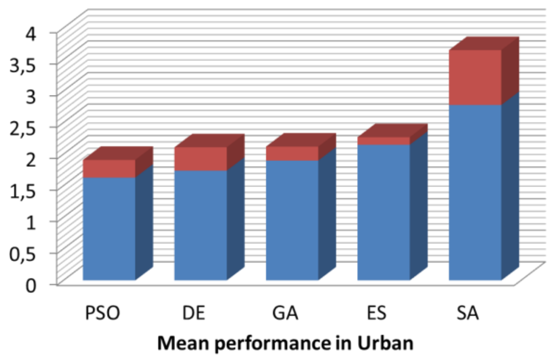
- Two realistic VANET scenarios at Málaga:
  - Urban
  - Highway

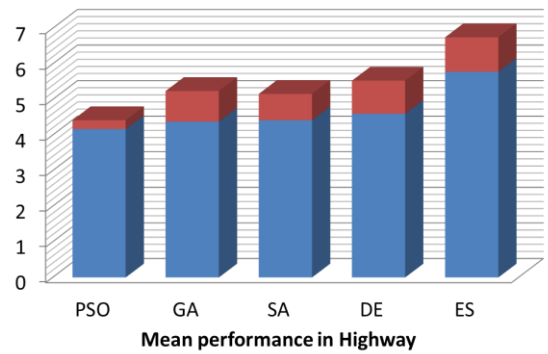


[GA12] J. García-Nieto, and E. Alba. **Automatic Tuning of Communication Protocols for Vehicular Ad-Hoc Networks Using Metaheuristics**. Eng. Apps of Art.Intel. (2010)

Results: Performance & QoS

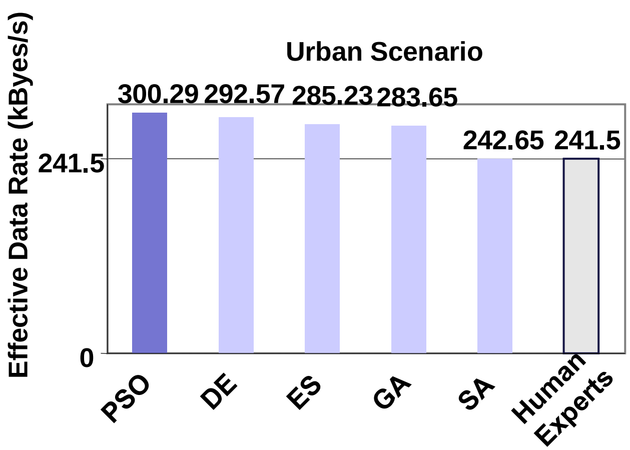
- Four algorithms to compare with: **DE, GA, ES, SA**

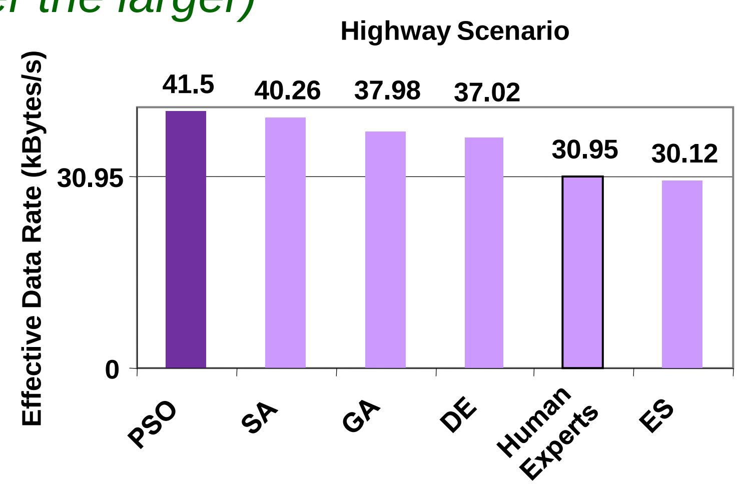




PSO: shows the best configuration in terms of **effective data rate**

- **QoS** results: *effective data rate (the better the larger)*





Signal Light Timing Programs

- Nowadays, the intense vehicular traffic in current cities provokes severe problems related to: pollution, congestion, security, noise, and many others

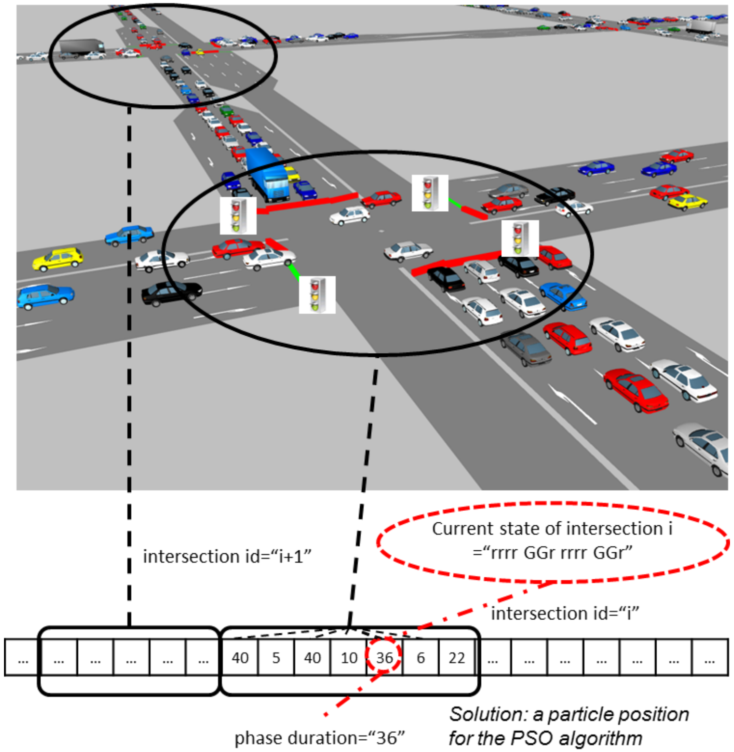
- Signal lights (SL) are configurable devices that partially control the flow of vehicles. However, the increasing number of SL's require a highly complex scheduling

Objective: **to find optimized timing programs (TPs) for all the SLs in a given area.**

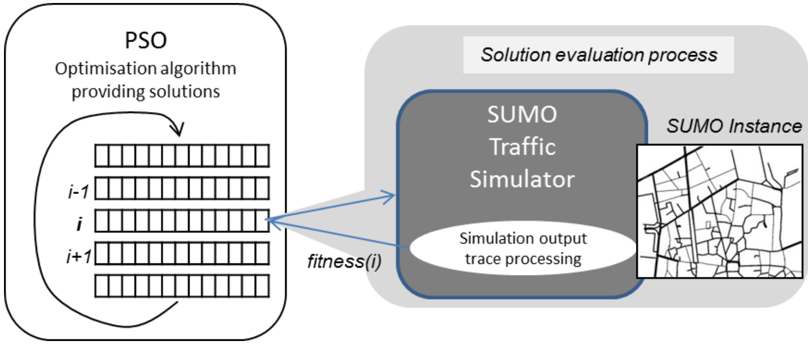
- **Our proposal**: **PSO-SL** coupled with SUMO, to **automatically search quasi-optimal solutions**

Strategy for Signal Lights

- Solution encoding: vector of integers where each element represents a phase duration of one state of SLs in intersections (SUMO structure of TPs)



- Optimization strategy: optimization algorithm (PSO) with offline simulation procedure (SUMO)



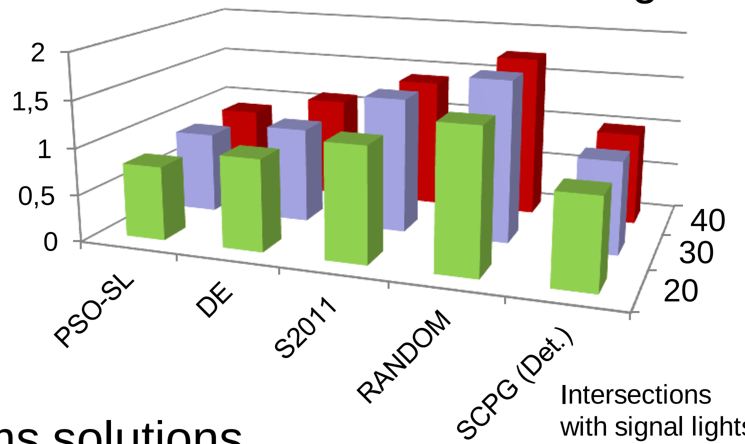
- Two realistic instances located at Málaga (Spain) and Bahía-Blanca (Argentina) from real digital maps

[GOA12] J. García-Nieto, E. Alba and C. Olivera. **Swarm intelligence for traffic light scheduling: Application to real urban areas**. Eng. Apps of Art.Intel. (2012)

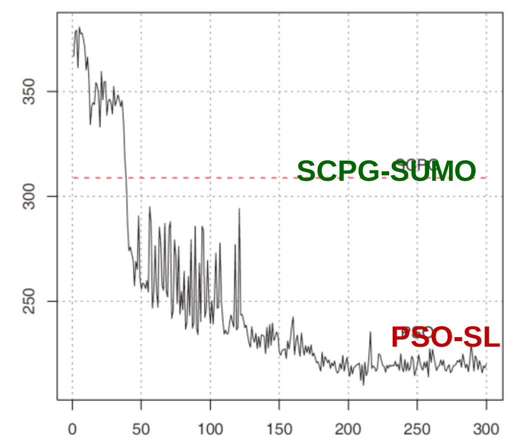
Results: Performance & Resulting Traffic

- Comparison of PSO-SL with other four strategies

PSO-SL shows better performance than the other techniques

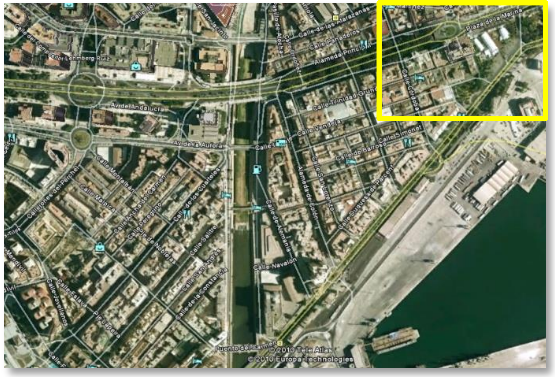


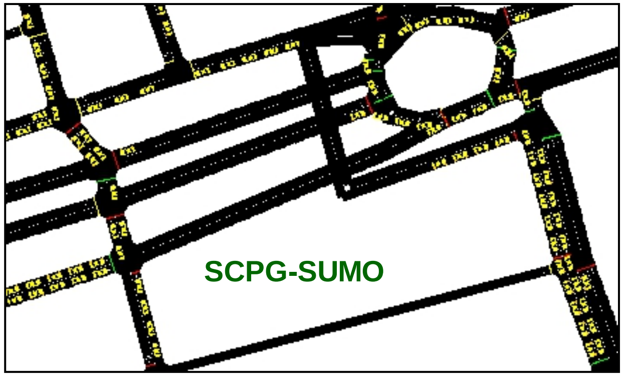
Overall journey time of all the vehicles

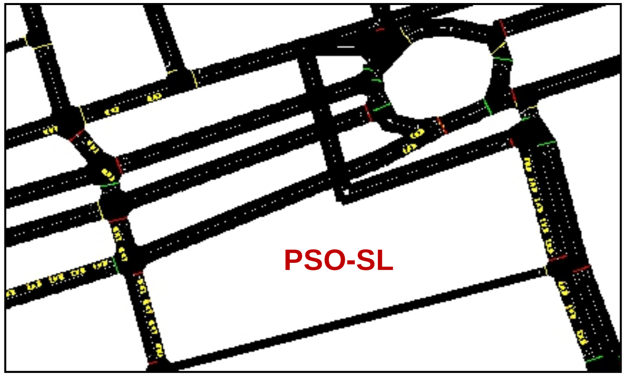


- Timing programs solutions

Reported timing programs alleviate the traffic congestion







Part IV

Conclusions and Future Work

General Conclusions

- Methodology
  - **Velocity modulation** avoids particles to move out of the search problem ranges. This is a good starting PSO for multimodal problems
  - A number **of 6 ± 2 informant particles** in the neighborhood makes the PSO to perform better than other combinations (like 2, as in the Standard PSO)
  - Hybridizing with **advanced LS** methods and **DE operators** mitigates the deficiencies observed in PSO when tackling **non-separable** problems

DEPSO	Successful results on CEC'05 and BBOB'09
RPSO-vm	Scalability analysis in the scope of SOCO'10
SMPSO	Well adapted to multimodal problems: ZDT, DTLZ, WFG
PSO6	Thorough analysis of the number of informants: CEC'05
PSO6-Mtsls	Located in the top of S.O.A. on continuous optimization: CEC'05+SOCO'10

General Conclusions

- Algorithmic proposals

Mechanism	Description	Proposals
Hybridization	Using differential evolution operators and advanced local search methods	**DEPSO** **PSO6-Mtsls**
Standard Improvement	Outperforming S.O.A. proposals	**RPSO-vm** **PSO6**
Multi-objective	Accurate computation of the optimal Pareto Front	**SMPSO**
Parallelism	Running sub-swarms in parallel	**8 Swarm-PMSO**

General Conclusions

- Real world applications
  - PSO is an excellent **general purpose optimizer** showing a successful performance for the three real world problems tackled here
    - **Most frequently selected genes** by PMSO also suggested by the reference literature: Nature & Science
    - Reported VANET protocol configurations improve over **human experts**
    - Resulting timing programs **alleviate traffic congestion** in realistic scenarios

PMSO	Parallel multi-swarm Geometric PSO 8 Island-swarm performs the best in terms of accuracy & speedup
PSO-SL	Adaptation to integer encoding Outperforms Standard 2011 and DE

Conclusions

Part IV

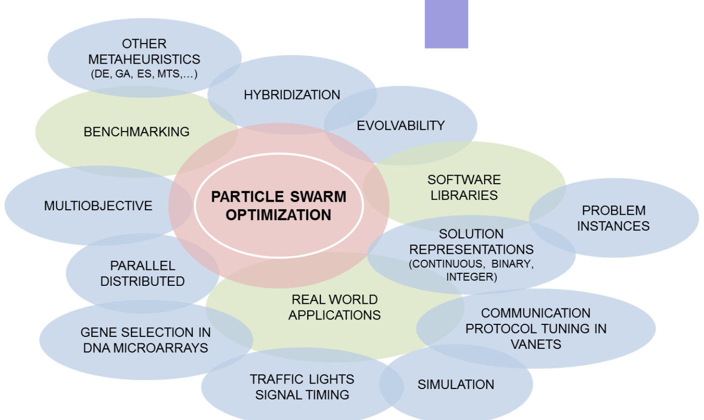
Our PSO proposals are **first class base-line optimizer** able of the best performance in modern benchmarking, as well as in present real-world optimization problems

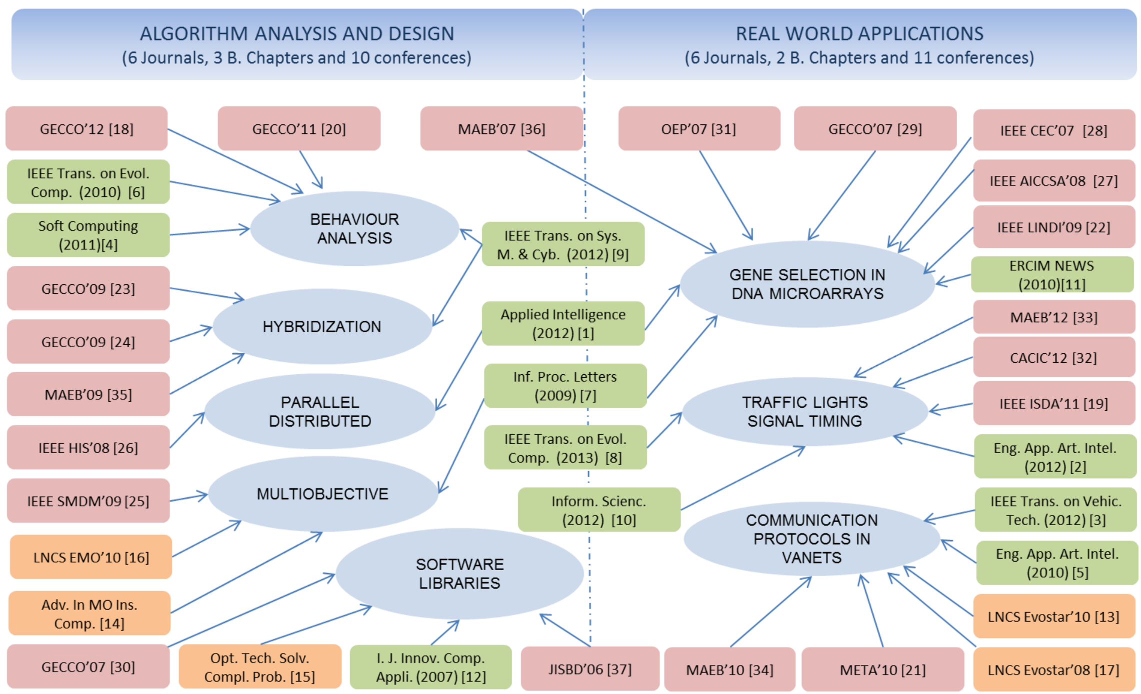
Results

(12 Journals, 5 B. Chapters, and 22 conferences)

PhD Thesis

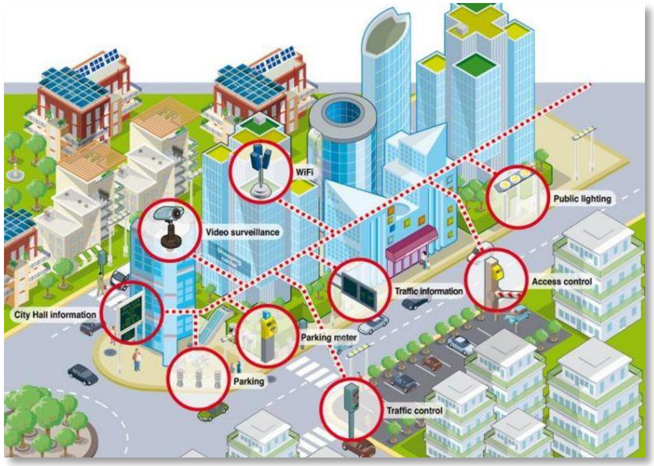
Topics to consider





Future Work

- Adaptive sets of informant neighbors (in run time)
  - Finding the best trade-off for exploitation-exploration
- Facing dynamic problems
  - Signal light timing programs on dynamic traffic environments
- Reducing vehicle emissions and fuel consumption
  - Optimized timing programs for green smart cities
- Deploying Swarms in Smart Devices
  - Design and development of particles running on smart terminals: phones, tables, vehicle's comp., drones, etc.; to deploy physical swarms



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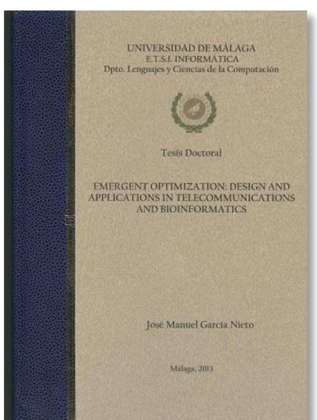
Thank you so much!!!

NEO

Comments & Questions

Emergent Optimization: Design and Applications in Telecommunications and Bioinformatics



PhD Thesis Dissertation

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