Procesamiento Paralelo para Problemas Multiobjetivo en Entornos Dinámicos

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Contents

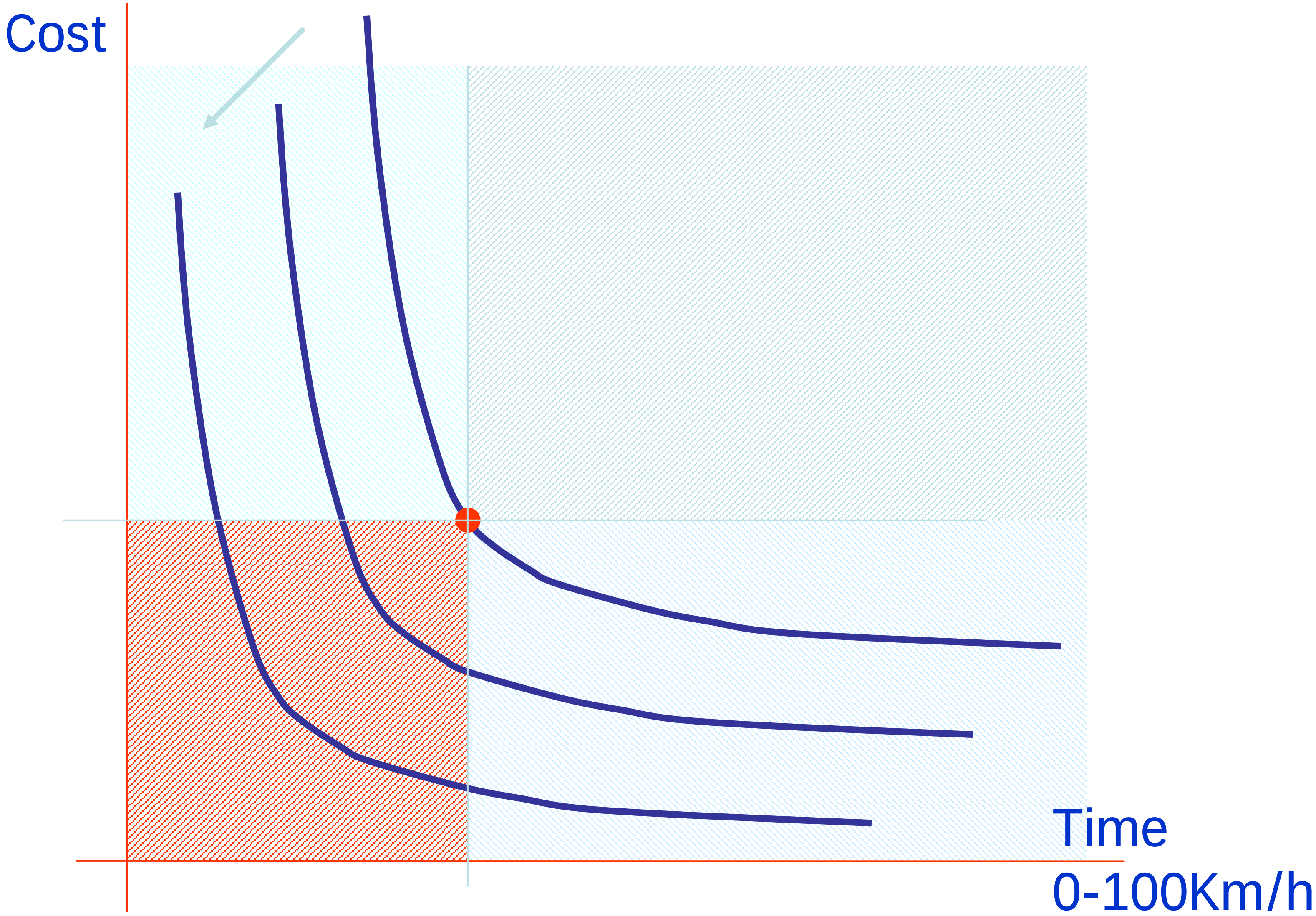
Introduction: Multi-objective Problems (I)

- Problems which have more than one objective function (frequently in conflict) to be optimized.

- There is not one unique optimal solution, but a set of solutions that are not worse than any of the rest.

- This set is called the Pareto optimal set (of solutions).

Introduction: Multi-objective Problems (II)



Introduction: Dynamic Multi-Objective Problems

- Problems in which the conditions or restrictions change over time, and so do the corresponding solutions at every instant.

- Most of the engineering problems are dynamic in nature.

- Examples: Scheduling, Resource allocation, Network exploitation (telecommunications, logistics, hydraulics, gas pipelines, etc)

Introduction: Dynamic Multi-Objective Problems

The problem of finding a **decision variable vector**

$$\mathbf{x^*(t)} = [x_1^*(t), x_2^*(t), \ldots, x_n^*(t)] \in R^n$$

satisfying a given restriction set

$$\mathbf{g}(\mathbf{x},t) \leq 0, \mathbf{h}(\mathbf{x},t) = 0$$

and **optimizing the function vector**:

$$\mathbf{f}(\mathbf{x},t) = \{f_1(\mathbf{x},t), f_2(\mathbf{x},t), \ldots, f_m(\mathbf{x},t)\}$$

Introduction: previous works

Multi-objective Evolutionary Algorithms

- Average funtions,
- VEGA (1984), *Schaffer*
- MOGA (1993), *Fonseca*
- NSGA-II (2000), *Kalyanmoy Deb*
- SPEA2 (2001), *Eckart Zitzler*

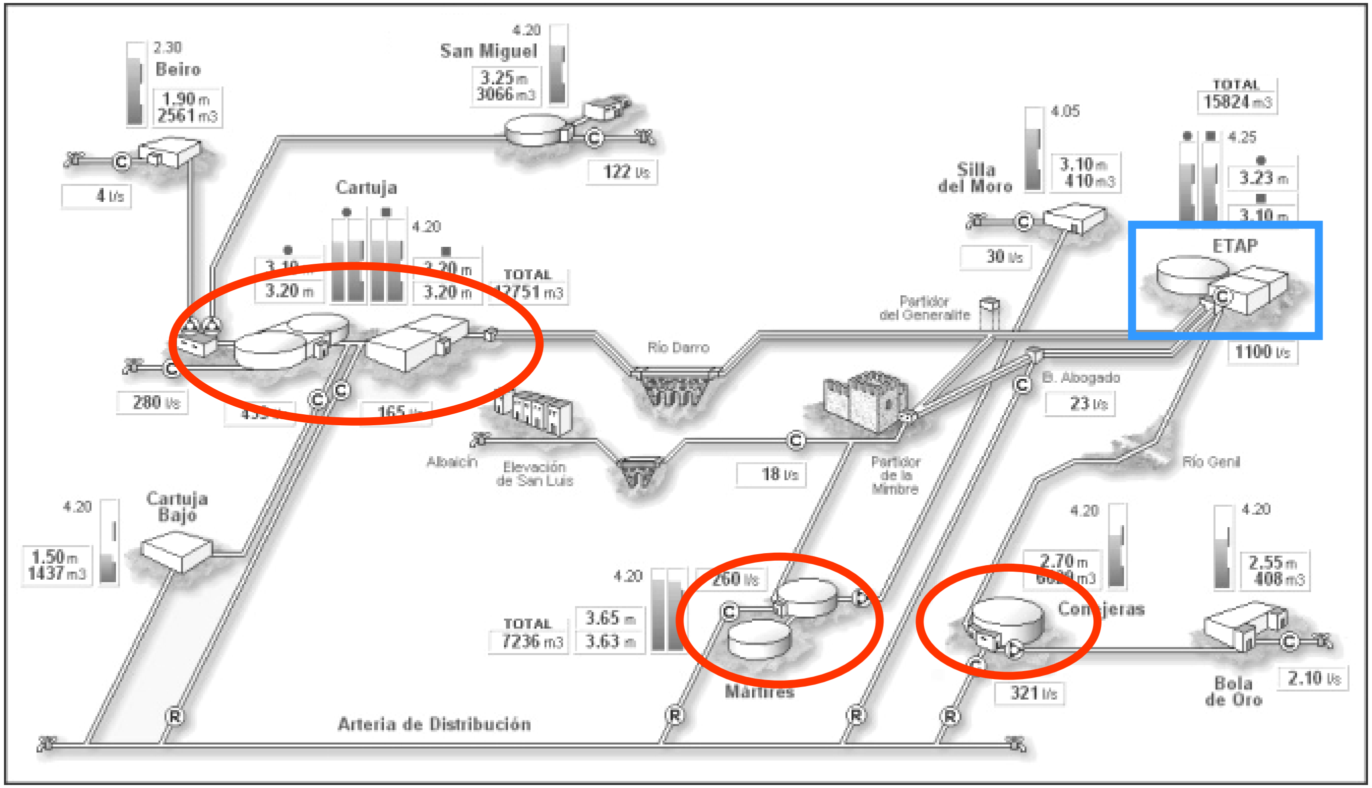
EvoDOP: http://www.aifb.uni-karlsruhe.de/mailman/listinfo/evodop

Parallel Processing

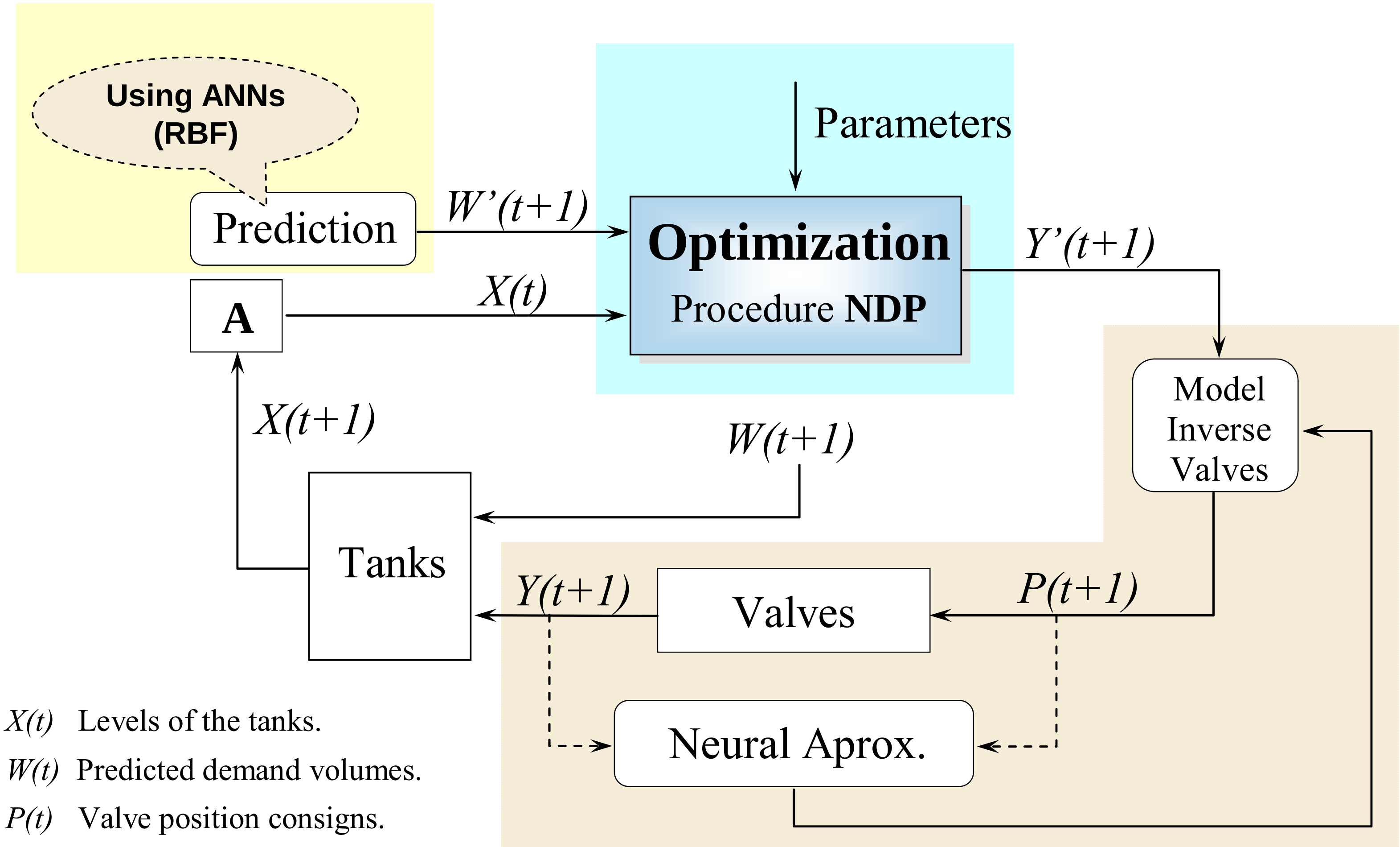
- MOGADES (2002), *Kamiura*
- Parallel NSGA-II (2004), *Sergio Nesmachnow*
- PSFGA (2004):
    - F. Toro, J. Ortega, E. Ros, S. Mota, B. Paechter, J. M. Martín, *PSFGA: Parallel Processing and Evolutionary Computation For Multiobjective Optimisation*, Parallel Computing 30 (5–6) (2004) 721–739.
    - F. Toro, E. Ros, S. Mota, J. Ortega, *Evolutionary Algorithms for Multiobjective and Multimodal Optimization of Diagnostic Schemes*, IEEE Trans. on Biom Eng.53 (2006)

Dynamic Multi-Objective Problems: Example (I)

Poblem of Control of Water Supply Network: distributing the flow that the water treatment station (*ETAP*), such that demand is satisfied, the tanks neither overflow nor fall below an established minimum water volume, and minimize valve movements.



Dynamic Multi-Objective Problems: Example (II)



X(t) Levels of the tanks.

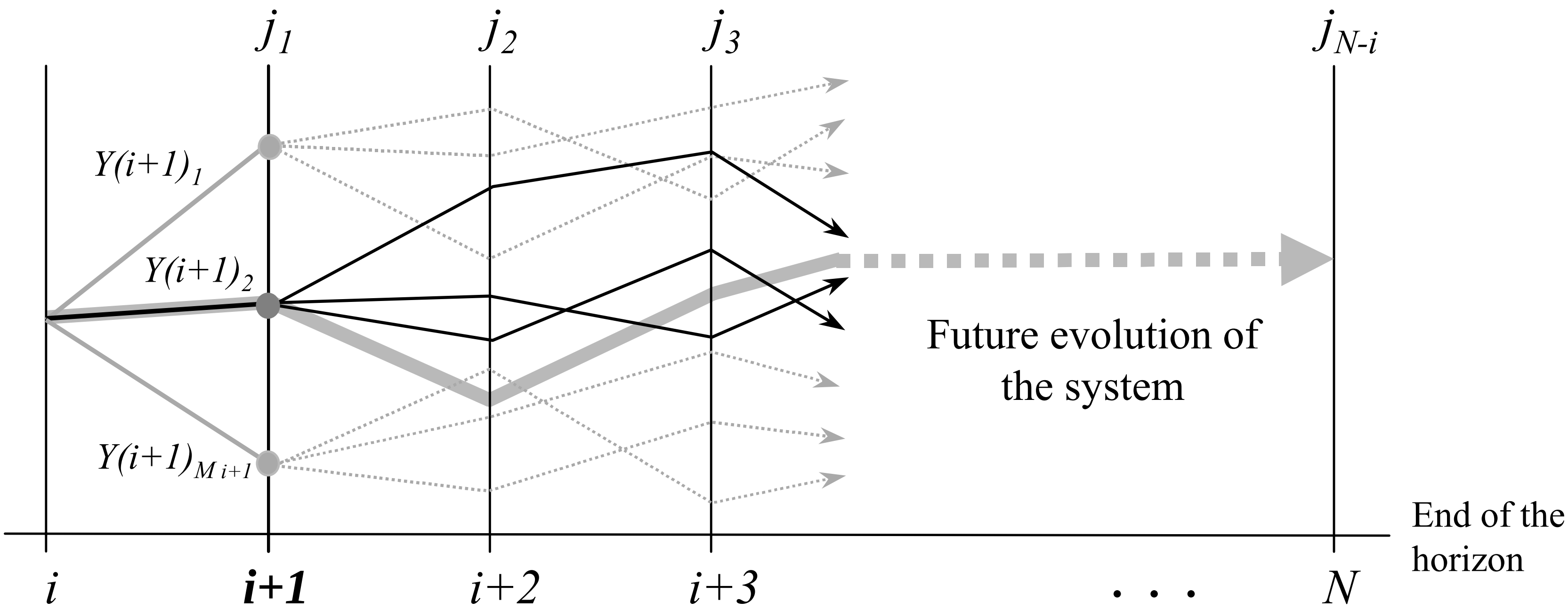
W(t) Predicted demand volumes.

P(t) Valve position consigns.

***Y(t)* Tank inputs volumes.**

Dynamic Multi-Objective Problems: Example (III)

- With predicted input vectors module simulation can estimate sets of feasible control values for the following stages, and generate sample trajectories in order to approximate the cost-to-go function at stage i+1:



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Parallel Processing: Expected Benefits

It is expected to get better performance

Regarding to the **multi-objective problem:**

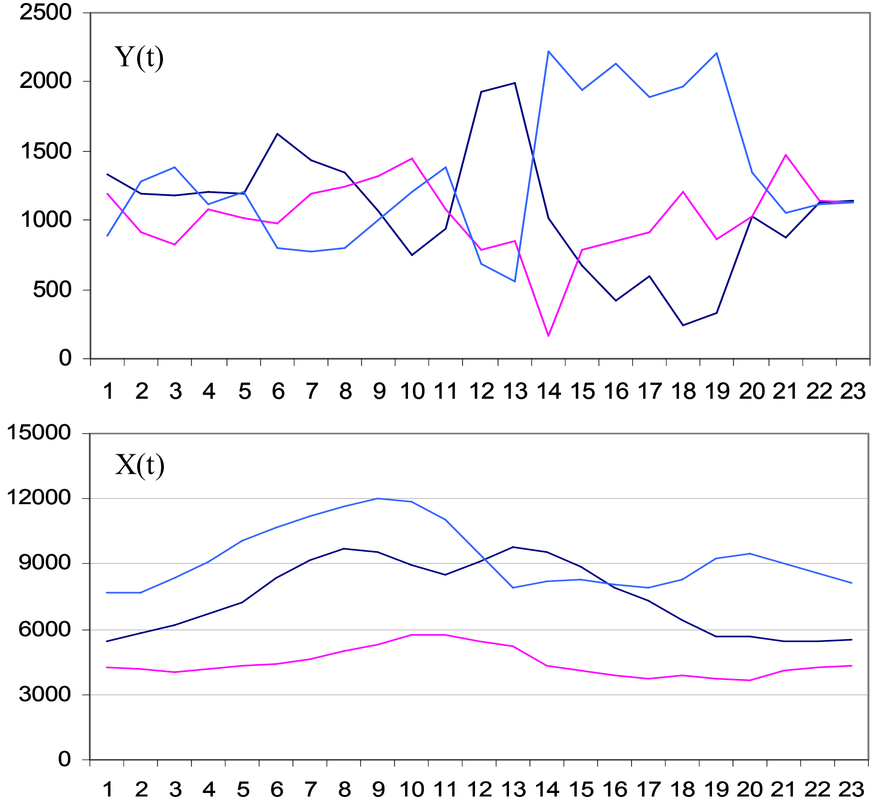
1. Solutions lying nearer to the actual Pareto front, and
2. More diversified solutions.

Regarding to the **dynamic problem:**

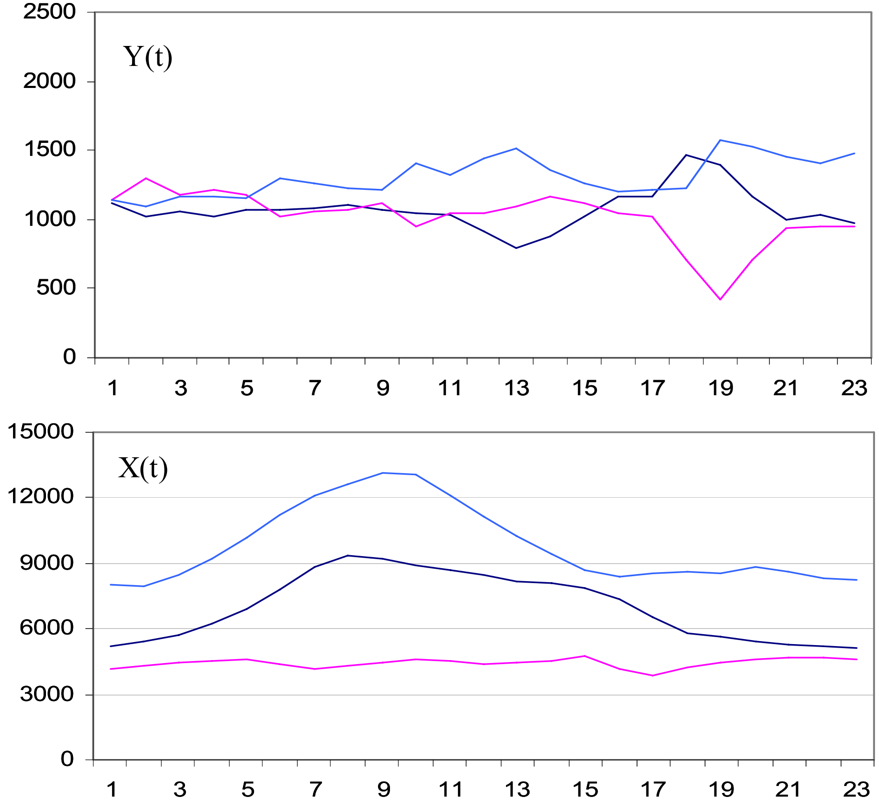
1. To get solutions suitable for the new problem conditions, before they will be needed, and
2. To be able to meet more restrictive time limits, by means of increasing the necessary resources for the solutions processing.
3. Diversity control (after changes and during execution)

Parallel Processing: Example (I)

- Improve the performance of the control procedure as more processors:



Results using only one of the processors



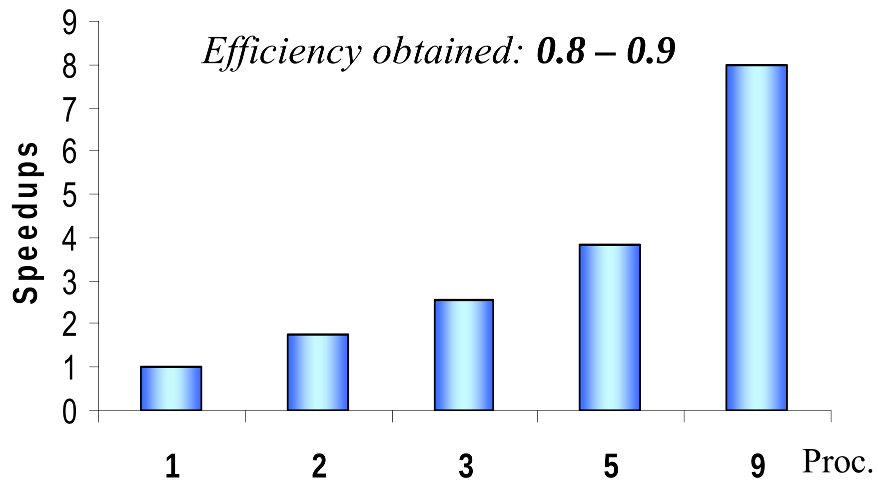
Results using eight processors

Parallel Processing: Example (II)

- Computing times and the speedups obtained by the parallel implementation of the procedure, using the PVM message-passing library in a cluster of 9 PCs

Proc./ Traj.	**8 Traj.**	**16 Traj.**	**32 Traj.**
1 Proc.	42,0 min.	74,7 min.	145 min.
4 Proc.	13,9 min.	25,6 min.	48,5 min.
8 Proc.	7,8 min.	11,1 min.	20,1 min.

Computing times for different number of trajectories and processors



Speedup obtained for 9 trajectories

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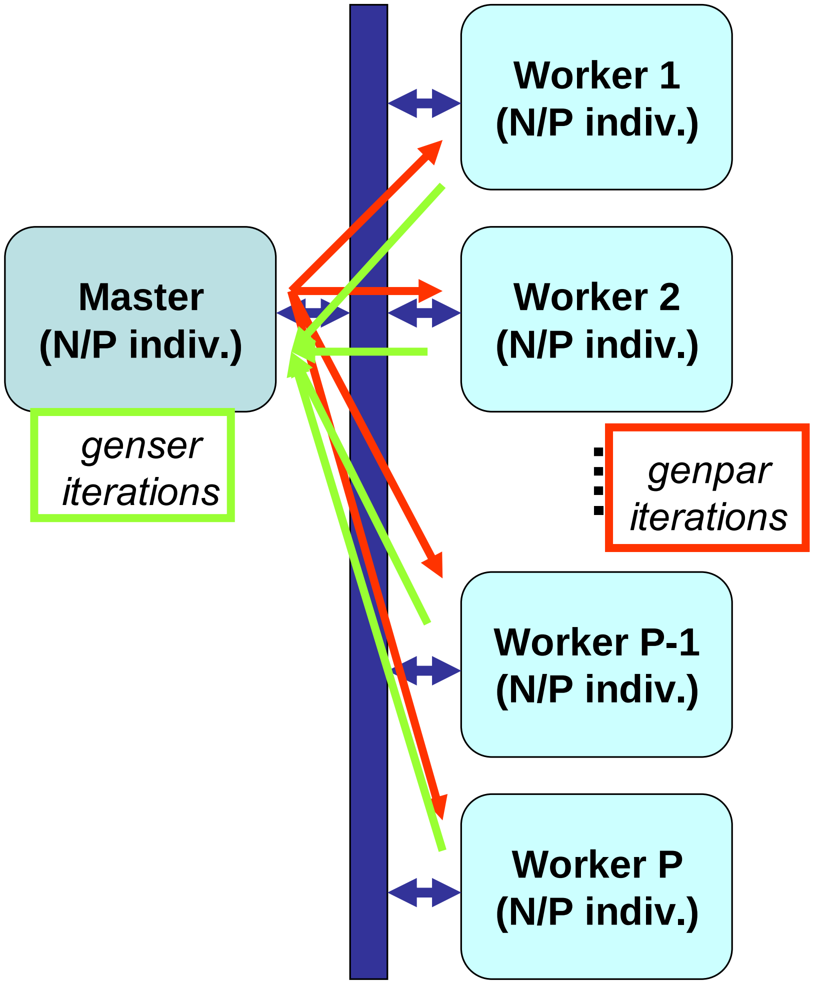
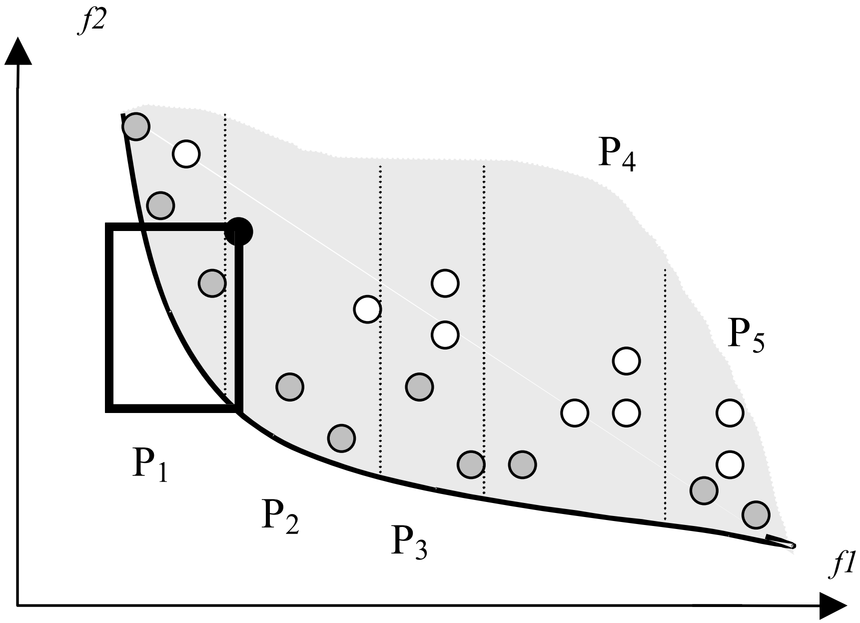
Description of the PSFGA Algorithm (I)

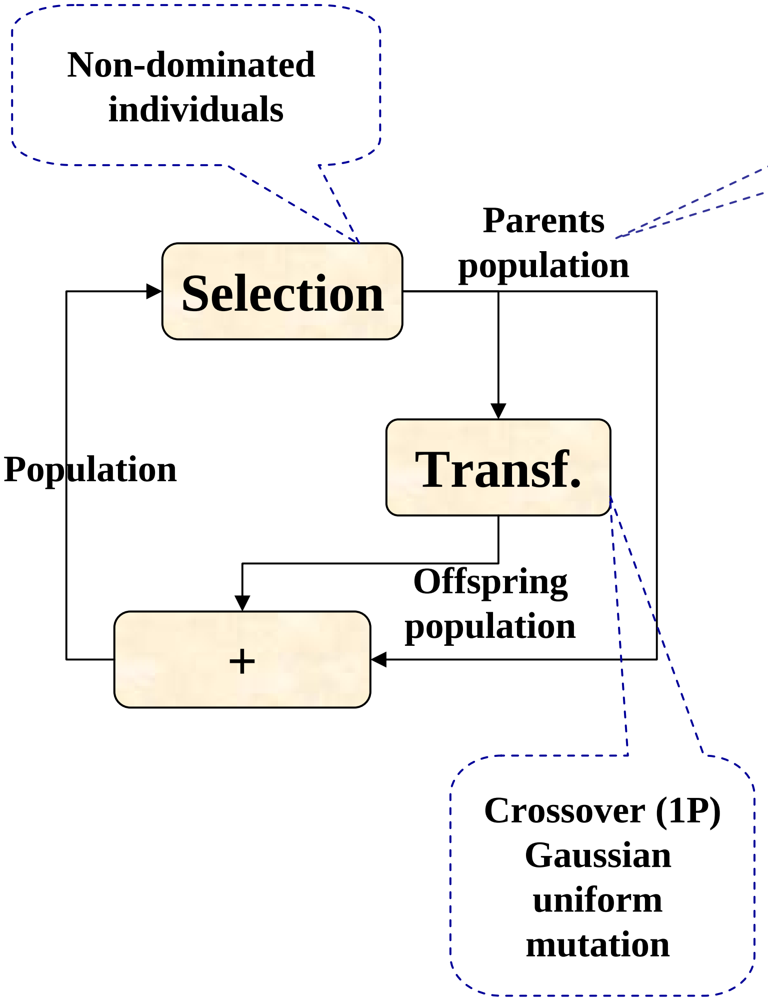
- In PSFGA, a master process generates ***subpopulations*** which are distributed among the worker processes,
- The workers will run the EA on the ***subpopulations*** during ***genpar*** iterations,
- After ***genpar*** iterations, the master receives the ***subpopulations***, runs the algorithm over the whole population (***genser*** iterations) and **selects the new population** to be distributed among the workers or to give as results to the problem,
- Selection is carried out from the **non-dominated** solutions which after **crossover** and **mutation** will generate the offspring.

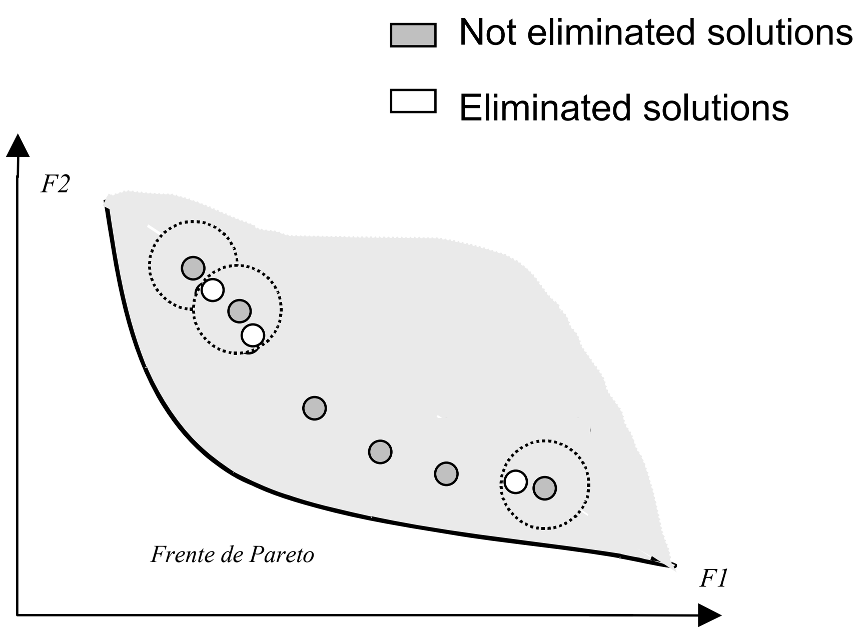
Description of the PSFGA Algorithm (II)





Description of the PSFGA Algorithm (III)





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Evaluation of the Algorithm

- Accuracy

$$acc(t) : \text{quality of the solution (in terms of } V(t), V_{max}(t), V_{min}(t)\text{)}$$

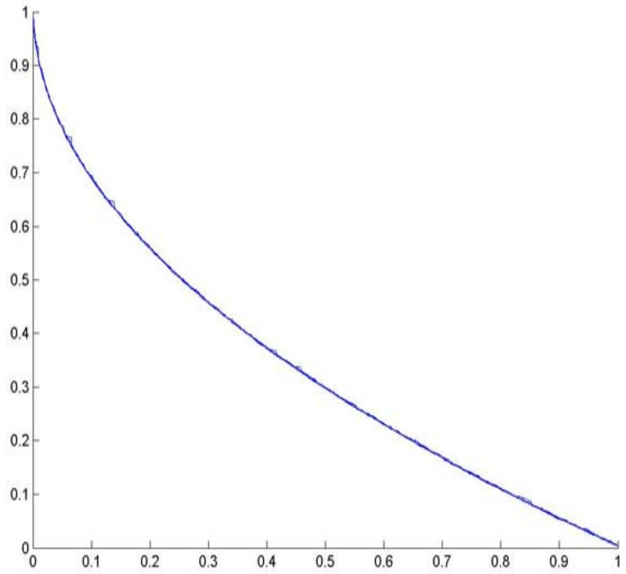
- Stability

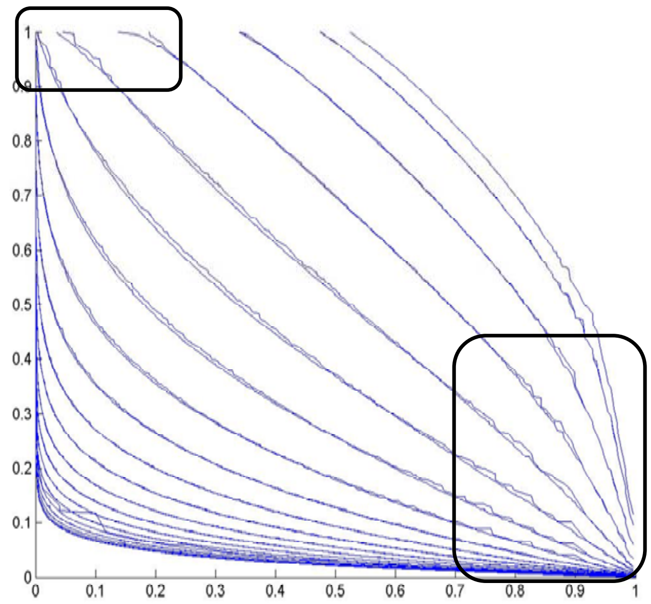
$$stb(t) = \max\{0, acc(t-1) - acc(t)\}$$

- Reaction

$$\mathrm{reac}(t,\varepsilon) = \min\left\{ t'-t \text{ such that } \left\{ \begin{array}{l} t < t' \leq \mathrm{Mgen} \\ \dfrac{\mathrm{acc}(t')}{\mathrm{acc}(t)} \geq (1-\varepsilon) \end{array} \right\} \cup \{\mathrm{Mgen} - t\} \right.$$

Experimental Results: Test Problems





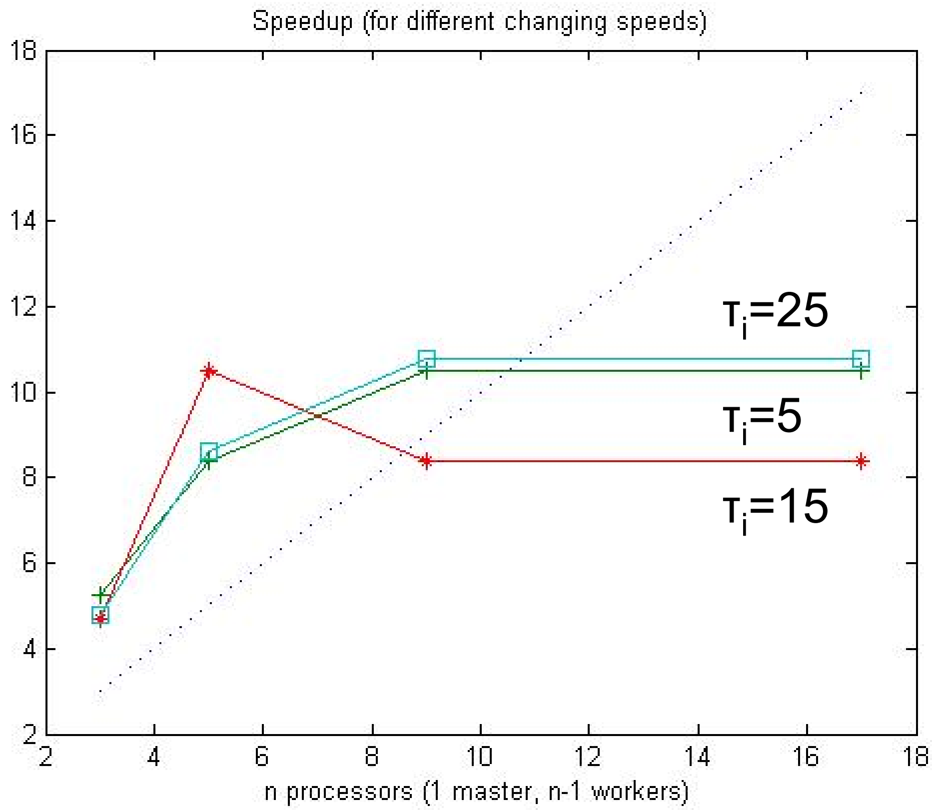
FDA1

$$f_2 = 1 - \sqrt{f_1}$$

FDA2

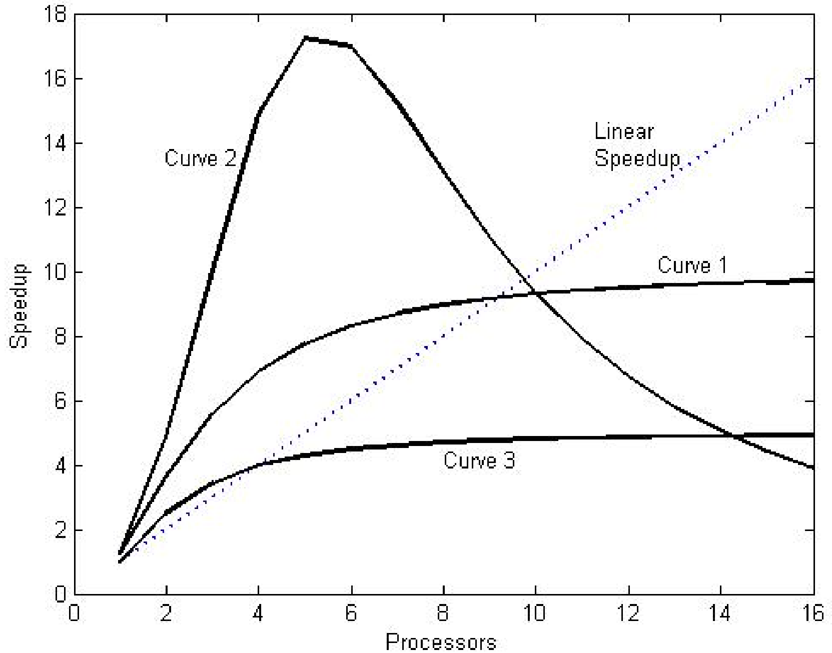
T intervalo entre cambios

Experimental Results: Speedup (I)



FDA2

Experimental Results: Speedup (II)



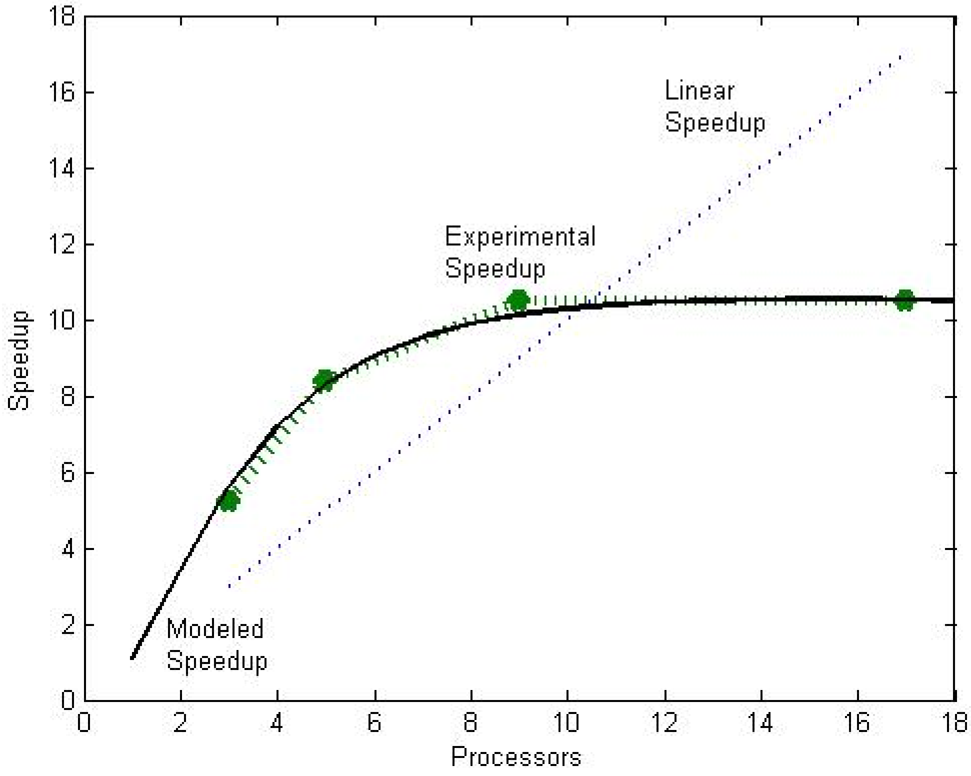
Ganancias Superlineales:

genser+genpar<gen

Mejores condiciones de diversidad y necesita menos iteraciones para alcanzar soluciones similares

$$S(P)=\frac{gen\times\left[(A\times M\times t_0)+(B\times M^r\times t_1)\right]}{genser\times\left[(A\times M\times t_0)+(B\times M^r\times t_1)\right]+genpar\times\left[(A\times\left(\frac{M}{P}\right)\times t_0)+(B\times\left(\frac{M}{P}\right)^r\times t_1)\right]+O(M,P)}$$

Experimental Results: Speedup (III)

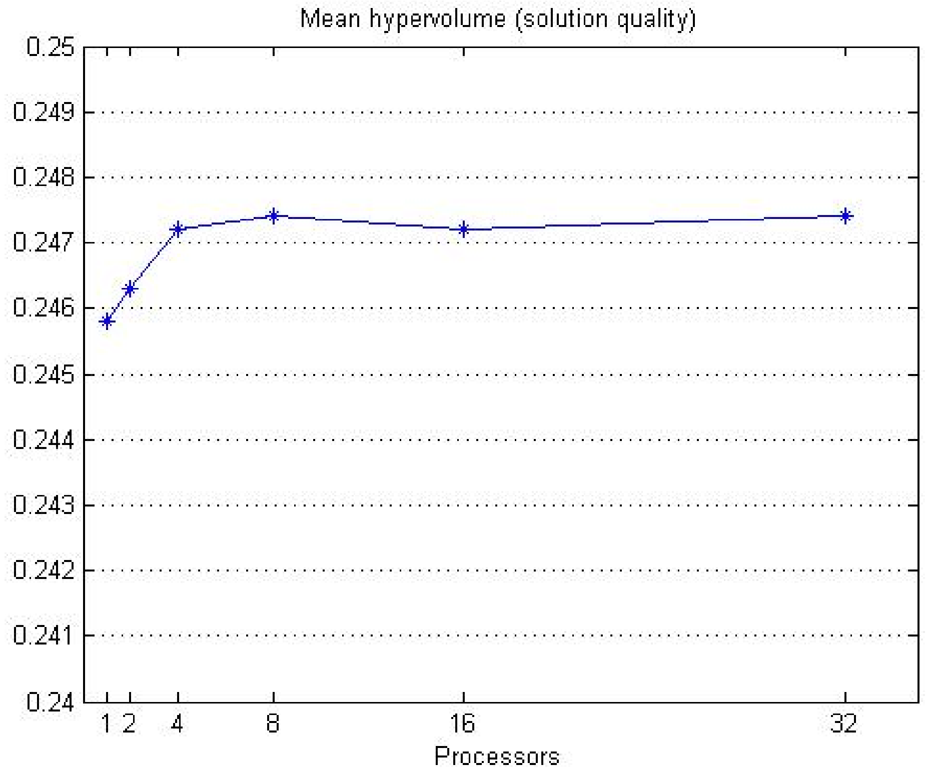


Experimental Results: Solution Quality

τ_i	Hiperv. (± 0.005)	acc (± 0.01)	stb (± 0.001)	reac (ε = 0.1)
5	0.345	0.97	0.0	5
10	0.350	0.99	0.0	5
15	0.355	1.00	0.0	5
20	0.347	0.98	0.020	5
25	0.352	0.99	0.0	5
30	0.347	0.98	0.014	5
35	0.347	0.98	0.0	5
40	0.344	0.97	0.010	5
45	0.349	0.98	0.00	5
50	0.345	0.97	0.009	5

FDA2

FDA1



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Conclusions and Future Work

- Parallel processing:
  - New schemes to distribute all or part of the selection process carried out by the master among the workers.
  - To study the way parallelism can improve diversity and convergence (emergent properties)
- Algorithm:
  - To add more test problems and real applications.
  - To study new adaptation and prediction strategies.

References

- Damas, M.; Salmerón, M.; Ortega, J.; Olivares, G., Pomares, H.:"Parallel Dynamic Water Supply Scheduling in a Cluster of Computers". *Concurrency: Practice and Experience,* Vol.13, pp.1281-1302, 2001
- F. Toro, J. Ortega, E. Ros, S. Mota, B. Paechter, J. M. Martín, "*PSFGA: Parallel Processing and Evolutionary Computation For Multiobjective Optimisation"*, Parallel Computing 30 (5–6) (2004) 721–739.
- F. Toro, E. Ros, S. Mota, J. Ortega, "*Evolutionary Algorithms for Multiobjective and Multimodal Optimization of Diagnostic Schemes"*, IEEE Trans. on Biom Eng.53 (2006)
- Cámara, M.; Ortega, J.; Toro, F.J.:"*Parallel Processing for Multi-Objective Optimization in Dynamic Environments*". Workshop on NIDISC, IPDPS'07, 2007.
- Cámara, M.; Ortega. J.; Toro, F.J.:"*The Parallel Single Front Genetic Algorithm (PSFGA) in Dynamic Multi-Objective Optimization*". International Workshop in Artificial Neural Networks (IWANN'07), 2007.