Application of metaheuristics to task-to-processors assignation problems

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Why metaheuristics?

- We use metaheuristics in different scientific problems
  … but we are not alone
- This presentation describes our experience with tasks mapping problems
- A common algorithmic scheme is used for the different metaheuristics
- A hierarchy of classes is proposed

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Contents

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- Components
  - 2 doctors
  - 10 PhD students, from the:
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Presentation of the Parallel Computing Group - University of Murcia

- Projects
  - Regional: **Adaptation and Optimization of Scientific Codes in Hierarchical Computational Systems**
    Collaboration with the Computational Electromagnetic group of the Universidad Politécnica de Cartagena
  - National: **Automatic Building and Optimization of Parallel Scientific Libraries**
    Collaboration with the universities: La Laguna, Jaume I of Castellón, Alicante, Politécnica de Valencia
  - Regional in preparation: **Solution of Biotechnology Problems with the Ben Arabí Supercomputer**
    Collaboration with the company Inbionova and the Plant pathology group

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- Applications
  - Orbits of artificial satellites - Observatorio Astronómico de la Armada Cádiz
  - Simulation of marine biosystems - Taxon Estudios Ambientales
  - Simultaneous equation models - Temporal series group, applications for medicine and psychology
  - Design of signal filters - Computational electromagnetic group
  - Physical engine of games - Centro de Supercomputación de Murcia
  - Biocatalizers - Inbionova
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Metaheuristics

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    Automatic obtention of model from a set of data
  - Design of signal filters
    Design of the filter to obtain a given response function
  - Molecule simulation
    Estimation of the parameters to obtain the function which describes an experiment
- Tasks-to-processors assignation problems
  - To automatically optimize the execution of parallel routines
    - For parallel algorithmic schemes
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Advantages of using metaheuristics

- General assignation problems are NP-complete
- Exact methods for specific problems, algorithms or systems
- In some cases the use of heuristics is satisfactory
- ... but in general it is not possible to obtain satisfactory assignations in a reduced time $\Longrightarrow$ metaheuristics
  - Provides a general framework for problems with different characteristics
    - Re-scheduling: new tasks, modifications in the system...
    - Hierarchical or distributed systems, on-chip systems...
  - Facilitates the development of different methods
  - Facilitates experimentation and tuning of the technique to the problem
  - Possible to combine different methods (hybridation)

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General metaheuristic scheme

Use of a scheme common to different metaheuristics

while not EndCondition(S) **do**
  if $|SS| > 1$ **then**
    $SS1$=Combine(SS)
  else
    $SS1 = SS$
  end if
  $SS2$=Improve($SS1$)
  S=IncludeSolutions($SS2$)
end while

General metaheuristic scheme

- A common scheme
  - New versions of a metaheuristic just by modifying a function or a parameter in the scheme
  - A new metaheuristic just by modifying some functions or parameters in the scheme
  - Hybrid metaheuristics just by combining functions from different metaheuristics
- Possible to develop a hierarchy of classes to facilitate the development of metaheuristics
- But a different infrastructure is necessary for each assignation problem

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Execution time model

- Our goal is to obtain the execution conditions which give the lowest execution time
- A model of the execution time is used. The model reflects:
  - The characteristics of the system
  - The possible modifications in the execution of the routine which should be selected to optimize the execution time

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Execution time model

- Parameters to be obtained:
  - Block size of computations
  - Block size of communications
  - ...
  - number of processors
  - number of processes
  - logical topology of the processes
  - processes to processors mapping...
- A large number of parameters, for which a general determination method is not available
- and for different problems, different heuristics or metaheuristics are preferable

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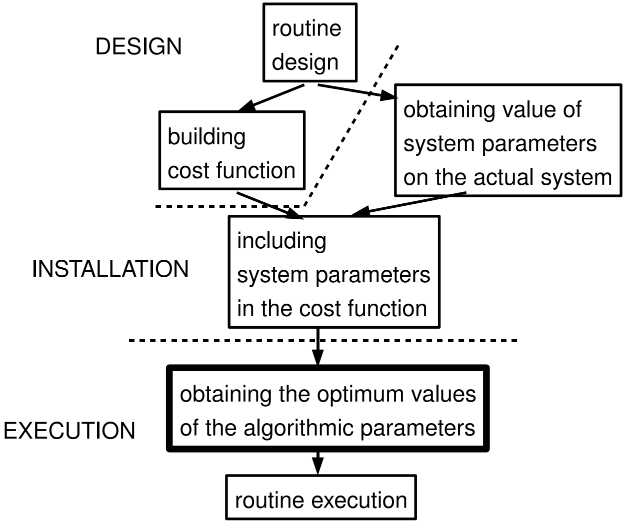
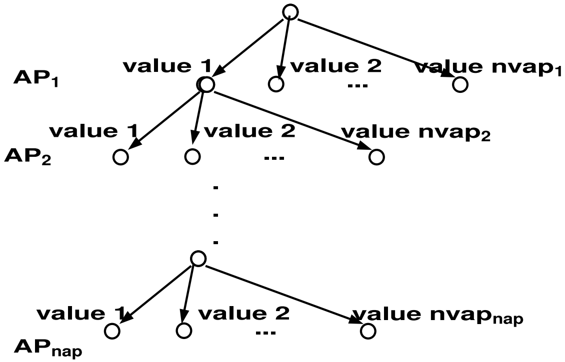
Optimization architecture



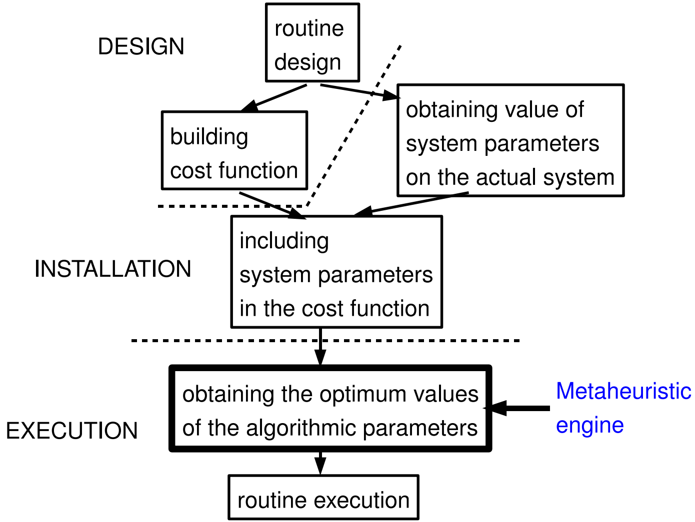
Decision tree

A large or huge decision tree



and it is impossible to use exact or analytical methods

Optimization architecture



Class hierarchy

- The development of a class hierarchy allows us to:
  - Reuse classes and methods
  - Add classes and methods
  - Develop new metaheuristics
  - Tune parameters and functions to the problem
  - Develop hybrid metaheuristics
  - Obtain a satisfactory metaheuristic for the problem
- but it is problem specific
- some typical problems could be included in the hierarchy
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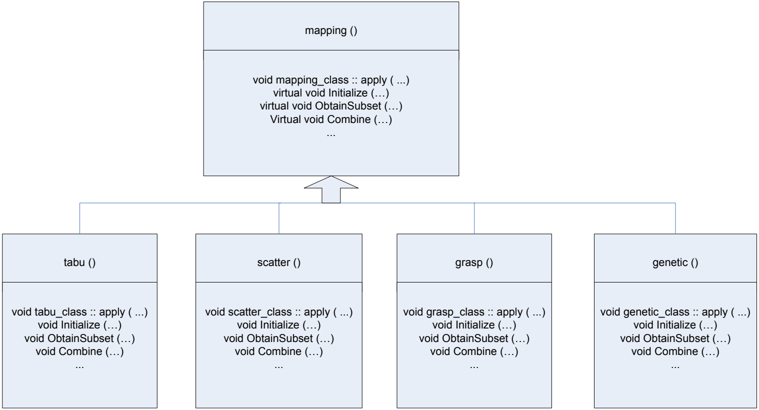
Classes hierarchy

As an example



General metaheuristic scheme

Use of a scheme common to different metaheuristics
possible reuse of functions

	Genetic	Scatter	GRASP	Tabu
Initialize	*	*	+	+
EndCondition	*	*	*	*
Combine	+	+		
Improve	-	+	+	-
Include	-	-	.	.

The problem

- An iterative scheme with computation and communication in each step
- A number of homogeneous processes: ideally the same volume of computation in each process
- Decide the number of processes and the number of processes assigned to each processor (d_i)
- The system is modelled with:
  - A vector t_c of costs of basic arithmetic operations on each processor
  - Two bidimensional arrays t_s and t_w, with the start and word-sending time between processes in two processors

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Execution time model

- No overlapping of computation and communication is considered: $t_{comp} + t_{comm}$
- The arithmetic cost is modelled: $t_{comp} = max_{i=1,\dots,P}\left\{n_{comp}(i)t_{c_i}\right\}$
- and the communication cost: $max_{i=1,\dots,P;\ j=1,\dots,P}\left\{n_{str}(i,j)t_{s_{ij}}\right\} + max_{i=1,\dots,P;\ j=1,\dots,P}\left\{n_{dat}(i,j)t_{w_{ij}}\right\}$
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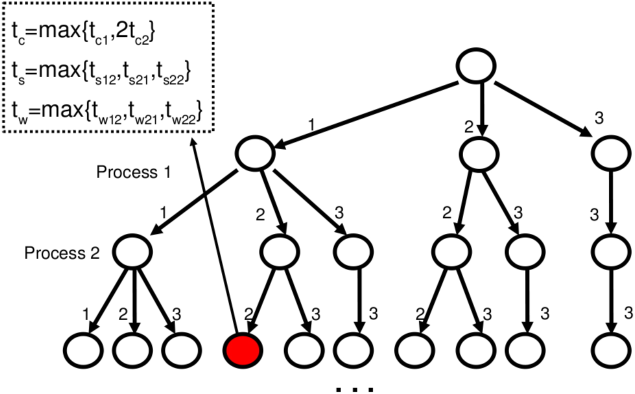
Assignation tree



Metaheuristics

- Metaheuristics experimented with:
  - Hill climbing
  - Tabu search
  - Scatter search
  - Genetic algorithms
  - Ant colony
  - Simulated annealing
- And exact methods with heuristics or probability:
  - Backtracking and Branch and Bound with pruning based on heuristics (possibly pruning nodes which could lead to the optimum solution) and tree traversal guided by heuristics
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Experience

- Easy development of metaheuristics
- Reuse of functions
- Easy development of parallel metaheuristics
- Application to dynamic programming and LU factorization
- Similar results for the different metaheuristics
- Better results (lower theoretical execution time and lower decision time) with metaheuristics

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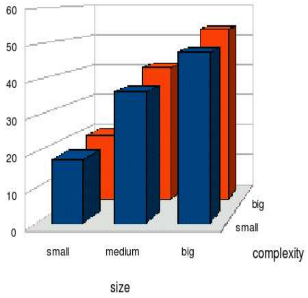
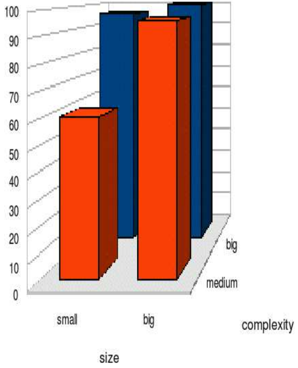
Comparison of Backtacking and Scatter Search

Percentage of runs in which Scatter Search obtains better Total Time (Modelled Time plus Decision Time) than backtracking with node pruning

real system with 6 processors ; simulated system with 60 processors





The problem

- A master processor generates a set of independent tasks that are solved by slave processors
- Each task has certain memory requirements and each processor has a certain amount of memory
- The assignation of tasks to slave processors is done statically: $d_i = j$ means task i is assigned to processor j
- Each processor recives a new task when it has processed the one previously assigned
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Execution time model

- Number of basic operations for each task: c_i, $i = 1, \ldots, T$
- Given assignation d, the cost in processor j: $t_{c_j} \sum_{l=1,d_l=j}^{T} c_j$
- For an assignation d the cost is: $\max_{j=1,\ldots,P} \left\{ t_{c_j} \sum_{l=1,d_l=j}^{T} c_j \right\}$
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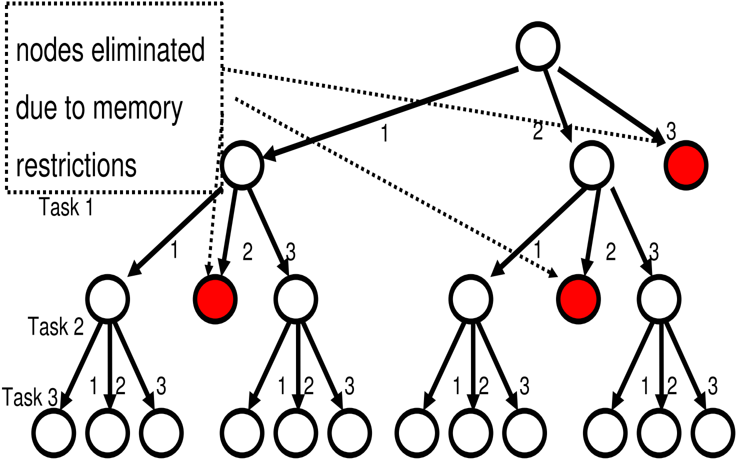
Assignation tree



Use of the class hierarchy

- Metaheuristics:
  - Tabu search
  - Scatter search
  - Genetic algorithms
  - GRASP
- Integrated in the hierarchy
- Common problem and solution classes
- Reutilization of functions
- Easy tuning to the problem
- Hybridation

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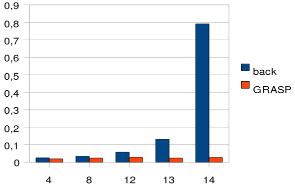
Example of function reutilization

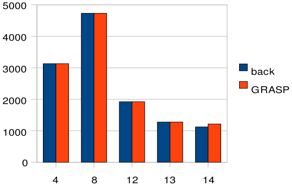
- The greedy functions used in GRASP can be used in
  - Scatter Search, in the improvement of the elements, which is done after each element is generated
  - Genetic Algorithms, in the individual generated in the mutation, so allowing the descendant of the individual to survive some generations and contribute to improve the population
  - Tabu Search, to improve the best element

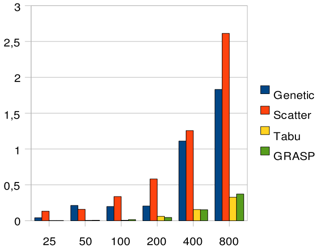
Comparison of metaheuristics

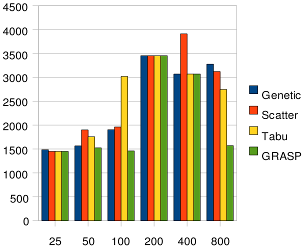
Mapping time



modelled time







The problem

- A master processor generates subproblems up to a certain level
- and assign the subproblems to the slave processors.
  The assignation can be:
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  - Cyclic
  - Solving an optimization problem by using metaheuristics,
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- The execution time is knc, with:
  - n number of nodes in the tree
  - c the cost of evaluation of each node, estimated at installation time
  - k the percentage of nodes generated, estimated at installation time for some representative inputs and updated at running time with a subproblem of the problem to be solved
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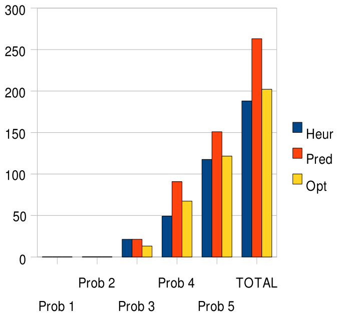
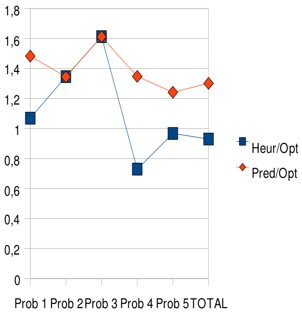
Preliminary results

Knapsack 0/1, problems of size 40. `Heur` obtention of the assignation with a greedy method, `Pred` with predetermined values from experiments with smaller problems, `Opt` the lowest experimental time obtained from executions varying the parameters but without approximating the optimization problem.





Conclusions

- Metaheuristics are useful to solve mapping problems
- We proposse to use a unified approach with a common algorithmic scheme and a class hierarchy
- This reduces programming and experiment costs
- But for each problem a different problem class and different functions
- It is necessary to develop a tool to facilitate the inclusion of new problems
- Until now preliminary results with some mapping problems

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and credits

- Metaheuristic scheme: Francisco Almeida, Juan-Pedro Martínez-Gallar
- Class hierarchy: Javier Cuenca, Antonio Llanes
- Iterative scheme: Ángel-Luis Calvo, Ana Cortés, Juan-Pedro Martínez-Gallar, Carmela Pozuelo
- Master-slave: Javier Cuenca
- Backtracking: Manuel Quesada
- Translation: Stephen Hasler

... and more

Application of metaheuristics to task-to-processors assignation problems

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