Competition on Permutation-based Combinatorial Optimization Problems

Leticia Hernando, Josu Ceberio, Alexander Mendiburu, Jose A. Lozano

Intelligent Systems Group
Department of Computer Science and Artificial Intelligence
University of the Basque Country UPV/EHU

Genetic and Evolutionary Algorithms Conference (GECCO 2014)
Vancouver, BC, Canada, 12-16 July 2014
The Aim

To obtain an overview of the performance of heuristic and metaheuristic algorithms on permutation problems
Submissions

• **Submission 1.** Mirah Alves and Romario Rogerio. *Greedy Randomized Adaptive Search Procedure (GRASP).*

• **Submission 2.** Mikel Artetxe. *A Randomized Tabu Search-based Memetic Algorithm for permutation-based combinatorial optimization problems.*
Submissions

• **Submission 1.** Mirah Alves and Romario Rogerio. *Greedy Randomized Adaptive Search Procedure (GRASP).*

• **Submission 2.** Mikel Artetxe. *A Randomized Tabu Search-based Memetic Algorithm for permutation-based combinatorial optimization problems.*

*Due to a lack of proposals we could not carry out the competition.*

*In the future, we will consider focusing on a particular problem, and provide more time to develop competitive proposals.*
Permutation-based Problems

TSP, QAP, PFSP, LOP, API
What are they?

- Specific subset of combinatorial optimization problems.
What are they?

- Specific subset of combinatorial optimization problems.
- Coded naturally as permutations.
What are they?

- Specific subset of combinatorial optimization problems.
- Coded naturally as permutations.
- Do no belong to the discrete and continuous domain problems.
The Problems

• Travelling Salesman Problem (TSP).

• Quadratic Assignment Problem (QAP).

• Linear Ordering Problem (LOP).

• Permutation Flowshop Scheduling Problem (PFSP).
The Problems

• Travelling Salesman Problem (TSP).
• Quadratic Assignment Problem (QAP).
• Linear Ordering Problem (LOP).
• Permutation Flowshop Scheduling Problem (PFSP).
• Artificial Permutation Instances

Artificial Permutation Instances

Aim:

• To generate instances with specific complexities
• To evaluate and compare algorithms in different scenarios
Artificial Permutation Instances

Aim:

• To generate instances with specific complexities
• To evaluate and compare algorithms in different scenarios

Inspiration:

• The landscape generator for continuous domains of Gallagher et al.
• Instead of using the Gaussian distribution, the Mallows model for permutation domains is used.
The Mallows model

\[ P(\pi | \sigma, \theta) = \frac{1}{\psi(\theta)} e^{-\theta d(\pi, \sigma)} \]
The Mallows model

\[ P(\pi | \sigma, \theta) = \frac{1}{\psi(\theta)} e^{-\theta d(\pi, \sigma)} \]

\( \sigma \rightarrow \) Central permutation
The Mallows model

\[ P(\pi | \sigma, \theta) = \frac{1}{\psi(\theta)} e^{-\theta d(\pi, \sigma)} \]

- \( \sigma \) → Central permutation
- \( \theta \) → Spread parameter
The Mallows model

\[ P(\pi | \sigma, \theta) = \frac{1}{\psi(\theta)} e^{-\theta d(\pi, \sigma)} \]

- \( \sigma \rightarrow \) Central permutation
- \( d(\pi, \sigma) \rightarrow \) Distance metric
- \( \theta \rightarrow \) Spread parameter
The Mallows model

\[ P(\pi | \sigma, \theta) = \frac{1}{\psi(\theta)} e^{-\theta d(\pi, \sigma)} \]

- \( \sigma \) → Central permutation
- \( \theta \) → Spread parameter
- \( d(\pi, \sigma) \) → Distance metric
- \( \psi(\theta) \) → Normalization function
The Mallows model

\[ P(m) = 0.1, \quad e = 0.3, \quad e = 0.5 \]
Instance Generator

• Choose $m$ central permutations $\rightarrow \sigma_1, \sigma_2, \ldots, \sigma_m$
Instance Generator

- Choose $m$ central permutations $\rightarrow \sigma_1, \sigma_2, \ldots, \sigma_m$

- Choose $m$ spread parameters $\rightarrow \theta_1, \theta_2, \ldots, \theta_m$
Instance Generator

- Choose $m$ central permutations $\rightarrow \sigma_1, \sigma_2, \ldots, \sigma_m$

- Choose $m$ spread parameters $\rightarrow \theta_1, \theta_2, \ldots, \theta_m$

- Choose $m$ weights $\rightarrow \omega_1, \omega_2, \ldots, \omega_m$
Instance Generator

- Choose $m$ central permutations $\Rightarrow \sigma_1, \sigma_2, \ldots, \sigma_m$
- Choose $m$ spread parameters $\Rightarrow \theta_1, \theta_2, \ldots, \theta_m$
- Choose $m$ weights $\Rightarrow \omega_1, \omega_2, \ldots, \omega_m$

- The fitness value of each permutation $\pi$ is calculated as:

$$f(\pi) = \max_i \{ \omega_i P_i(\pi|\sigma_i, \theta_i) \}$$
Particularities

By tuning the parameters, different shapes of landscapes can be generated.

- Fix the number of local optima (Mallows models)
- Define the size of the attraction basins of the local optima by tuning the spread parameters and the weights.
Competition on Permutation-based Combinatorial Optimization Problems

Thank you for your attention!!

Comments, suggestions, questions... competition.gecco2014@ehu.es

Or

contact with me!