

Parallel Genetic Programming

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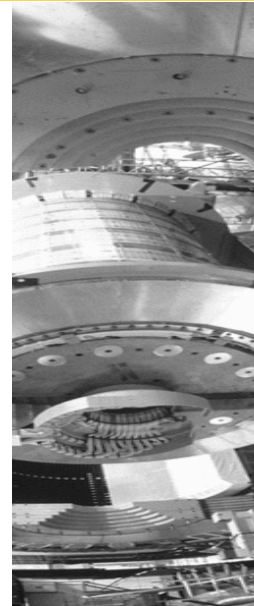


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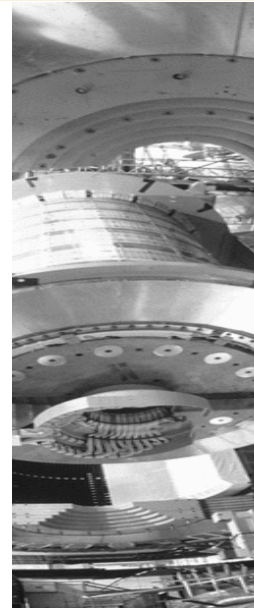
Summary:

- Introduction.
- History.
- Parallel GP.
- The Island Model.
- Successful Applications.
- Future.



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Some considerations

- Genetic Programming can be considered a Machine Learning system:
 - “[machine learning] is the study of computer algorithms that improve automatically through experience [Mitchell, 1996].
- The emphasis is on *learning* (instead of on *knowledge*).
- The dream of computers that program themselves [Samuel, 1963] could be reached soon.

What's Genetic Programming?

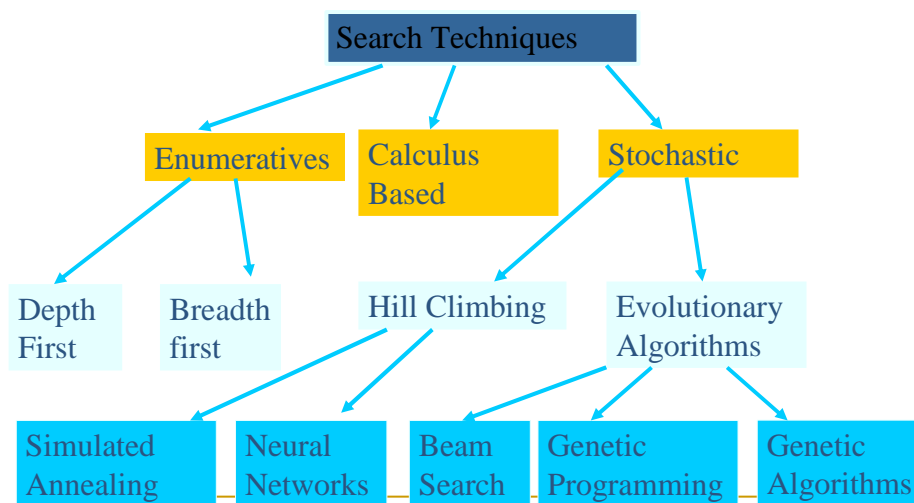
- According to Banzhaf et al*, GP is a system that induce computer programs by evolutionary means.
- GP (Koza, 1992) is a kind of Evolutionary Algorithm (EA). (Genetic Algorithms, Genetic Programming, Evolutionary Strategies, Evolutionary Programming).
- EAs can be seen as search techniques (stochastic search technique).

*Banzhaf, W., Nordin, P., Keller, R.E., Francone, F.D. Genetic Programming, an Introduction. Morgan Kaufmann 1998.

Introduction

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Different Search Techniques



As classified by Banzhaf et al

Introduction

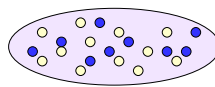
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How does an EA work

- A summary:
 - $T=0$;
 - Initialize and evaluate $[P(t)]$
 - While not stop_condition do
 - $P'(t)=\text{variation } [P(t)]$
 - Evaluate $P'(t)$
 - $P(t+1)=\text{select } [P'(t),P(t)]$
 - $T=t+1$
 - end while

How does GP work?

Individuals
compete for
resources

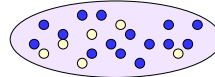


Population and
Individuals

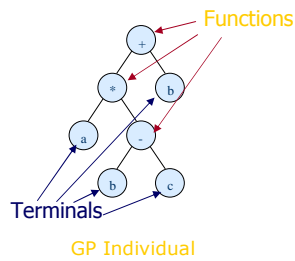
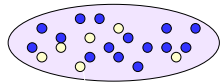
Reproduction
& Heredity



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How does GP work?



Genetic Operators:

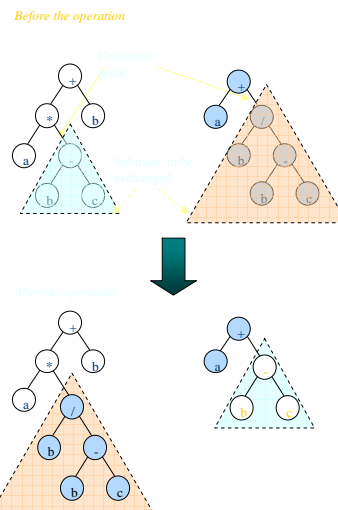
- Crossover.
- Mutation.
- Selection.
- Reproduction.

Fitness Function

Genetic programming

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Genetic Programming



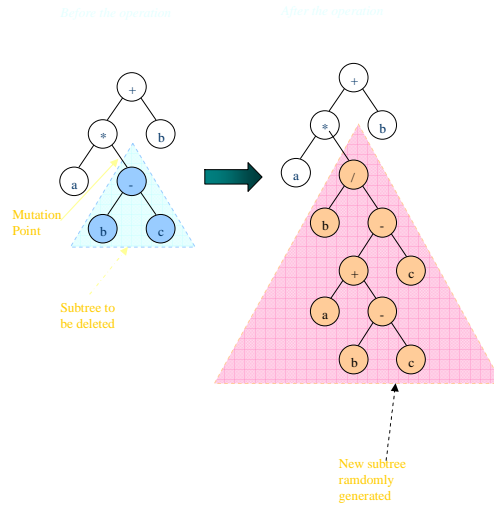
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Relies on the Building block hypothesis
Genetic programming

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Genetic Programming

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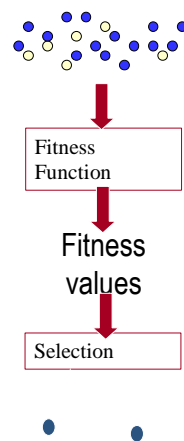


Genetic programming

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Genetic Programming

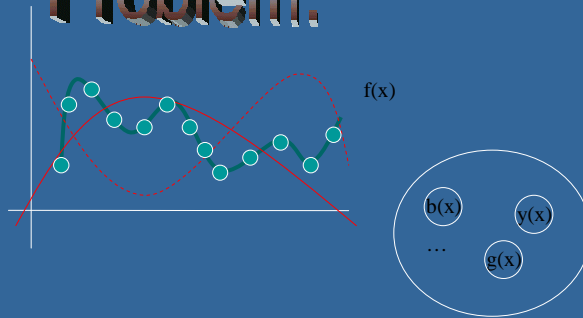
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Genetic programming

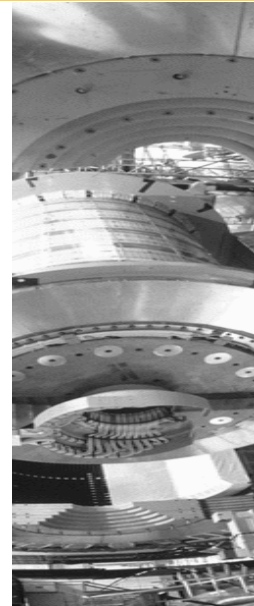
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Problem:



Summary:

- Introduction.
- History.
- Parallel GP.
- The Island Model.
- Successful Applications.
- Future.



History

- There are two main ideas behind Parallel Eas:
 - Increase performances:
 - in principle, by adding processors, memory and interconnection networks and putting them to work together on a given problem.
 - Modifying the underlying algorithm can also help in the finding of solutions.

History

- Ideas involving both EAs and Parallel Computing can be traced back to Holland, 1976.
- But the field had to wait until early 1980s when parallel implementations appear.
- Grefenstete, 1981, was one of the first in examining some issues concerning parallel implementations of Gas.

History

- Other researchers began more systematic studies: Gross, Cohoon, Tanese, Pettey, Georges-Schleter, Mühlenbein, and Manderick*.
- They studied Hypercubes parallel architecture, distributed models, theoretic models, island models, and cellular model.

*See "Parallelism and Evolutionary Algorithms", E. Alba & M. Tomassini, IEEE Transactions on Evolutionary Computation, Vol. 6, NO. 5, Oct 2002, 443-462 for a review summary.

Parallel EAs: History

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Parallelism & EAs

- Flynn model is still widely accepted for classifying computer architectures.
- The taxonomy is based on the notion of instruction and data stream:
 - SISD: Single instruction, Single Data stream.
 - SIMD: Single Instruction, Multiple Data stream (the preferred model).
 - MISD: Multiple instruction, single data stream.
 - MIMD: Multiple instruction, multiple data stream.
- Shared or Distributed Memory.

Parallel GP

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Taxonomy

- Parallel EAs can be classified attending to different features.
- M Nowostawski and R. Poli 1999:
 - Master/Worker: A single population and the fitness evaluation of multiple individuals in parallel.
 - Static subpopulations with migration.
 - Static overlapping subpopulations without migration.
 - Massively Parallel genetic algorithms.
 - Dynamic demes.
 - Parallel Steady-state Ga
 - Parallel Messy Ga
 - Hybrid methods.

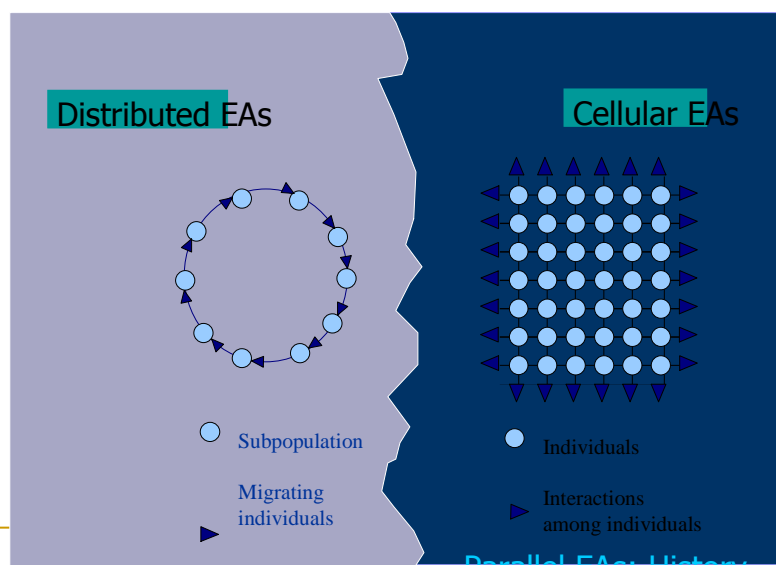
Taxonomy

- M. Tomassini, 1999:
 - Global parallel evolutionary algorithm (parallelization at the fitness level) also called by the author master/worker model (coarse-grained model).
 - Island distributed evolutionary algorithms (population based approach).
 - Cellular evolutionary algorithm (fine-grained model).

Structured EAs

- Structured populations has been used for improving EAs.
- Two main types of algorithms:
 - Distributed EAs.
 - Cellular EAs.
- On the opposite side, panmictic EA is the classic model.
- None of the models require a parallel implementation.

Structured EAs

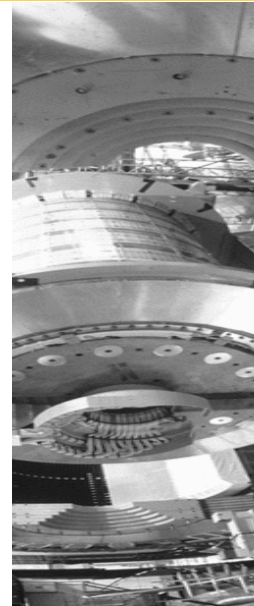


Nonstandard Structured EAs

- We could use different parameters/representations in different subpopulations (Tanese, Lin & Punch & Goodman, Herrera & Lozano & Moraga).
- These algorithms are sometimes called heterogenous.

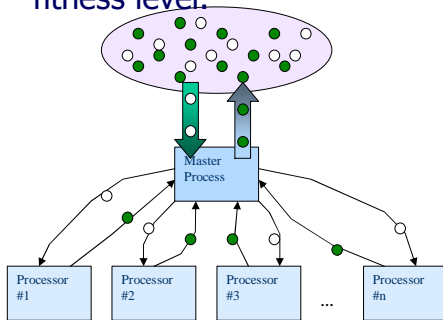
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Parallel Models

Parallellising at the fitness level.



This model is also called "global model".

Why should we use a parallel model?

- We want to increase performances.

How could we parallelise?

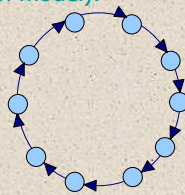
- At the individual level.
- At the population level.
- At the fitness evaluation level

Parallel GP

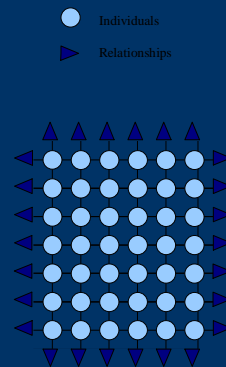
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Parallel Models

Parallellising at the population level (also called island model or coarse-grain model).



● Subpopulation
▶ Migrating individuals



Fine-grained model (also called Grid or Cellular model)

Parallel GP

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Parallel GP: A review

- **Juillé and Pollack 1995** presented one of the first attempts to parallelize GP.
- They implemented a global model, although also presented some result using sub-populations.
- The proposal was somehow specific for the SIMD model they were using.
- One of their aims was to reduce interprocessor communication.

Parallel GP : A review

- **P. Tuffs, 1995**, presented the same year another master/worker parallel version of GP.
- He approached a classification problem by means of GP. -the development of a system to do data mining on a fairly large (multi-gigabyte) database of credit-card transactions. The task was to classify customers and predict their future behavior-
- Probably it was the first attempt to parallelize GP (the book correspond to year 1993, although was published on 1995).

Parallel GP : A review

- **Andre and Koza 1996** presented another Parallel GP Implementation using a network of 66 transputers (VLSI device containing 32 bit on-chip processor, memory and links)
- They employed the island-model.
- An appropriate migration rate showed improvement in the computational effort required for the Boolean 5-parity function. (64 demes, SubPop_size=500, Migration_rate=5%)
- The main conclusion was that Parallel GP could achieve super-linear speedups.

Parallel GP : A review

- **K. Stoffel and L. Spector 1996**, implemented a parallel version of GP using linear programs evaluated by means of a stack.
- Several processors generate independently its own segment of the next generation.
- They implemented crossover in parallel: Individuals from different processors may undergo crossover.

Parallel GP : A review

- **Oussaidène et al 1997**, presented a parallel implementation of GP for trading model induction.
- They employed the **global model** architecture (parallelization at the fitness level), employing a master/worker model, where each node from the network is in charge of evaluating individuals coming from a master node.
- The master node is in charge of the main GP algorithm.
- The model may undergo a load imbalance problem.

Parallel GP: A review

- Results offered by Koza were questioned later by **W. F. Punch 1998**. His experiments on the Royal Tree problem were not so optimistic. His main conclusions were that multiple-solution problems would be more amenable to multiple populations than single-solution problems.
- On the other hand, non-deceptive problems would be more amenable to multiple populations than deceptive problems.
- He only tried a set of parameters for the parallel model.

Parallel GP : A review

- **Fernandez et al 1999**, presented experimental results on an island-model implementation of GP.
- Although results were preliminar, this is the first time some important parameters of the island-model are tested (communication topology).

Parallel GP : A review

- **Folino et al, 2000**, presented a new implementation of GP using the cellular model.
- **Fernández et al, 2000**, studied more deeply the relationship among several important parameters for the island-model (subpop size, number of subpop, communication topology).

Parallel GP : A review

- The latest results on both the island and cellular GP models have been presented very recently:
 - F. Fernández et al., 2003, described latest results with the island-model, while G. Folino et al, 2003, presented a Cellular Scalable implementation for GP. Their results are compared with previously described results using parallel GP.

Parallel GP tools

- Many GP tools allow the use of “demes” but simulated in a sequential fashion.
- There have been several parallel implementations during the last few years.
- Several languages (C, java, C++) and communication frameworks (sockets, java rpc, pvm, mpi ...) have been employed.

Communication Tools

- **PVM: Parallel Virtual Machine** (V.S. Sunderam, "PVM: A framework for parallel distributed computing," J. Concurr. Practice and Experience, vol.2, no.4, pp. 315-339, 1990")
- **MPI: Message Passing Interface.** (Message Passing Interface Forum, "MPI: A message-passing interface standard," Int. J. Supercomput, Applic., vol.8, no.3-4, pp.165-414, 1994)
- **GLOBUS.**
- **Others (Sockets, Java-RMI...)**

Parallel GP tools

- **Chong, 1998**, presented DGP, a java based distributed approach to genetic programming on the Internet.
- **F. Fernández et al, 1999**, developed a parallel GP tool implementing the island-model, and communicating subpopulations by means of PVM. This tool was later improved by means of MPI (**Fernández et al, 2000**).
- **Spezzano et al, 2001**, presented CAGE: A tool for parallel genetic programming applications. They implemented the cellular model.
- Classic LilGP software (**Punch**) also has a couple of parallel version implemented using PVM and MPI (see **Fernández parallellilgp**)

Parallel GP tools

- **DREAM** project: It is aimed at providing a framework for evolutionary computation.
- It allows distributed computing.
- Any Evolutionary Algorithm could be used, by adjusting some parameters, within DREAM.
- Founded by European Union.
- See:
<http://www.dcs.napier.ac.uk/~benp/dream/dream.htm>

Parallel GP tools

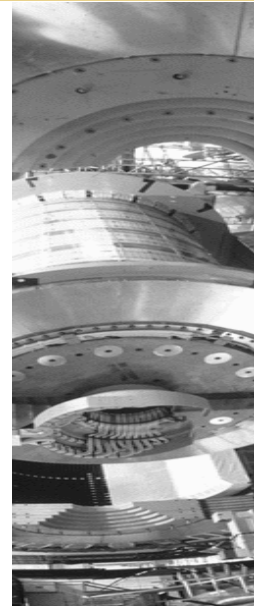
- **Paradiseo**: Parallel and Distributed Evolving Objects.
- It is based on **EO** (Evolutionary Computation Framework).
- Includes tools for:
 - Population Based Metaheuristics.
 - Single Solution Based Metaheuristics.
 - Multi-Objective Metaheuristics.
 - Parallel and Distributed...

Parallel GP tools

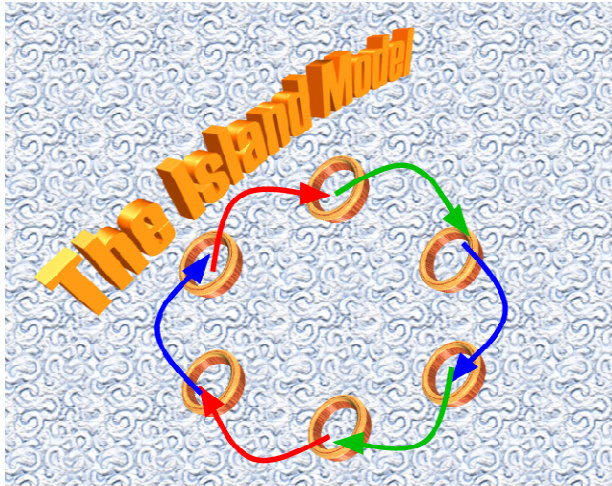
- **ECJ**: A Java-based Evolutionary Computation Research System.
- Includes asynchronous Island Model over TCP/IP.
- Multiobjective Optimization.,

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Island Model



Important Parameters:

- Size of Subpop.
- Topology.
- Communication rate.
- Granularity.
- Synchronization.

Important concern:

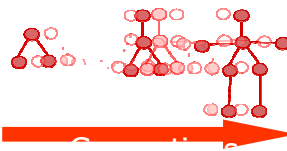
- Comparing results.

The Island Model

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Island Model – Comparing results

- Traditionally experimental results are shown comparing **Fitness/Generation**.
- Two reasons for avoiding this kind of comparisons:
 - The Bloat phenomenon in GP.

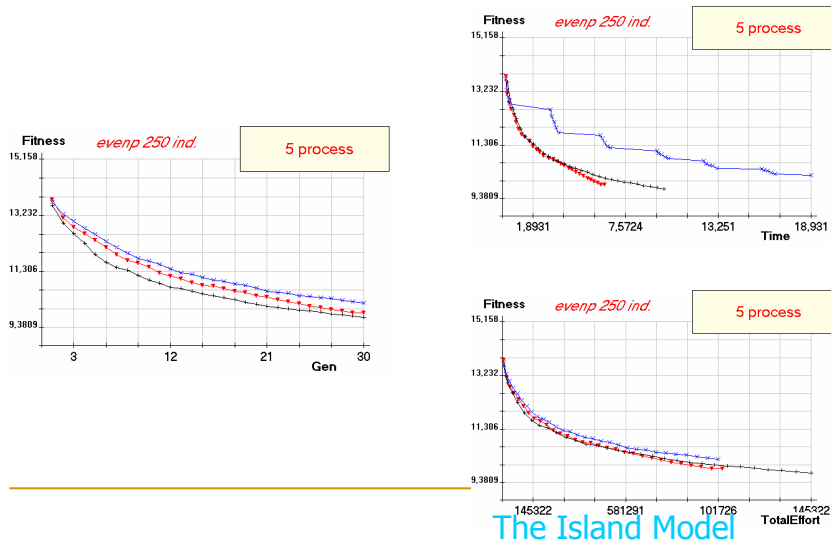


- Populations with different size require different time to evaluate a generation.

The Island Model

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Island Model – Comparing Results



The Island Model

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Island Model – Measuring Results

- Proposal: Evaluate **Fitness/Effort** (for convergence) or **Fitness/Time** (for speedup)

(Fernández, Galeano, Gómez).

Computational effort:

The total number of nodes GP has evaluated for a given number of generations.

$$PE_g = i * p * avg_length_g$$

p: the number of populations

i: the number of individuals per population

avg_length_g: the average length of individuals in all the populations in generation g.

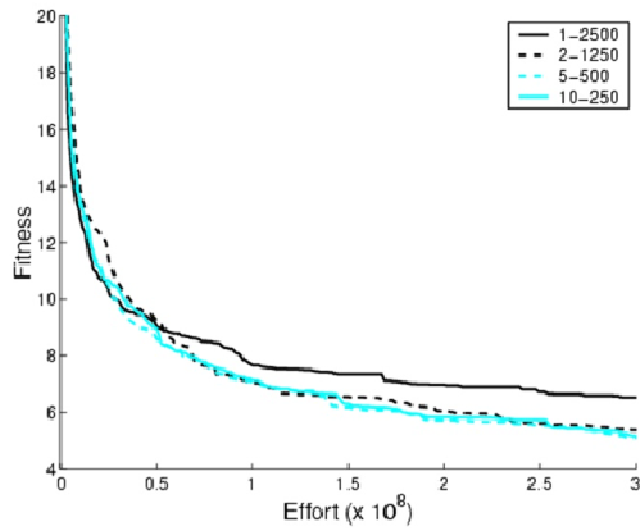
The computational effort E_g at a generation g is:

$$E_g = PE_g + PE_{g-1} + \dots + PE_1 + PE_0$$

The Island Model

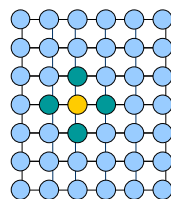
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Island Model – Comparing Results



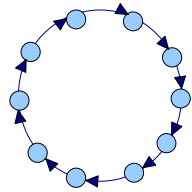
Island Model - Topology

- **Andre and Koza 1996** connected each subpopulations with 4 neighbors in the N, E, W, S directions.



Island Model - Topology

- **Punch, 1998**, used a typical Island model with ring topology.



Ring Topology

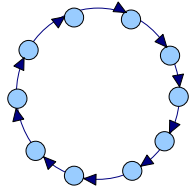
- He employed that topology for his experiments but no comparisons with different topologies were provided in the paper.

The Island Model

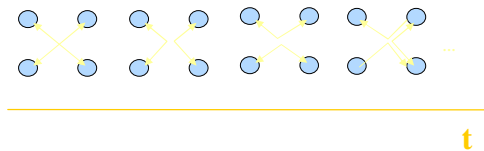
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Island Model - Topology

- **Fernandez et al 2000** introduces a random topology and compare it with grid and ring topology.



Ring Topology



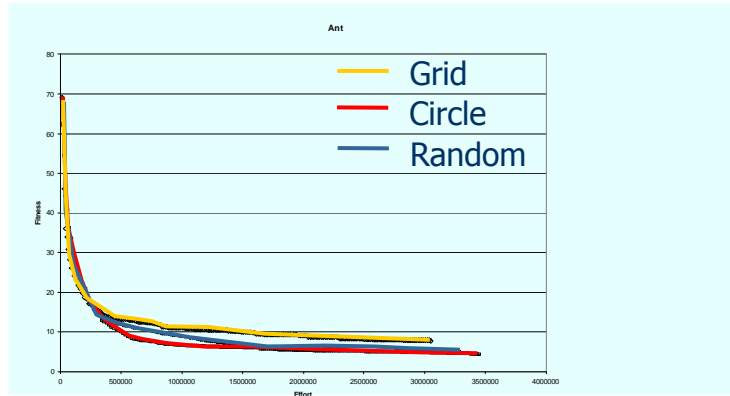
Random Topology: It changes dynamically

- The main conclusion is that if the remaining parameters stay fix, there are no significant differences when changing topology.

The Island Model

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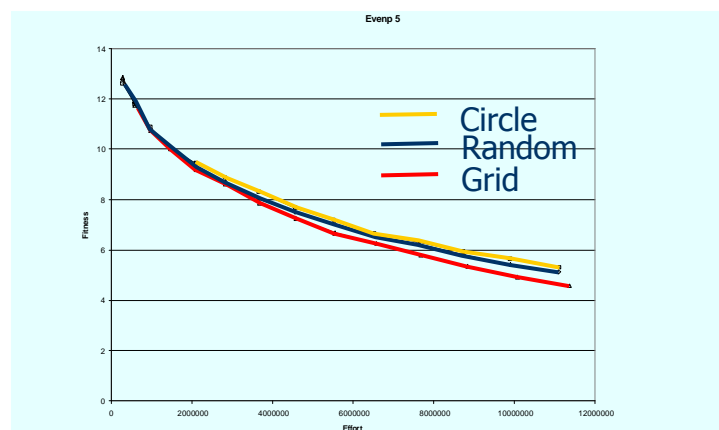
Island Model - Topology



The Island Model

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Island Model - Topology



The Island Model

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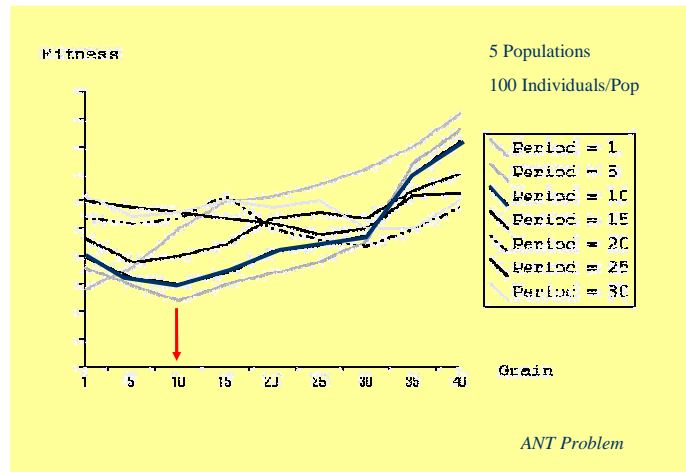
Island Model – Migration Rate

- How many individuals should migrate each migration step?
- Depending on the number of individuals, results are different. The limits are:
 - 0 individuals migrating (isolated populations)
 - All the individuals migrating.
- Different migration rates applied in literature:
 - **Juillé & Pollack**: 1 migrating individual per subpopulation.
 - **Andre and Koza**: 0%-8% migrating individuals per subpop.
 - **Punch 1998**: 2 individuals.

Island Model – Migration Rate

- **Fernandez et al 2003**: best migration rate is between 5% and 10% in 4 test problems (2 classic and 2 real-life problems):
 - Even Parity 5.
 - Ant Problem.
 - Routing and Placing circuits on FPGAs.
 - Medical Diagnosing.

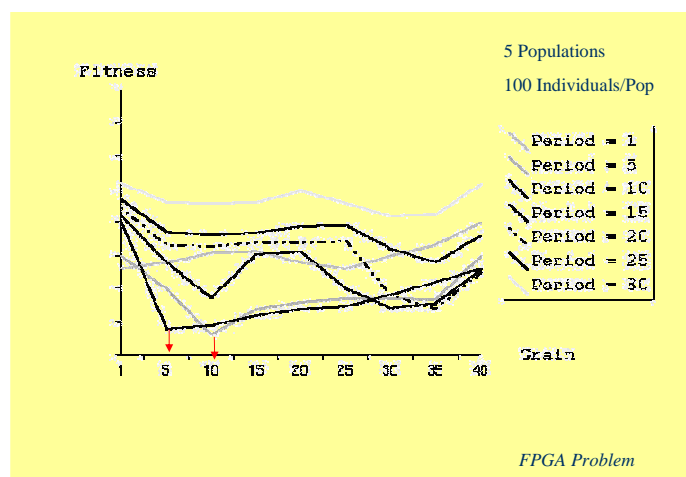
Island Model – Migration Rate



The Island Model

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Island Model – Migration Rate



The Island Model

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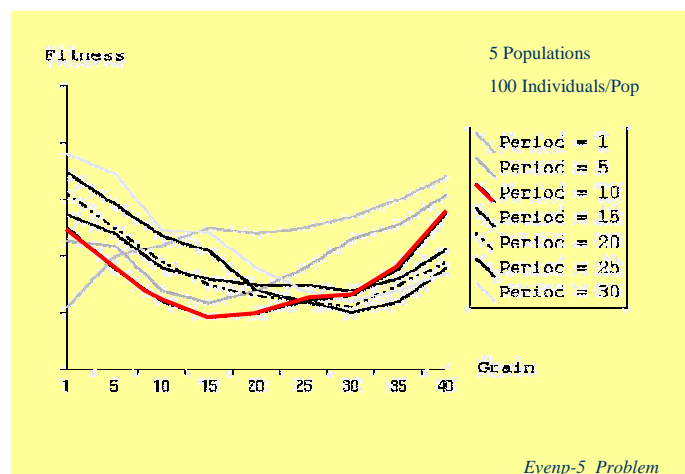
Island Model – Migration Frequency

- Both **Juillé & Pollack** and also **Andre and Koza** employ migration every generation.
- In **Punch 1998**, subpop. wait for 10 generations before the migration step.
- In **Fernandez et al 2003**, a wider study have been carry on, comparing different frequencies.
- Best convergence results appear when about 10% of individuals from each subpopulation are sent every 5-10 generations.

The Island Model

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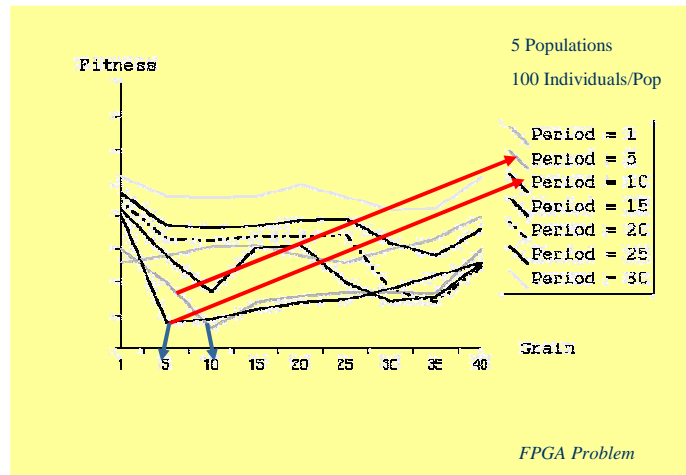
Island Model – Migration frequency



The Island Model

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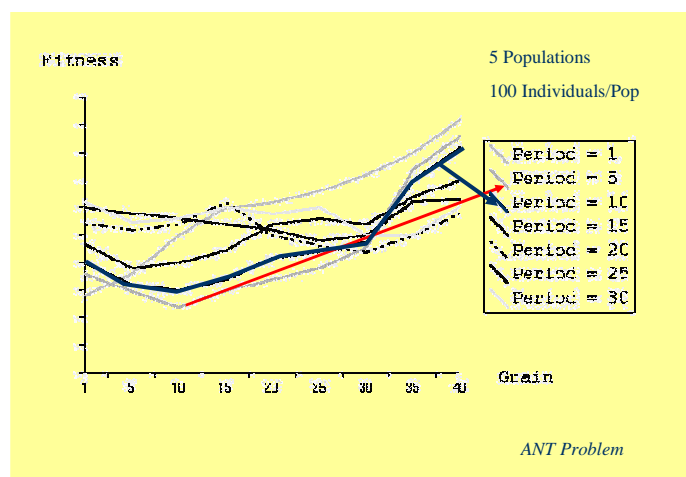
Island Model – Migration summary



The Island Model

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Island Model – Migration Rate



The Island Model

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Island Model – Migration Summary

- For large values of the grain, exchange individuals less frequently.
- For low values of the grain, exchange more frequently.
- Recommendation: Exchange 10% of the population every 10 generations.

Island Model – Subpop. Size

- Experiments presented by **Andre & Koza**, make use of the large computational capability of the network they employed.
- 32000 individuals are distributed among 64 demes, each with 500 individuals.
- **Punch 1998**, employed 5 populations, 200 individuals each, and also 7 populations, 700 individuals each.

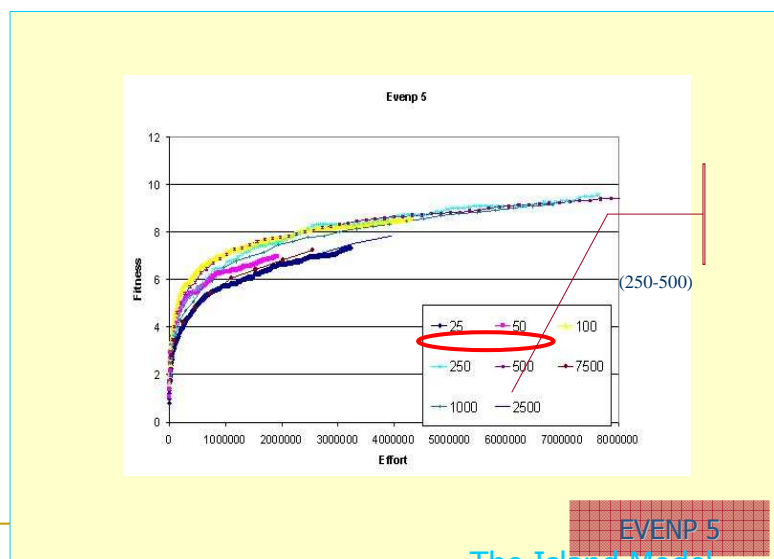
Island Model – Subpop. Size

- F. Fernández et al., 2003, presents a set of trials.
- Conclusions:
 - There is a number of individuals with which best results are obtained (regardless of the number of subpops).
 - We must carefully select the number of subpops, not any number of populations obtain the same results.

The Island Model

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Island Model – Subpop. Size

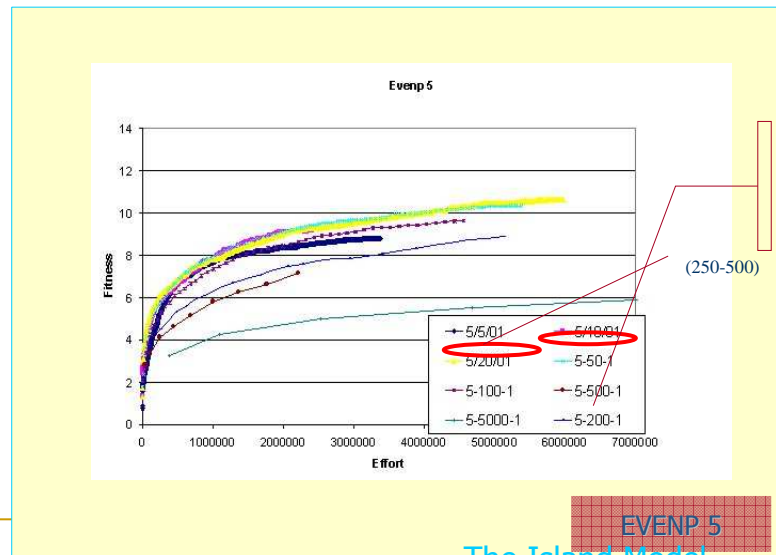


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The Island Model

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Island Model – Subpop. Size



The Island Model

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Island Model – Synchronisation

- Synchronism is an important issue when using Parallel GP: different individuals may require different processing time for their evaluation.
- Two models:
 - Synchronous: Exchange step takes place at a given generation.
 - Asynchronous: Populations send individuals when they are ready, and check every generation if new incoming individuals are awaiting.

The Island Model

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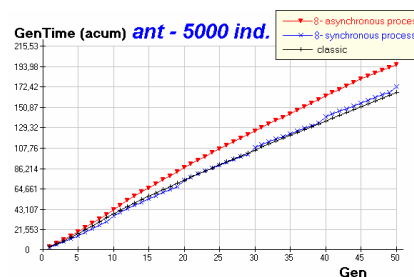
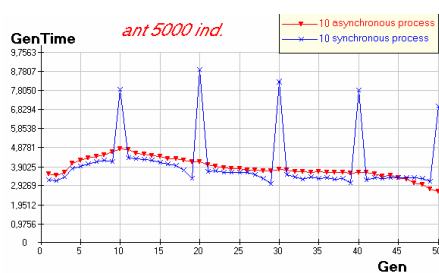
Island Model – Synchronisation

- **Andre and Koza** worked with an asynchronous model: each generation is typically working on different generations after a few ones.
- **Dracopoulos and Kent**, employed the synchronous model in both the global and island models.
- **Fernández et al, 2002**, presented a study comparing synchronous and asynchronous models in monoprocesor systems.

The Island Model

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Synchronous - Asynchronous



Results obtained using 1 pro

Synchronous model better for monoprocesor system.
Asynchronous model better for parallel systems.

The Island Model

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Synchronous - Asynchronous

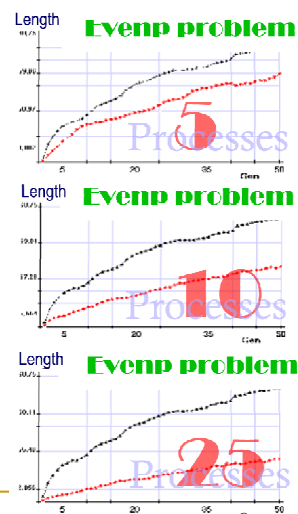
- **Tongchim and Chongstitvatana**, presented a comparison among models using a restricted migration policy.
- Their results only focus on a problem, and shows better performance with the asynchronous model.

The Island Model

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Island Model - Bloat

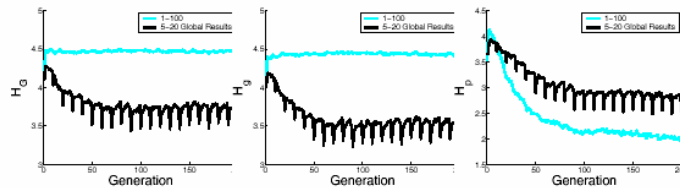
- The Island Model seems to prevent the bloat phenomenon.



The Island Model

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Some comments on diversity



Genotypic diversity decreases.
Phenotypic diversity improves.

What about fault tolerance?

- Fault tolerance is an important issue.
- Different techniques have been employed:
 - Check pointing.
 - Redundancy.
 - Others...
- Is GP Fault tolerant?

What about fault tolerance?

Figure 2. Even parity 5 problem, with a population length of 2000 and 10% volatility rate

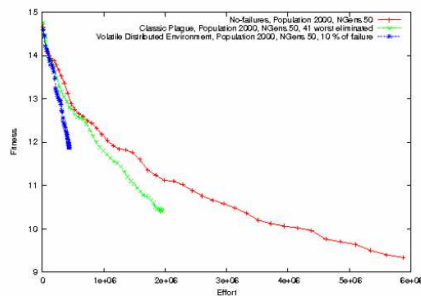
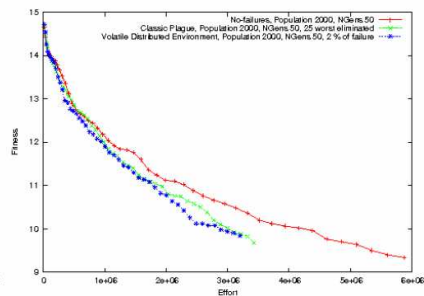


Figure 3. Even parity 5 problem, with a population length of 2000 and 2% volatility rate

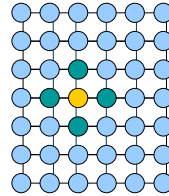


The Cellular Model

- Folino et al, 2003, have presented a comparison with panmictic and island model approach.
- The method provides results of similar quality than the island model (an small error in the comparisons seems to favor the cellular model in the paper, but a detailed revision shows that results are similar).
- They apply the model to induce decision trees.

The Cellular Model

- Each individual is located in a grid position.
- Individuals interact only with their neighboring ones.

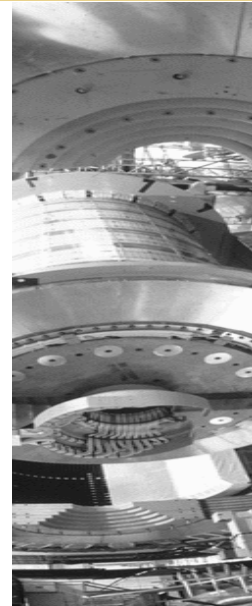


The Island Model

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Summary:

- Introduction.
- History.
- Parallel GP.
- The Island Model.
- **Successful Applications.**
- Future.



Some Applications

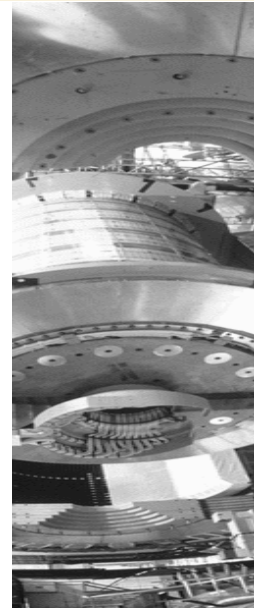
- **C. Miccio et al, 1995**, described an implementation on a T3D computer for inducing binary decision diagrams.
- **M. Oussaidène et al**, presented an application to trading model induction.
- **F. Fernández, 2001**, described a proposal for solving the problem of Placement and Routing of circuits on FPGAs.
- **Folino** apply the cellular model to generate decision trees.

Some Applications

- **Koza et al 2000**, presents a list of “Human-Competitive results obtained by Means of Genetic Programming”, including:
 - **Synthesis of Analog Circuits.**
 - **Synthesis of PID controllers.**
 - **Applications to biomedicine (protein detection).**
 - **Previously patented inventions, reinvented.**
 - **Some patented invention.**

Summary:

- Introduction.
- History.
- Parallel GP.
- The Island Model.
- Successful Applications.
- **Future.**



Future

- Some topics for future research:
 - Theoretical models.
 - Heterogeneous models.
 - Improvements by means of better scheduling policies.
 - Bloat phenomenon.

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