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Improving performance

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The best of the rest

- Multicriteria optimization
- Parallelization
- Self-evolving parameters
- Hybrid evolutionary algorithms

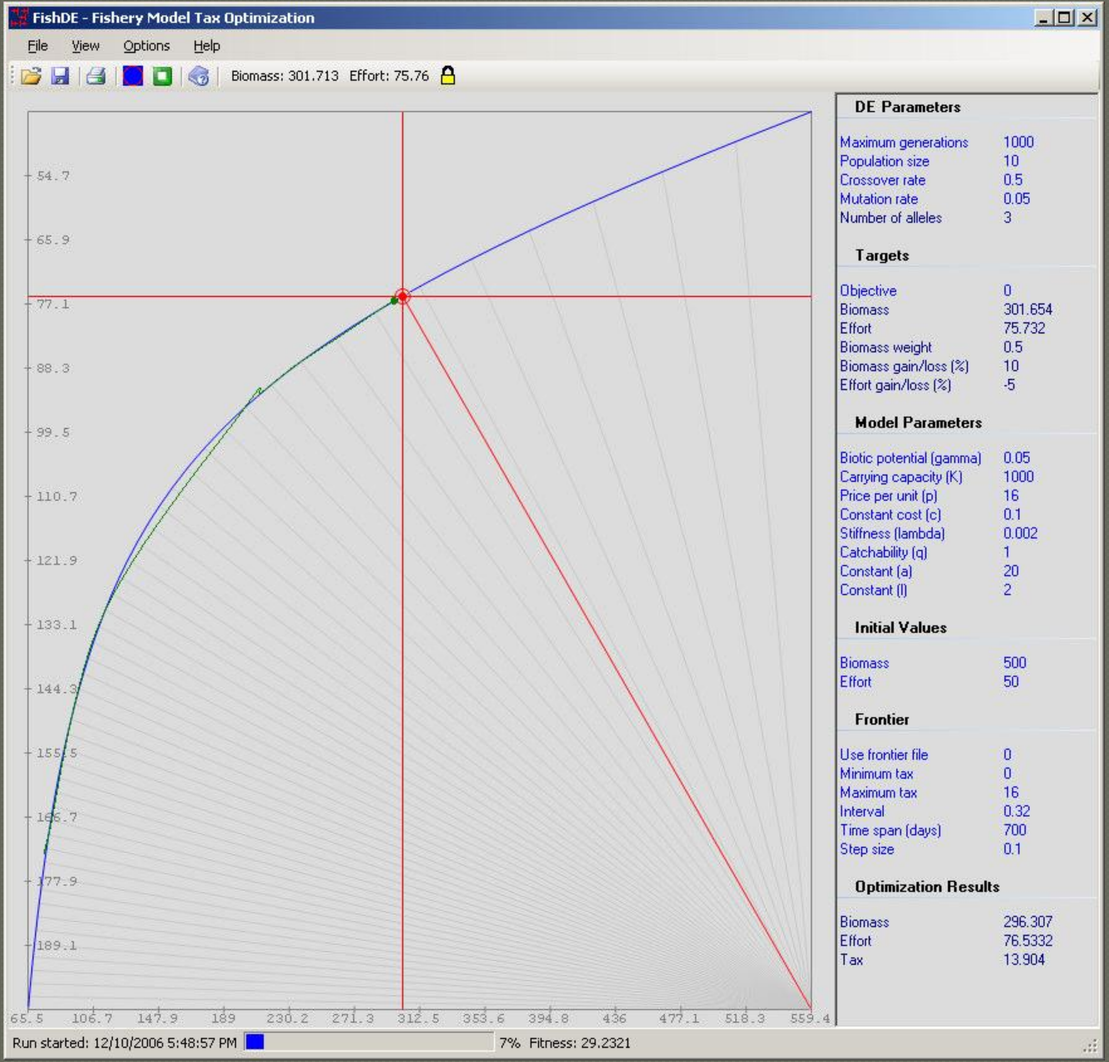
Multicriteria optimization

- Independent problems
  - Scaling
- Dependent problems
  - Scaling
  - Co-evolution (concurrency)
  - integration of objective functions in a single fitness function
- Real multicriteria problems
  - Trade offs - cannot eat and have the cake at the same time!
  - But can decide how much to eat and how much to keep!

Pareto

- No unique solution -> a set of equivalent solutions
- Pareto optimal
  - An improvement in any criterion will result in loss of fitness of other criteria
  - Set of all possible solutions at the Pareto optimal
  - Tip: calculate and keep the Pareto set for downstream decisions

Pareto or frontier?



MCO fitness

- Most common: weighting
  - Self-evolving
    - accounts for how far can you go in each direction
    - can reach higher fitness than achievable with a predetermined fitness
  - Manual
    - user controlled
- Simple scaling function

$$f = -1 * \sum_i^n \frac{\sum_j^m (x_{ij} - y_{ij})^2}{\sigma_{x_i}^2}$$

Parallelization

- EAs are embarrassingly parallel
  - Ideal for multi cores and low cost clusters
  - Main difficulty is to get the processors talking
  - Main bottleneck is the network lag
- Simplest parallelization
  - Run the same job independently on different machines
- More exciting
  - Master-slave model
  - Island model

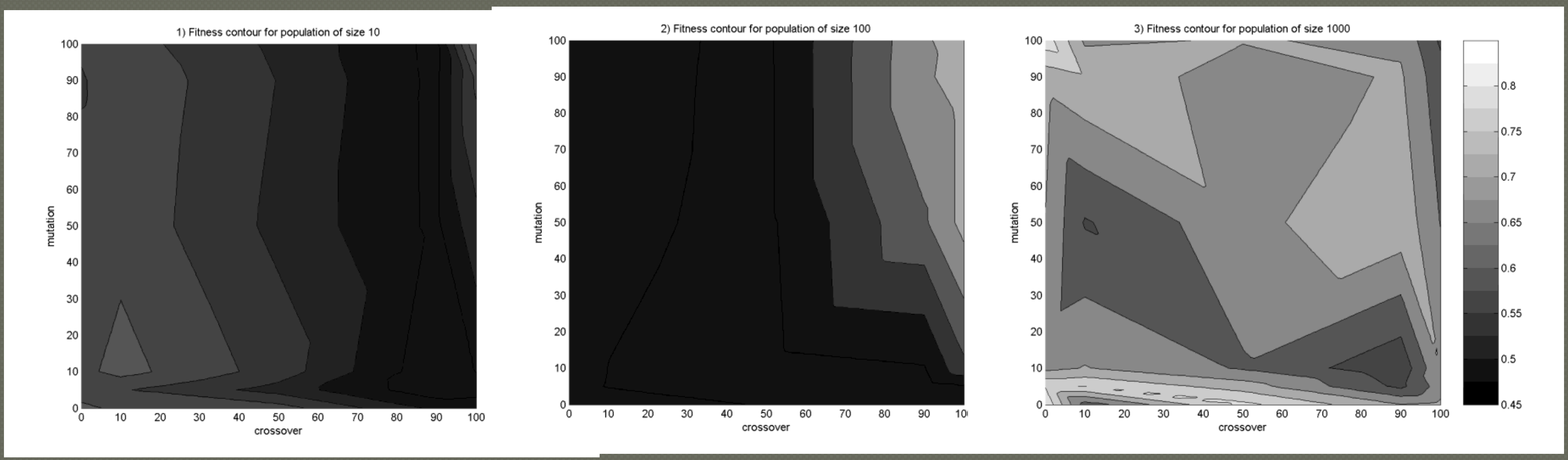
Self-evolving parameters

- Can be tricky to manually adjust the parameters

- Evolve problem and EA parameters concurrently
  - DE inherently evolves parameters
  - Common in ES and EP
  - Less common in GA and GP

- Simple strategy (GA/GP)
  - Evolve the EA parameters using ‘real’ fitness gain as fitness

Effect of parameters on fitness



Hybrid algorithms

- Different classes of EAs
  - Explore the best properties of each
  - Current trend is to blur the line
- EAs with other optimizers
  - e.g. hill climbing, gradient search…
- EAs with other techniques
  - e.g. expert systems, neural networks, self organizing maps…

DE-GEP

```
Initialize random values for variables within a set of constraints
Do until (termination criterion)
{
Iteration i
{
        GEP
        Initialize random population of models
        Replace chromosome 0 with best model
        Do until GEPGeneration = GEPMaxGenerations

        {
                Select
                Crossover
                Mutate
                Evaluate
                Replace
                Generation++
        }
        If (GEP Best Model Improves Fitness)
                Replace model with best model from GEP
        Else Keep original model

        Bloat Reduction Method
        DE
        Use Best Model to optimize variables
        Initialize random population of variables within constraints
        Replace chromosome 0 with best variables
        Do until DEGeneration = DEMaxGenerations

        {
                Select
                Crossover
                Mutate
                Evaluate
                Replace
                Generation++
        }
        If (DE Best Values Improve Fitness)
                Replace variables with best values from DE
        Else Keep original variables
                i++
} }
```

Advantages of the HDE-GEP

- Uses each method within it's specific domain
- Allows the use of a different fitness function for structure discovery and parameterization
- Increases variability of the population, avoiding premature convergence
- Greatly improves model discovery

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