Theory and Applications of Bio-Inspired Algorithms

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Optimizing the Layout of 1000 Wind Turbines

accurate, efficient, and parallelizable
optimization algorithms for the layout of large wind farms

Motivation

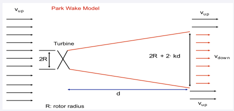
Wind Energy:

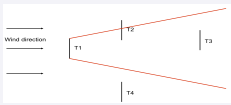
Source: Cooperative Institute for Research in Environmental Science

- Major player in renewable energy
- Huge market, challenging questions

Wind farm layout tools:

- Identify the best layout of wind turbines according to energy capture,
- model free stream wind flowing through an area with sited turbines, while taking wake effects and turbulence intensities into account.
- Key component: the optimizer algorithm.





Challenges for the optimizer:

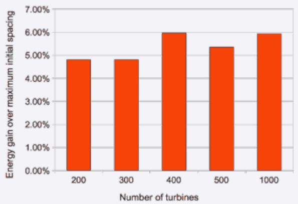
- large numbers of turbines & large farm areas
- constraints on feasible sitings
- expensive wake models

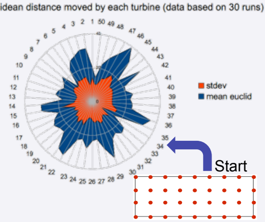
State of the art:

- Few turbines, mediocre results, unrealistic assumptions

Achievements

So far: raised the bar from 6-50 to 1000 turbines





- General purpose algorithm: CMA-ES is a very powerful evolutionary algorithm approach to deal with complex problems. It respects the correlations between the turbine positions via self-adaptation of the covariance matrix of a multivariate normal distribution.

  [Published at "European Wind Energy Association 2011" (industry conference) and presented at "Clean Energy 2011" (Go8C9 conference)]

- Problem-specific algorithm, reduced computational complexity of an evaluation (formerly: quadratic (<30 seconds), now linear <1s).

  [To be submitted]

Computational Complexity of Genetic Programming

backing up practice with theory

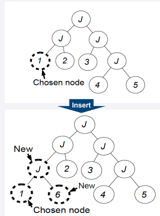
Motivation

Genetic programming (GP):

- Successfully applied in various fields, such as symbolic regression, financial trading, medicine, and bioinformatics
- Theory lacks behind application

Computational Complexity Analysis:

- Make statements on the expected time that a GP system needs to solve a problem
- Identify the problems' features that makes them easy/difficult to solve, and, if possible, present improvements



Challenges in the analysis:

- Compared to numerous related work, the solution size can vary, which makes the progress of the GP system mathematically difficult to handle.

State of the art:

- Field is very young, with initial results on atypical problems

Achievements

Results on the sorting problem

Fitness function	(1+1) GP* single	(1+1) GP* multi
INV	$O(n^3 T_{max})$	$O(n^3 T_{max})$
HAM	∞	$\Omega\left(\left(\frac{n}{e}\right)^n\right)$
RUN	∞	$\Omega\left(\left(\frac{n}{e}\right)^n\right)$
LAS	∞	$\Omega\left(\left(\frac{n}{e}\right)^n\right)$
EXC	∞	$\Omega\left(\left(\frac{n}{e}\right)^n\right)$

- Measuring sortnedness: Pairs in order, longest ascending sequence, Hamming distance, ...
- The choice on how to measure sortedness can make the difference between runtimes that are polynomial or exponential (or infinite) in the number of elements to be sorted.
- When parsimony is added (a common approach in GP applications), the smaller solutions are preferred, which results in polynomial runtimes for many sortnedness measures.

Fitness function	(1+1) GP^p single	(1+1) GP^p multi
HAM	$O\left(T_{max} \cdot \left(n^2 + \log T_{max}\right)\right)$	$O\left(T_{max} \cdot \left(n^2 + \log T_{max}\right)\right)$
RUN	∞	$\Omega\left(\left(\frac{n}{e}\right)^n\right)$
LAS	$O\left(T_{max} \cdot \left(n^2 + \log T_{max}\right)\right)$	$O\left(T_{max} \cdot \left(n^2 + \log T_{max}\right)\right)$
EXC	∞	$O\left(T_{max} \cdot \left(n^3 + \log T_{max}^2\right)\right)$

- Although atypical as well, this is the problem with which the complexity analysis of evolutionary algorithm on combinatorial problems started in 2004–now the latter field is buzzing.

  [Available as part of a book chapter of "Genetic Programming – Theory and Practice 2011", and as a technical report. Results presented at "Theory of Randomized Search Heuristics 2011"]

Next, the primal use-case will be investigated: symbolic regression.

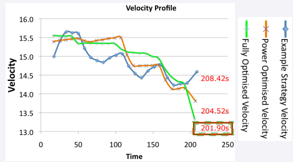
Other projects

Evolving Pacing Strategies to Win Olympic Gold

Team Track Pursuit

Source: http://www.youtube.com/watch?v=NbQfARcngm0

- The cyclists cycle as a team against a second team.
- In the energy-saving linear formation, the first cyclist uses the most energy, while the others benefit from his slipstream.
- We evolve racing strategies that tell the cyclists how quick they should go, and when to change the order.

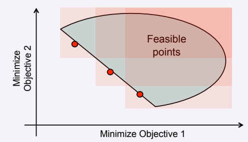


[Best Paper award achieved at "Metaheuristics International Conference 2011". Collaboration with the Australian Institute of Sports.]

Efficient Optimization of Many Conflicting Objectives

Multi-objective optimization

- Goal: find a set of compromise solutions, approximating the true set of compromise solutions (called Pareto front)



Set of resulting solutions should be

- Close to the true Pareto front, covering the entire Pareto front, and evenly distributed

State-of-the-art approaches have drawbacks

- Crowding, computationally expensive (hypervolume: runtime increases exponentially with the number of dimensions), …

Our algorithm

- outperforms state-of-the-art (when it comes to a particular quality measurement, and under time restrictions), and its runtime increases only linearly with the number of dimensions.

[Published at "International Joint Conference on Artificial Intelligence 2011"]

And…

Wind Farm Energy Output: improve the prediction of the production to improve sales by adjusted prices.

Meta-Learning for the Travelling Salesperson Problem: learn features of instances to select the right solver from an ensemble.