Summary of Evolutionary Computation for Wind Farm Layout Optimization

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ABSTRACT

This paper presents the results of the second edition of the Wind Farm Layout Optimization Competition, which was held at the 22nd Genetic and Evolutionary Computation COnference (GECCO) in 2015. During this competition, competitors were tasked with optimizing the layouts of five generated wind farms based on a simplified cost of energy evaluation function of the wind farm layouts. Online and offline APIs were implemented in C++, Java, Matlab and Python for this competition to offer a common framework for the competitors. The top four approaches out of eight participating teams are presented in this paper and their results are compared. All of the competitors' algorithms use evolutionary computation.

CCS CONCEPTS

• **Applied computing → Computer-aided design**;

KEYWORDS

Real-world problem, Wind farm layout optimization

1 INTRODUCTION

Wind farm design is a complex task and the recent trend of larger farm sizes has greatly increased demands on designers. Traditionally, a small, well-connected, land area is divided into smaller cells and turbine placement among cells is decided through a simple search algorithm with a pre-specified cost function. This function is usually limited to minimizing inter-turbine wake interferences and thus maximizing energy capture. Few approaches consider additional factors such as operation and maintenance costs, turbine costs, or cable layout.

Modern farms cover large areas and boast hundreds, and sometimes even thousands, of turbines. The layout design process is iterative, computationally expensive, burdened with global and

local constraints, and ultimately controlled by subjective assessments due to the involvement of a variety of stakeholders. During each step, designers must either refine an incremental layout or propose a new layout which they have generated by incorporating new constraints. Additionally, evaluating a layout requires varied multi-disciplinary models and sub-modules that are extremely computationally expensive.

The wind farm layout optimization problem is the identification of turbine positions in a 2-D plane such that the energy capture is maximized while costs associated with a number of other factors are minimized. The energy capture for a turbine takes into account the wind scenario (wind force distribution and terrain), the turbines' power curve (power generated by the turbine in function of the wind input) and wake effects (inter-turbine interferences) [2]. Many approaches have been tested to optimize both the positing and the number of turbines on a layout. Extensive reports on the state of the art of existing techniques are available in Khan et al. [1] and Samorani [3].

In an article published in the Renewable Energy Journal, DOI https://doi.org/10.1016/j.renene.2018.03.052, we report on a competition we ran at the Genetic and Evolutionary Computation Conference 2015 (GECCO 2015) during which experts from the evolutionary computation community optimized wind farm layouts. Eight teams participated and proposed innovative algorithms, all evaluated in the same context: the same wind scenarios, power curve and wake effect models. This paper summarizes the competition context and the top four algorithms.

2 COMPETITION RULES AND FRAMEWORK

The first edition of the wind farm layout optimization competition, held at the 2014 Genetic and Evolutionary Computation COnference (GECCO), consisted in only optimizing the wake free ratio, the actual energy output over potential output without wake. The second edition focuses on the economic viability of the produced layouts. Layouts generated by the competitors' algorithms are evaluated in the cloud on 5 unknown wind scenarios (wind rose, layout shape and obstacles, turbine specifications, etc.) using the cost function presented below. In order to keep the computation cost acceptable, the competitors have a finite number of possible evaluations: they can only call the evaluation function 10,000 times for all 5 scenarios combined. This limited amount of evaluation credits aims to

represent the CPU cost of layout evaluation and to promote efficient algorithms. This metric was preferred to CPU time because the computation was held on a shared research cluster with no exclusive access guaranteed. In order to develop their algorithms, competitors also have access to 20 known scenarios, 10 without obstacles and 10 with obstacles, all different from the ones used during the competition.

In order to reduce the competitors' development efforts, we have developed an open-source API, called WindFLO, that implements the cost function and the inter-turbine interference model in multiple languages (C++, Java, Matlab and Python)[1]. The API provides a simple GA as an example of use of the library and the competitor algorithms presented hereafter. This library can be of interest to the evolutionary computation community as a benchmark for new algorithms and new development.

3 COMPETITORS' ALGORITHMS

The second edition of the competition received a total of 8 submissions. In this paper, the top 4 approaches are presented. In our opinion, they are the most relevant to the wind farm optimization community and provide the best results in term of quality of layouts obtained. These algorithms are summarized in the following: *3s-MDE*: from Carlos Segura, Guillermo LÃşpez Buenfil, Mario Ocampo Pineda, Sergio Ivvan Valdez PeÃśa, Salvador Botello Rionda, and Arturo HernÃąndez-Aguirre. The 3-Stages Memetic Differential Evolution (3s-MDE) starts by creating a surrogate model which approximates the cost function. Then, a memetic differential evolution is used to pre-optimize the model based on a geometric distortion of a layout based on rhomboids. The pre-optimized layout is then refined by locally modifying the candidate solution. The more accurate model is used only to evaluate solutions with a promising behaviour in the surrogate model. *CMA-ES*: from Ilya Loshchilov and Frank Hutter, this second approach uses the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) to optimize a layout described by 5 variables: scale (horizontal and vertical), shift from the origin, rotation, and shift from a given location. *SSHH*: from Ahmed Kheiri and Ed Keedwell, the Sequence-based Selection Hyper-Heuristic (SSHH) approach discretized the layout and then a solution is represented by three integer variables that corresponds to the distance between neighboring turbines and a shift factor. A hidden Markov model produces a sequence of low level heuristics which create the final layout. *GM*: from Brian Goldman, the Goldman Method (GM) presented in this paper uses a pair of lattice vectors to calculate turbine locations. It also uses the cost of substation, which is larger than the turbine cost itself, to leverage the size of the evaluated layouts. A deterministic best-improvement local search method is then used to optimize the lattice vectors.

4 COMPETITION RESULTS

The algorithms presented in the previous section, in addition to four others not described in this paper, were run on the 5 scenarios presented in the competition rules section. As mentioned above, the competitors were given a budget of 10,000 evaluations to split between the 5 scenarios for computational cost reasons. As a basis of comparison, we have compared the results to a genetic algorithm.

Scenario	3s-MDE	CMA-ES	SSHH	GM	GA
1	$\mathbf{1.16}_{4422}E^{-3}$	$1.17_{2731}E^{-3}$	$1.18_{1129}E^{-3}$	$1.18_{5466}E^{-3}$	$1.26_{9266}E^{-3}$
2	$\mathbf{1.00}_{929}E^{-3}$	$1.02_{9998}E^{-3}$	$1.03_{9825}E^{-3}$	$1.04_{4906}E^{-3}$	$1.15_{8464}E^{-3}$
3	$\mathbf{6.26}_{867}E^{-4}$	$6.30_{916}E^{-4}$	$6.40_{241}E^{-4}$	$6.49_{096}E^{-4}$	$6.91_{265}E^{-4}$
4	$6.53_{861}E^{-4}$	$\mathbf{6.53}_{56}E^{-4}$	$6.66_{205}E^{-4}$	$6.64_{341}E^{-4}$	$7.18_{626}E^{-4}$
5	$\mathbf{1.14}_{2309}E^{-3}$	$1.15_{2661}E^{-3}$	$1.16_{7168}E^{-3}$	$1.16_{033}E^{-3}$	$1.26_{9238}E^{-3}$

Table 1: Cost of energy, compared to the state-of-the-art layout optimization (binary GA).

GAs have been used many times in this domain and offer a familiar and standard benchmark against other algorithms from the field of evolutionary computation. For this problem, a GA optimizes a binary genome that decides whether or not a turbine is located in each grid of a discretized layout. Parameters of the GA are provided in the journal paper. Table 1 shows the gain obtained by participants in comparison to the GA. Further analysis on convergence, problem encoding and surrogate models are discussed in the journal paper.

5 CONCLUSION

This paper presents the results of the 2015 competition on wind farm layout optimization. With this event, we were able to propose innovative algorithms to optimize large wind farms with a strong computational constraint. Thanks to this competition, we were also able to compare these approaches with state-of-the-art algorithms and observe the potential improvement of the optimization algorithms used to generate the wind farm layouts.

This competition also provides a framework to compare future algorithms with existing ones on a comparative basis. The competition framework is freely available in multiple programming languages (C++, Java, Matlab and Python) with a set of randomly generated wind scenarios. Real-world scenarios could be easily added to the scenario set by the wind industry.

Because solutions were obtained with acceptable computational costs in this competition, we can now imagine targeting new optimization objectives. The 3D structure of the terrain, and/or heterogeneous wind distribution within the terrain, heterogeneous wind turbines with different height, width and power curves could be considered. In this competition, cable and road networks were not taken into account, but these are of great importance for the initial investment to build the wind farm. They could be added to the framework and the cost of energy function in order to be addressed by the optimization algorithms.

REFERENCES

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[1]This API is available on github: https://github.com/d9w/WindFLO