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Selection Hyper-heuristics for Solving the Wind Farm Layout Optimisation Problem

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1 Introduction

During the last two centuries, energy consumption from non-renewable sources has reached its peak while demand for energy has increased. Therefore transitioning to renewable energy sources is now recognised. Wind turbine technology is a promising source of renewable energy, and hence efficient wind farm layout is needed so that each turbine produces as much energy as possible. The placement of wind turbines directly impacts the efficiency of the wind farm as turbines are close enough to influence each other's performance due to aerodynamic interactions (wakes) [7].

The wind farm layout optimisation problem is considered a highly complex NP-hard problem, for which exact methods are unsuitable. There is a wide and varied literature on the use of evolutionary algorithms for the optimisation of wind farm layouts [5,6]. These algorithms have proven to be very effective at finding near-optimal solutions to a large number of problems in the energy industry. However, a new breed of optimisation algorithms known as hyper-heuristics is beginning to be applied to these problems. Hyper-heuristics are automated methodologies for *selecting* or *generating* heuristics to solve multiple computationally difficult optimisation problems [1]. They combine simple heuristics to create bespoke algorithms for specific problem domains, and have proven successful on other optimisation problems (see for example [2,3]). This work investigates the use of selection hyper-heuristics to wind farm layout optimisation that could possibly outperform conventional evolutionary approaches in terms of solution quality and run-time. There are two main components in a single-point-based search selection hyper-heuristic: *heuristic selection* and *move acceptance* as identified in [4].

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2 Solution Method

The wind farm layout optimisation problem involves finding the optimal positions of wind turbines in a 2-dimensional plane, such that the cost of energy is minimised taking into account several factors such as wind speed, site characteristics, turbines features, wake effects and existence of obstacles.

Our approach discretises the site into a number of cells, and solutions to the problem are represented as a vector of boolean to decide the absence or presence of turbines in the cells of the grid. The simplest form of a selection hyper-heuristic is a stochastic local search method which combines a simple random heuristic selection method (SR) with an improve or equal acceptance method (IE). The proposed approach, denoted as SR-IE, is implemented in this study using an open source software tool based on a generic API, referred to as WindFLO[1], designed for benchmarking purposes. This tool contains problem domain specific details, such as, the evaluation function computing the cost of energy. Moreover, a set of benchmark problem instances (terrain sizes, obstacles, wind forces, layout shapes, ...) can be downloaded from the WindFLO website. The evaluation function used in this study is as follows:

$$f = \frac{\left(c_t * n + c_s * \lfloor \frac{n}{m} \rfloor\right) + c_{OM} * n}{\left(1 - (1 - r)^{-y}\right)/r} * \frac{1}{8760 * P} + \frac{0.1}{n} \tag{1}$$

where f is the cost of energy, $c_t = \$750,000$ is the turbine cost, $c_s = \$8,000,000$ is the price of a substation, $m = 30$ is the number of turbines per substation, $r = 3\%$ is the interest rate, $y = 20$ years is the farm lifetime in years, $c_{OM} = \$20,000$ per year is the operation and maintenance costs, n is the number of turbines of the layout, P is the layout's energy output reported by the WindFLO API [5].

Selection hyper-heuristics operate by using a prefixed pool of low level heuristics by which a randomly initialised solution is improved over the search time. The low level heuristics used in this study are as follows:

- **LLH1** replace a single cell at random.
- **LLH2** swap two cells at random.
- **LLH3** ruin 10% of cells and rebuild at random.
- **LLH4** ruin 30% of cells and rebuild with all 0s or all 1s.
- **LLH5** is a first improvement hill climbing that searches for the first best solution between adjacent solutions.
- **LLH6** select two rows in a grid and exchange with a crossover rate of 20%.
- **LLH7** select two columns in a grid and exchange with a crossover rate of 20%.

Hence, SR chooses and applies a perturbative low level heuristic with a probability of 86%. Having LLH5 local search method as one of the low level heuristics creates an iterated local search like overall approach [3].

3 Results

The WindFLO API provides an implementation of a genetic algorithm (GA) as a baseline approach whose performance is compared to the proposed method, SR-IE. Both algorithms are applied to three instances each for five trials, and the termination

[1] `https://github.com/d9w/WindFLO`

Table 1 Parameters of the GA

Parameter	Value
Population size	20
Mutation rate	5%
Crossover rate	40%
Selection	4-player tournament with elitism

Table 2 Summary of experimental results. Best values are highlighted in bold

	SR-IE			GA		
Instance	Best	Avg	Std	Best	Avg	Std
Ins-1	**0.001115**	**0.001115**	6.32E-08	0.001181	0.001186	8.38E-06
Ins-2	**0.001474**	**0.001477**	2.22E-06	0.001483	0.001484	1.33E-06
Ins-3	**0.002319**	**0.002326**	5.24E-06	0.002377	0.002388	7.68E-06

criterion is set to 2000 layout evaluations. The performance of each method is measured using the cost of energy provided in Equation 1. Table 1 provides the parameter values for GA; and SR-IE is parameter free method.

Table 2 presents the results, which clearly shows that the SR-IE hyper-heuristic improves significantly on the performance of the GA on all trials.

We will be performing further experiments using more problem instances and additional selection hyper-heuristics and report the results at the conference.

References

1. Burke, E.K., Gendreau, M., Hyde, M., Kendall, G., Ochoa, G., Özcan, E., Qu, R.: Hyper-heuristics: a survey of the state of the art. Journal of the Operational Research Society **64**(12), 1695–1724 (2013)
2. Kheiri, A., Keedwell, E.: A hidden markov model approach to the problem of heuristic selection in hyper-heuristics with a case study in high school timetabling problems. Evolutionary Computation **25**(3), 473–501 (2017)
3. Kheiri, A., Özcan, E.: An iterated multi-stage selection hyper-heuristic. European Journal of Operational Research **250**(1), 77–90 (2016)
4. Özcan, E., Bilgin, B., Korkmaz, E.E.: A comprehensive analysis of hyper-heuristics. Intelligent Data Analysis **12**(1), 3–23 (2008)
5. Wilson, D., Awa, E., Cussat-Blanc, S., Veeramachaneni, K., O'Reilly, U.M.: On learning to generate wind farm layouts. In: Proceedings of the 15th Annual Conference on Genetic and Evolutionary Computation, GECCO '13, pp. 767–774. ACM, New York, NY, USA (2013)
6. Wilson, D., Cussat-Blanc, S., Veeramachaneni, K., O'Reilly, U.M., Luga, H.: A continuous developmental model for wind farm layout optimization. In: Proceedings of the 2014 Annual Conference on Genetic and Evolutionary Computation, GECCO '14, pp. 745–752. ACM, New York, NY, USA (2014)
7. Zhang, P.Y.: Topics in wind farm layout optimization: Analytical wake models, noise propagation, and energy production. Ph.D. thesis, University of Toronto (2013)