

Multi-objective Evolutionary Algorithms and Hyper-heuristics for Wind Farm Layout Optimisation

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Abstract

Wind farm layout optimisation is a challenging real-world problem which requires the discovery of trade-off solutions considering a variety of conflicting criteria, such as minimisation of the land area usage and maximisation of energy production. However, due to the complexity of handling multiple objectives simultaneously, many approaches proposed in the literature often focus on the optimisation of a single objective when deciding the locations for a set of wind turbines spread across a given region. In this study, we tackle a multi-objective wind farm layout optimisation problem. Different from the previously proposed approaches, we are applying a high-level search method, known as selection hyper-heuristic to solve this problem. Selection hyper-heuristics mix and control a predefined set of low-level (meta)heuristics which operate on solutions. We test nine different selection hyper-heuristics including an online learning hyper-heuristic on a multi-objective wind farm layout optimisation problem. Our hyper-heuristic approaches manage three well-known multi-objective evolutionary algorithms as low-level metaheuristics. The empirical results indicate the success and potential of selection hyper-heuristics for solving this computationally difficult problem. We additionally explore other objectives in wind farm layout optimisation problems to gain a better understanding of the conflicting nature of those objectives.

Keywords: Wind farm, Layout design, Optimisation, Hyper-heuristics, Evolutionary algorithms, Operation research

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1. Introduction

Wind power is an increasing source of renewable energy, harnessed through wind turbines on onshore and offshore areas. 320 Gigawatts (GW) of wind power capacity, doubling the figure in 2014, is expected to be installed in Europe by 2030 [1]. The wind farm layout optimisation (WFLO) problem involves determining the best locations for wind turbines in a given region considering certain objectives subject to a variety of constraints. WFLO is a computationally difficult problem to solve, and a crucial goal is minimising the cost of energy (COE) which has been extensively studied in the scientific literature [2]. COE embeds multiple components under a single objective formulation, including installed capital cost, annual operation and maintenance cost, the number of turbines, the annual energy production (AEP) and more. In some studies, researchers and practitioners focus on improving AEP as a single objective due to its relatively considerable effect on COE [3]. Hence, the positions of turbines are optimised to maximise AEP. Then again, AEP gets influenced by several other key factors, such as wind source, terrain conditions, type, number and spacing of wind turbines, etc.

In this paper, we deal with one of the multi-objective WFLO problem variants adopted from [4]. AEP is maximised through the minimisation of wake loss. Instead of using the classical approach of applying a multi-objective evolutionary algorithm (MOEA) to solve the multi-objective WFLO problem, we demonstrate the effectiveness and potential of *selection hyper-heuristics* (Section 2.3) as solution methods, exploiting the strengths of multiple MOEAs. Moreover, we explore the conflicting nature of several objectives including minimisation of COE, maximisation of AEP and minimisation of the number of turbines under a multi-objective hyper-heuristic framework.

Our motivations for conducting this work are as follows. Firstly, MOEAs utilise different strategies for balancing exploration (capability of jumping to a different region in the search landscape where the global optimum is potentially located whenever needed) and exploitation (capability of performing local search) while searching the solution space (Section 2.1). Thus, this provides us with a research question - can we combine the strengths of different MOEAs to solve unseen problem instances? Secondly, there is a growing number of studies reporting the effectiveness of selection hyper-heuristics as general purpose solution methods for a range of computationally difficult real-world problems from educational timetabling to vehicle routing [5]. Thirdly, to the best of the authors' knowledge, there has been no studies on hyper-heuristics for solving multi-objective WFLO problems so far.

This work is organised as follows. We first provide a background on general multi-objective optimisation problems, related work on multi-objective WFLO problems and hyper-heuristics in Section 2. Then we formulate our multi-objective WFLO problem model in Section 3. Our methodologies are presented in Section 4. The experimental design and empirical results are discussed in Section 5. More insights of different trade-offs in multi-objective WFLO problems are explored in Section 6. Finally, our conclusion and future work are in Section 7.

2. Background and Related Work

2.1. Multi-objective Optimisation Problem (MOP)

Definition 1. (MOP) Without loss of generality, we define an MOP as minimising a set (or a vector) of objectives $F(x)$, where $F(x) = (f_1(x), f_2(x), \dots, f_k(x))$. Suppose that a decision variable x_i is a d -dimensional vector, say, $x_i = [x_i^1, x_i^2, \dots, x_i^d]$ and a solution x consists of a vector of n decision variables.

$$\begin{aligned}
 & \textit{minimise} [F(x) = (f_1(x), f_2(x), \dots, f_k(x))] \\
 & \textit{subject to} \\
 & \qquad g_i(x) \leq 0, \qquad i = 1, 2, \dots, m \\
 & \qquad h_j(x) = 0, \qquad j = 1, 2, \dots, p \\
 & \qquad x = [x_1, \dots, x_n] \qquad x \in \Omega
 \end{aligned}$$

where m is the number of inequality constraints and p is the number of equality constraints. Multiple objectives can be combined under a single-objective formulation (e.g., via multiplication or weighted average). The distinguishing difference between MOPs and single-objective optimisation problems is that the approaches to former problems optimise a set of objectives simultaneously, eventually providing a set of ‘trade-off’ solutions, namely *Pareto Set*, while the approaches to the latter only optimise one objective at a time providing a single resultant solution. The Pareto set contains solutions whose one objective can not be improved without worsening at least one other objective. The corresponding vectors of objectives form a *Pareto Front (PF)* in the objective space.

Because of the real-world complexities of multi-objective problems, including large search space, non-linear objective functions and (or) constraints, disjoint PFs, the traditional (or exact) oper-

ational research (OR) techniques often fail to produce “satisfactory” results. Hence, heuristic optimisation methods, particularly multi-objective evolutionary algorithms (MOEAs) are widely used for solving MOPs due to their ability in generating multiple solutions even in a single run and being less sensitive to the varying geometries of PFs [6].

In this study, we have used three well-known MOEAs, Nondominated Sorting Genetic Algorithm-II (NSGA-II) [7], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [8] and Indicator-based Evolutionary Algorithm (IBEA) [9]. Each approach employs a different strategy for preserving the diversity of solutions during the search process and so perform ranking, selecting and replacing (or truncating) solutions, differently. More specifically, NSGA-II uses a fast non-dominated sorting to rank the solutions, and assigns a *crowding distance* (a measure of the density of solutions for any specific PF) to each solution. SPEA2 assigns a ‘fitness’ to each solution considering the number of individuals which dominates that solution and the distance to the k-th nearest neighbour. Moreover, this approach iteratively removes a solution which has the minimum distance to its k-th nearest neighbour until the size of the current population reduces to a predefined parameter *population size*. IBEA ranks solutions based on their contributions to the performance indicator in use, such as hypervolume or ϵ indicator [9]. The solution with the least contribution in the population is removed one at a time to maintain the fixed population size. Each algorithm shows a different behaviour during the search process due to their differing components. Their behaviours on a WFLO benchmark are presented in Section 5.2.

In a single-objective optimisation problem, the quality of solutions can be directly assessed by an evaluation function. However, there is no clear criterion regarding how to evaluate a population of trade-off solutions generated by different MOEAs. Therefore, many quality indicators are designed to assess the PFs containing trade-off solutions from different perspectives.

In this study, the following indicators are used: size of space covered (SSC), also know as S-matrix or *hypervolume* [10], uniform distribution (UD) [11], ratio of non-dominated Individual (RNI) [11] and algorithm effort (AE) [11]. Hypervolume is defined as the space covered by a PF with respect to a reference point (also known as an inferior point). It is usually used to evaluate a multi-objective algorithm’s convergence ability. UD, a value in [0,1], measures the uniformity of the distribution of non-dominated individuals on the PF. A higher value of UD indicates that the solutions on a PF are distributed more uniformly. RNI, a value in [0,1], is the percentage of non-dominated individuals in a population. AE is the number of solution evaluations per CPU time

in second. Each indicator illustrates the strength of an MOEA from a different view. The higher the value, the better the performance of an algorithm is with respect to the given indicator. A comprehensive review of quality indicators used in MOEAs can be found in [12]. More on MOEAs can be found in [6].

2.2. Related Work on Multi-objective WFLO Problems

Kusiak *et al.*[13] modelled a bi-objective WFLO problem, i.e. maximising the energy production and minimising the constraint violation of the minimum inter-distance between any two turbines, and solved it by Strength Pareto Evolutionary Algorithm (SPEA) [10]. Veeramachaneni *et al.* [14] presented a Multi-objective Particle Swarm Optimisation (MOPSO) algorithm which combined a general purpose MOPSO [15] algorithm with problem-specific repair strategies to maximise the energy capture and minimise the layout cost. The layout cost was modelled in terms of the land area usage and the number of turbines. Kwong *et al.* [16] considered minimising the noise production while maximising the energy production in their bi-objective model, using General NSGA-II to solve this problem. Tong *et al.*[17] proposed a bi-level multi-objective WFLO framework which maximised the wind farm annual capacity factor and the land area per MW installed. The authors reformulated this bi-objective problem as a constrained single-objective optimisation problem and applied Mixed-Discrete Particle Swarm Optimization (MDPSO) to solve this reformulated problem. A real case study was presented in Csicsbot *et al.* [18]. The authors utilised a multi-objective genetic algorithm (GA) to obtain an optimal placement of wind turbines by maximising the power production while restricting the budget of installed turbines in the Gokceada Island onshore wind farm. Tran *et al.*[4] designed problem-specific crossover and mutation operators and embedded them in three general MOEAs (NSGA-II, SPEA2 and IBEA) individually to solve a three-objective WFLO problem with different numbers (30, 50, 70 and 200) of turbines. More details about their problem model are in Section 3.

A comprehensive literature review of the WFLO problem and methodologies in use can be found in [2].

2.3. Hyper-heuristics

Definition 2. (*Hyper-heuristics* [5]) *A hyper-heuristic is “a search method or learning mechanism for selecting or generating heuristics to solve computational search problems”*

A metaheuristic, such as a GA or particle swarm optimisation, is “*a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimisation algorithms*” [19]. Based on this recent definition, hyper-heuristics can be considered as a subset of metaheuristics. The distinguishing feature of hyper-heuristics is that they, as high-level methods, perform search over the space formed by a set of low-level heuristics which explore the space of solutions. The low-level heuristics can be (neighbourhood) operators, such as crossover, mutation, local search, or they could be themselves metaheuristics.

There is a logical separation between the high-level hyper-heuristic control strategy and low-level (meta)heuristics under the originally proposed framework, enabling component based development [20]. A hyper-heuristic is allowed to access problem domain independent information (such as the objective value of a solution) and perform some bookkeeping (such as maintaining performance indicator(s) for each low-level (meta)heuristic). The advantage of using hyper-heuristics is that the same method or its components can be reused without requiring any change, assuming that the low-level (meta)heuristics are already implemented. Even, the low-level (meta)heuristics are replaceable.

Hyper-heuristics can be categorised in different ways with respect to different criteria. Considering the nature of the heuristic search space, two main types of hyper-heuristics have been observed: (1) *heuristic selection* methods that choose one of the low-level (meta)heuristics to apply at a given time and (2) *heuristic generation* methods for generating new (meta)heuristics from given components. From the number of incumbent solutions used during the search process perspective, hyper-heuristics perform single-point based or multi-point based search. The majority of hyper-heuristic studies are on selection hyper-heuristics which perform single-point based search [5] improving a single complete solution, iteratively. In this framework, first, one of the low-level (meta)heuristics is chosen based on a certain selection strategy. Then, this low-level (meta)heuristic is applied to a single candidate solution to generate a new solution. After that, a decision is made on whether to accept or reject this new solution based on a certain acceptance strategy. Thus, this framework consists of two main components: (1) heuristic selection method and (2) move acceptance method as identified by Bilgin *et al.*[21] and Özcan *et al.*[22]. Both components are executed iteratively until termination. Each iteration is referred to as a “decision point” (DP).

On the other hand, there are a few studies on selection hyper-heuristics which perform multi-point (population) based search, i.e. at each DP, a selected low-level (meta)heuristic processes

multiple solutions for a number of steps. In this study, we focus on such selection hyper-heuristics performing multi-point based search in the context of multi-objective optimisation. The choice function based multi-objective hyper-heuristic proposed by Maashi *et al.* [23] is one of the limited studies in this area. An on-line learning mechanism based on four quality indicators (see Section 4.2.3) is designed to select an appropriate MOEA to perform at each DP. Two different move acceptance strategies: Great Deluge Acceptance [24] and Late Acceptance (LA) [25, 26] are modified to solve MOPs [27].

The empirical results demonstrate the effectiveness and advantages of solving continuous MOPs compared to underlying MOEAs (NSGA-II, SPEA2 and MOGA [28]) both on Walking Fish Group (WFG) benchmark problems and a real-world problem - vehicle crashworthiness problem. A brief review of other multi-objective hyper-heuristic approaches is presented in [23]. A recent review of hyper-heuristics both on single-objective and multi-objective can be found in [5].

3. Problem Formulation

The three-objective WFLO problem presented by Tran *et al.* [4], is tackled in this study to obtain the best locations for a given number of turbines on the WF area. The three objectives are to maximise the energy production and minimise both the cable length connecting all turbines and the land covered by the turbines within the given WF area. Two constraints are considered, i.e. wind farm boundary constraint (no turbine can be placed outside the given WF area) and minimum turbine spacing constraint (any two turbines cannot be placed within a certain distance, that is, eight times the rotor radius in this case). The decision variables are the positions of n turbines in a given WF denoted as an array of 2D coordinates $(X, Y) = [(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i), \dots, (x_n, y_n)]$, where (x_i, y_i) is the position of the i^{th} turbine.

The problem formulation is as follows. Given a rectangular wind farm with length l , width w

minimise $\{1/E(P), MST, A\}$

subject to

$$1 \leq x_i \leq l, 1 \leq y_i \leq w, \quad i \in [1, \dots, n]$$

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq 8R, \quad i \neq j \in [1, \dots, n],$$

where MST is the cable length computed using the Prim’s Minimum Spanning Tree algorithm [29], considering that each turbine is a node, and the Euclidean distance between each pair of turbines represents the weight on each arc of an undirected weighted graph. A is the used land area determined by the convex hull of turbine locations which are computed using the Grahams algorithm [30], $E(P)$ is the total expected energy production from this WF using a given layout, R is the rotor radius of a wind turbine.

$E(P)$ is given by Eq. (1).

$$E(P) = \sum_i \int_{\theta} P(\theta) \int_v f(v)p(v(\theta), \kappa, c_i(\theta, X, Y)), \quad (1)$$

where v is the wind speed following a Weibull distribution represented by $p(v(\theta), \kappa, c_i(\theta, X, Y))$ estimated from the wind data considering turbine locations (X, Y) , and $P(\theta)$ represents the probability distribution of the wind source as a function of wind direction θ . The energy production of each turbine contributing to $E(P)$ varies depending on the wake effect caused by nearby turbines. Park model [13] is utilised to calculate this wake effect. In this model, the wake effect reduces the wind sources available on a turbine i by decreasing the scale parameter c of the estimated Weibull distributed wind source for the whole WF (also known as free-stream wind source). Hence, each turbine has its scale parameter c_i . The shape parameter κ is not affected for any turbine in this model. The scale parameter $c_i(\theta)$ is decided by the velocity deficit that turbine i experienced from the nearby turbines in the wind direction θ . The reduced wind speed on each turbine i in each wind direction θ influences the power output of that turbine. A sigmoid power curve function $f(v)$ is used in this model. More specifically, if the wind speed is smaller than the cut-in speed or greater than the cut-out speed, no energy is produced. If the wind speed is between the cut-in speed and the rated speed, the power output follows a linear function. If it is within the range of the rated speed and the cut-out speed, then the turbine generates its rated power. The readers can find more details on the calculation of $E(P)$ in [13].

4. Methodologies

In this section, we present the details of the framework enabling the use of multi-objective hyper-heuristic (MO_HH) methodologies.

4.1. MO_HH Framework

The general algorithmic framework for the MO_HHs used in the experiment is provided in Algorithm 1. First, initialisation process, including generation of initial solutions and setting up of the relevant data structures of the selection hyper-heuristic takes place (Step 2). This process is followed by iterative improvement of a population of trade-off solutions using multiple multi-objective metaheuristics. At each DP, an MOEA is chosen using the metaheuristic selection method (Step 4) and applied (Step 5) to the input set of solutions (P_{in}) for a fixed number of steps (i.e., generations), producing a set of new solutions (P_{new}). Then some data/parameters relevant to algorithmic components get updated (Step 6), which is followed by move acceptance (Step 7), deciding the next input population from the pool of solutions formed by the union of current and newly generated solutions for the next DP. This whole process terminates after iterating for a fixed number of DPs, and the Pareto set is returned.

The initialisation (Step 2) and update (Step 6) processes are used by choice function MO_HHs to initialise and update the utility (choice function) score of each MOEA when a new population is generated, respectively. More explanations can be seen in Section 4.2.3. No initialisation and updating schemes are required by the fixed sequence or random choice MO_HHs.

Algorithm 1: MO_HH Framework

```
1  $h$  : index of the chosen heuristic;  $P_{in}$  : input population;  $P_{new}$  : newly generated population;
2 Initialise();
3 while (!stop criteria are satisfied) do
4    $h \leftarrow$  ChooseMOEA() ;
5    $P_{new} \leftarrow$  ExecuteMOEA(  $h$ ,  $P_{in}$ ,  $g$ );
   // execute MOEA  $h$  for  $g$  generations using input population  $P_{in}$  to produce
   // a new population  $P_{new}$ 
6   Update();
7    $P_{in} \leftarrow$  ApplyMoveAcceptance( $P_{new}$ ,  $P_{in}$ );
   // use AM, GDA or BA as the move acceptance strategy
end
```

4.2. Heuristic Selection Methods

In this study, well known and modified heuristic selection methods as selection hyper-heuristic components are used for choosing the right multi-objective metaheuristic at each DP.

4.2.1. Random Choice (RC)

This method simply chooses a random low-level metaheuristic. It is usually used as a reference approach for performance assessment of the learning hyper-heuristic methods. The initial population of solutions are created randomly.

4.2.2. Fixed Sequence (FS)

Considering that the low level (meta)heuristics are chosen and applied one after and other during the search process, it has been of interest to find a good sequence (or sequences) of low-level (meta)heuristics for a given problem instance [5]. A simple approach would be making use of low-level (meta)heuristics in a predefined sequence. This (meta)heuristic selection method utilises a fixed permutation of low-level (meta)heuristics, where each (meta)heuristic is executed consecutively in that order. The initial set of solutions is randomly produced.

4.2.3. Choice Function (CF)

The CF heuristic selection method proposed by Maashi *et al.* [23] assigns a score to each low-level metaheuristic indicating its performance and the metaheuristic with the maximum score is chosen at each DP. This approach intends to balance intensification (choosing the best performing low-level metaheuristic) and diversification (giving a chance to a metaheuristic which is not selected for a long time) in one function. The CPU seconds elapsed since the last call to a low-level (meta)heuristic serve as the diversification component, while the intensification part is modelled using a two-stage ranking scheme.

In the first stage of the scheme, each MOEAs is ranked with multiple quality indicators separately, in particular, hypervolume, RNI, UD, and AE. The second stage uses the frequency of best quality indicators that each MOEA achieves. Suppose that the framework contains three different MOEAs denoted as h_1, h_2, h_3 , if h_1 achieves the best rank in hypervolume, UD and RNI, h_2 also performs best in RNI and UD, while h_3 only gets the best rank in hypervolume, the frequency ranking ($\text{Freq}_{\text{rank}}(h)$) of h_1, h_2, h_3 are 1,2,3, respectively based on the two-stage ranking scheme.

The final score (or value) for a given MOEA (h) is computed by the CF function Eq. (2).

$$CF(h) = \alpha f_1(h) + f_2(h), \forall h \in H \quad (2)$$

where α is a positive valued parameter, H contains all indices of MOEAs, h is the index of an MOEA. The intensification component (f_1) is defined as

$$f_1(h) = 2(N + 1) - \{Freq_{rank}(h) + RNI_{rank(h)}\} \quad (3)$$

where N is the total number of MOEAs. $Freq_{rank}(h)$ is the rank of the frequency count of the best-ranked indicators of heuristic h , $RNI_{rank(h)}$ is the RNI rank of h . Following the above example, we know $RNI_{rank}(h) = 1,1,3$; combining the $Freq_{rank}(h) = 1,2,3$ for each MOEA, we can get $f_1(h) = 6,5,2$ for h_1, h_2, h_3 respectively. $f_2(h)$ is the elapsed CPU time (in seconds) since the time h was last called. MOEA with the highest value from CF is selected.

The initialisation scheme for the Choice Function based MO_HHs is a greedy strategy which executes each MOEA h for a fixed number of generations and then computes all four indicators (hypervolume, RNI, UD and AE) individually to initialise the two-stage ranking mechanism as explained above. MOEA with the highest CF value (calculated by Eq. (2)) is chosen as the initial h to be applied starting the search process.

4.3. Move Acceptance Methods

Move acceptance methods play an important role in hyper-heuristics by deciding whether to accept or reject candidate solution(s) produced by the selected heuristic. There are many various simple and elaborate move acceptance methods used as a part of metaheuristics in single objective optimisation. Maashi *et al.* [27] modified and evaluated two such elaborate move acceptance for multi-objective optimisation: GDA and LA. However, since the empirical results showed that LA does not perform well, it is not used in this study.

4.3.1. All-Moves (AM)

All solutions generated by the selected metaheuristic are accepted.

4.3.2. Great Deluge Acceptance with D metric (GDA)

Great Deluge Algorithm was originally designed by Dueck [31] for single objective problems. The main idea of this algorithm is to accept a worse solution only if it is better than the threshold

which is referred as *Water Level*. The threshold increases linearly with a fixed step parametrised as UP every time after a solution is accepted. This algorithm is integrated into hyper-heuristics as an acceptance strategy in various single objective hyper-heuristic approaches. Maashi *et al.* [27] modified this acceptance strategy to adapt to multi-objective hyper-heuristics by using *D metric* [32] as the indicator to decide whether to accept or reject the candidate population. The D metric measures the objective space coverage difference between two fronts. For example, $D(A, B)$ is the space covered by front A, but not by B. The pseudo code of GDA is shown in Algorithm 2.

Algorithm 2: GDA Pseudo Code

```

1 A: the previous accepted front; B: the newly generated front; LEVEL: water level,
   initialised with a small value;
2  $D(B, A) = SSC(A + B) - SSC(A)$ ;
   // space only covered by B, not by A
3 if ( $D(B, A) > LEVEL$ ) then
4    $A := B$ ;
5    $LEVEL = LEVEL + UP$ ;
```

4.3.3. Best Acceptance

A simple way of using the idea of only-improving move acceptance strategy in a multi-objective optimisation framework would be to accept the ‘best’ set of solutions maintaining history. In this study, we present the Best Acceptance (BA) which ranks all the solutions from the pool of the newly generated solutions and the population of recently accepted. Then the ‘best’ n solutions (where n is the population size) are allowed to survive as the input population for the next DP, requiring the use of ranking and other supporting functionalities. Any of the three underlying MOEAs’ ranking and truncating mechanisms (removal of excess solutions whenever the size of the population exceeds n) can be applied in this best acceptance strategy. In this work, we use the NSGA-II’s ranking and truncating mechanism.

Due to the stochastic nature of operators (e.g., crossover, mutation), they may generate solutions which have already existed in previous populations. These duplicate solutions can degrade the performance of hyper-heuristics. Thus, we remove those duplicate solutions in BA strategy. The

pseudo code of BA is shown in Algorithm 3.

Algorithm 3: BA Pseudo Code

```

1 A and B are two Pareto fronts.;
2 Union := Merge(A,B);
3 Unionnew ← Remove duplicated solutions in Union;
4 while (Unionnew.size() > Population Size) do
5   Rank the solutions using the NSGA-II ranking mechanism ;
6   Remove the worst solution in Unionnew based on crowding distances;
7 return: Unionnew;

```

5. Experiments

In this study, our goal is to evaluate and compare the performances of different multi-objective hyper-heuristic approaches mixing/controlling three MOEAs {NSGA-II, SPEA2, IBEA} as low-level metaheuristics.

5.1. Experimental Design

Wind turbine parameters are fixed as provided in [13]. The rotor radius is set to 38.5 m, cut-in speed to 3.5 m/s, rated speed to 14 m/s, rated power to 1.5 MW and height to 80 m. A real world wind scenario (scenario 2) from [13] is used in this work. The wind farm is restricted to a land area of 3×3 km² and 30 turbines are to be placed within this area.

The algorithmic parameters of the MOEAs used in this work are set to the same values as provided in [4], i.e. population size to 50, archive size to 50, total solution evaluations to 20000. Problem specific operators (block swap crossover and movement mutation) designed by Tran *et al.* [4] are utilised in all the algorithms in this work, with the crossover probability of 0.3 and mutation probability of 0.9.

Our hyper-heuristics approaches are conducted using five different DP settings in {10, 20, 30, 40, 50}. For Choice Function based MO_HHs, 1000 solutions for each MOEA are used to initialise the two-stage ranking scheme in order to select the initial heuristic to be applied. No such initialisation is needed by the RC or FS metaheuristic selection methods.

The parameter α for Choice Function based MO_HHs and UP for the GDA strategy are tuned referring to the ranges of both parameters provided in [33] in different DP settings. More specifically, α is set as 10 for the Choice Function based MO_HHs. UP is set as 0.01 for 10 DPs, 0.003 for 20 and 30 DPs, 0.0003 for 40 and 50 DPs. Distance sharing σ_{share} in UD quality indicator is set as 0.01 in normalized space as in [23]. The reference point for hypervolume (S metric) and D metric regarding 30 turbines' experiments is (area: 9 km², energy production: 10526 KW, cable length: 17 km). This reference point is set based on trial runs of single MOEAs choosing the highest (worst) value of each objective.

Each algorithm is executed for 30 independent trials on a computer with 64-bit Intel Core i3 3.4GHz\8G\120G configuration. Non-parametric statistical test - one-sided Wilcoxon Rank-Sum Test (also known as MannWhitneyWilcoxon U test) is applied to determine whether there is any statistically significant performance difference between two algorithms with respect to hypervolume. The confidence level is set as 95%.

5.2. Results and Observations

In this section, we compare the performances of selection hyper-heuristics as well as the three individually executed MOEAs with respect to different quality indicators, including {Hypervolume, RNI, UD}. As we mentioned in Section 4.3.3 that except the MO_HHs embedding BA, all hyper-heuristics could have duplicate solutions in a population which are undesirable. More duplicate solutions suggest a decrease in the strength of the corresponding algorithm in preserving potentially more useful solutions. Thus, additional to those three quality indicators mentioned earlier, we propose and use another performance metric, i.e. *ratio of duplicated non-dominated individuals* (RDI), denoting the percentage of duplicate non-dominated solutions in the final population produced by an algorithm.

Table 1 summarises the experimental results comparing the performance of MO_HHs and MOEAs for the WFLO problem instance based on those four metrics. The best performance with respect to the hypervolume is achieved by the random choice - great deluge acceptance (RC-GDA) hyper-heuristic. For the Fixed Sequence MO_HHs, the permutation of <SPEA2, NSGA-II, IBEA> performs 'slightly' better than the rest of the permutations obtaining the highest hypervolume (Due to the space limitation, we skip the empirical results from those experiments.). The experimental results indicate the varying behaviour of MOEAs and hyper-heuristics.

Table 1: Performance of individual MOEAs and hyper-heuristics with 10 DP setting for 30 turbines based on different metrics. The higher hypervolume, RNI and UD, the better. The smaller RDI, the better. ‘-’ means 0. *STD* indicates standard deviation.

	Hypervolume		RNI		RDI		UD	
	Mean _{STD}	Median	Mean _{STD}	Median	Mean _{STD}	Median	Mean _{STD}	Median
CF-AM	11.0743 _{0.1505}	11.1137	0.9355 _{0.0538}	0.9394	0.3073 _{0.0902}	0.3163	0.4649 _{0.1189}	0.4363
CF-GDA	11.1228 _{0.0700}	11.1271	0.9265 _{0.0511}	0.9384	0.3013 _{0.0677}	0.2970	0.4887 _{0.0611}	0.4913
CF-BA	11.1489 _{0.0862}	11.1519	0.9993 _{0.0036}	1.0000	-	-	0.8328 _{0.0981}	0.7849
FS-AM	11.2114 _{0.0692}	11.2045	1.0000 _{0.0000}	1.0000	-	-	0.9945 _{0.0297}	1.0000
FS-GDA	11.2178 _{0.0911}	11.2286	0.9927 _{0.0254}	1.0000	0.0284 _{0.0861}	-	0.9470 _{0.1450}	1.0000
FS-BA	11.2082 _{0.0661}	11.2001	1.0000 _{0.0000}	1.0000	-	-	0.8843 _{0.0905}	0.8348
RC-AM	11.1007 _{0.1504}	11.1340	0.9790 _{0.0392}	1.0000	0.1274 _{0.1577}	0.0600	0.7400 _{0.2393}	0.7122
RC-GDA	11.2284 _{0.1127}	11.2322	0.9770 _{0.0354}	1.0000	0.1796 _{0.1811}	0.1000	0.7104 _{0.2661}	0.6838
RC-BA	11.2012 _{0.1416}	11.1986	1.0000 _{0.0000}	1.0000	-	-	0.8766 _{0.0968}	0.8348
NSGA-II	10.5838 _{0.0946}	10.5783	1.0000 _{0.0000}	1.0000	0.0860 _{0.0302}	0.0800	0.6953 _{0.0220}	0.6986
SPEA2	10.8830 _{0.0813}	10.8723	1.0000 _{0.0000}	1.0000	-	-	1.0000 _{0.0000}	1.0000
IBEA	11.0293 _{0.3511}	11.1258	0.9453 _{0.0430}	0.9623	0.4150 _{0.0543}	0.4200	0.4414 _{0.0585}	0.4329

The statistical test between any pair of algorithms with respect to hypervolume is shown in Tab. 2.

Behaviour of MOEAs: IBEA performs significantly better than NSGA-II and SPEA2 considering hypervolume. However, due to the lack of diversity mechanism in IBEA, the median RDI of the final population is 42%. This value is much higher than those of the NSGA-II and SPEA2 approaches, which are 8% and 0%, respectively. Considering that IBEA has the highest RDI, it is reasonable that it has the lowest UD.

SPEA2 has a similar ability of generating non-dominated solutions (RNI) in a population as NSGA-II, but SPEA2 converges better (a higher hypervolume) and the solutions spread more uniformly (a higher UD) than NSGA-II. IBEA converges the best (the highest hypervolume) among all the three MOEAs, but with limited ability of generating diversified solutions (a lower RNI and UD) than SPEA2 and NSGA-II.

Behaviour of Hyper-heuristics: Overall, each of the nine hyper-heuristics yields significantly

Table 2: Wilcoxon Rank Sum Test of hypervolume between any two algorithms. ‘<’ means significantly worse than; ‘≤’ indicates slightly worse than; ‘>’ means significantly better than; ‘≥’ is slightly better than. The comparison direction is rows versus columns. For example, CF-GDA is slightly better (‘≥’) than CF-AM.

	CF-AM	CF-GDA	CF-BA	FS-AM	FS-GDA	FS-BA	RC-AM	RC-GDA	RC-BA	NSGA-II	SPEA2
CF-AM											
CF-GDA	≥										
CF-BA	>	≥									
FS-AM	>	>	>								
FS-GDA	>	>	>	≥							
FS-BA	>	>	>	≤	≤						
RC-AM	≥	≥	≤	<	<	<					
RC-GDA	>	>	>	≥	≥	≥	>				
RC-BA	>	>	≥	≤	≤	≤	>	≤			
NSGA-II	<	<	<	<	<	<	<	<	<		
SPEA2	<	<	<	<	<	<	<	<	<	>	
IBEA	≥	≤	≤	<	<	<	≤	<	<	>	>

better performance when compared to NSGA-II and SPEA2 with respect to hypervolume. The same phenomena have been observed for IBEA for most of the cases. However, the performances of CF based MO_HHs and RC combined with all-move acceptance strategy (RC-AM hyper-heuristic) are ‘slightly’ better than IBEA with respect to hypervolume (with no statistical significance).

Random Choice and Fixed Sequence MO_HHs also achieves higher RNI and UD than the single MOEA which suggests that both selection MO_HHs exhibit a better diversification ability. From the move acceptance perspective, BA and GDA perform similarly considering hypervolume, but both of them are significantly better than AM when combined with CF and RC metaheuristic selection methods.

To develop a further understanding regarding why selection hyper-heuristics, particularly, Random Choice and Fixed Sequence MO_HHs outperform each of the three MOEAs with respect to hypervolume, we have arbitrarily chosen RC-GDA to visualise the PFs generated by this approach as opposed to the ones obtained by each MOEA. The non-dominated solutions obtained by RC-GDA, NSGA-II, SPEA2 and IBEA over 30 trials are collected, and then projections of Pareto fronts are plotted using the following combinations of objectives:

- maximisation of the power output and minimisation of the land area usage

- maximisation of the power output and minimisation of the minimum spanning tree
- minimisation of the land area usage and minimum spanning tree

Figure 1 shows the comparison between RC-GDA and underlying MOEAs. Note those points that ‘look like’ dominated by others on the same front (i.e. with the same colour) are not dominated since they have better performance on the third objective.

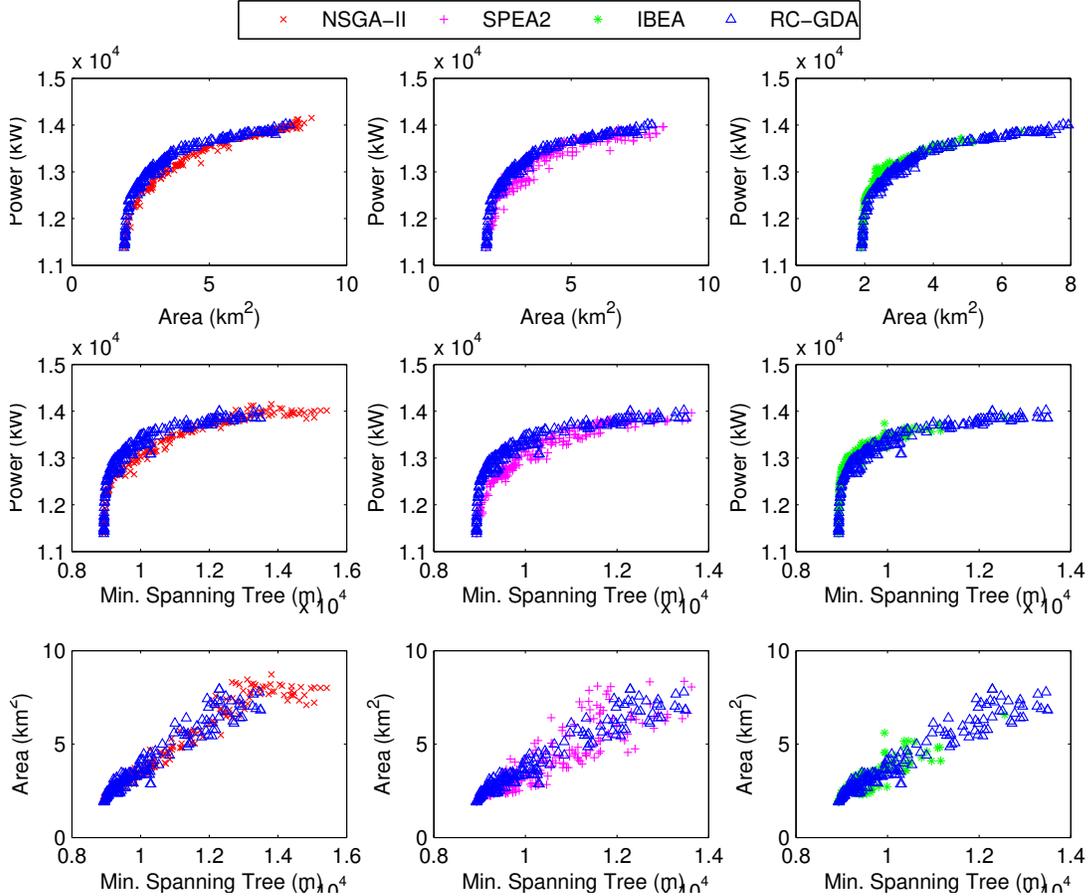


Figure 1: Pareto front projections obtained from NSGA-II, SPEA2, IBEA and RC-GDA considering three different combinations of objectives: Power-Area, Power-Minimum Spanning Tree and Area-Minimum Spanning Tree.

We can see that the PF of RC-GDA clearly dominates PFs generated by NSGA-II and SPEA2 both from convergence and spread perspectives. However, RC-GDA does not converge better than IBEA, but RC-GDA spreads wider than IBEA which explains why RC-GDA is still significantly

better than the IBEA considering hypervolume.

RC-GDA mixes all three MOEAs which gives better chance to explore different regions of a PF produced at each DP, resulting in more diversified solutions and better hypervolume than only using a single MOEA, possibly because different MOEAs have strengths of exploiting and exploring different regions of a PF. In our case, IBEA tends to exploit the region of the PF which maximises AEP within a small land area (i.e. 2 to 5 km²), while NSGA-II and SPEA2 have better performance of exploring the regions which maximise AEP in a larger land area (i.e. 2 to 9 km²). In other words, different MOEAs can work together achieving a better trade-off solutions, eventually.

Apart from that, a strong positive linear correlation between the two objectives, i.e. minimising the minimum spanning tree and the land usage is observed in Fig. 1. More specifically, the Pearson product-moment correlation coefficients (PPMCC) [34] of both objectives for the resultant trade-off solutions obtained from NSGA-II, SPEA2, IBEA and RC-GDA are 0.9628, 0.8771, 0.9021 and 0.9661 respectively, where this value is in [-1,1], and 1 represents total positive correlation. The high PPMCCs suggest that it is potentially redundant to optimise both of those objectives under a multi-objective problem formulation and perhaps one of the objectives can be ignored or both can be merged into a single objective. It is evident that multi-objective WLFO models should be designed carefully.

6. Problem Exploration

Multi-objective WFLO problems can be modelled in various ways as briefly reviewed in Section 2.2. Our model, as formulated in Section 3, is to maximise AEP, minimise the cable length and the land area by optimising the positions of a fixed number of turbines (30 turbines). Even though we are not considering minimising COE or the number of turbines in our model, it is still of interest to see how our solutions would be reflected on those two important objectives and the potential trade-offs among these objectives.

To do this, we run one of our hyper-heuristics - Fixed Sequence (<SPEA2, NSGA-II, IBEA>) - Best Acceptance using a serial of turbine numbers (20, 25, 30, . . . , 100) 30 trials each, utilising the same parameters described in Section 5.1. Then we collect all the non-dominated solutions' energy production to compute the COE values for each turbine number setting.

Many variants of COE can be found in the scientific literature. In our analysis, we are using two COE models based on the formulation provided at the GECCO 2015 Wind Farm Layout Com-

petition [35]. In the original competition model setting, every 30 turbines require one substation. Since it is questionable to assume that every 30 turbines require one substation, we only keep this setting in our first COE model, but not in the second one. The purpose of using these two variants of COE models is to further investigate the effect of different COE models or settings on forming PFs.

The first COE model with substation setting is formulated as Eq. (4).

$$COE_1 = \frac{(C_t * n + C_s * \text{floor}(\frac{n}{m})) * ES + C_{OM} * n}{(1 - (1 + r)^{-y})/r} * \frac{1}{8760 * P} \quad (4)$$

where Economies of scale (ES) is defined as

$$ES = \frac{2}{3} + \frac{1}{3} * e^{-0.00174n^2} \quad (5)$$

$C_t = \pounds 487,500$ per turbine cost¹, n is the number of turbines. $C_s = \pounds 5,200,000$ is the cost per substation. $m = 30$ denotes that one substation is needed for 30 turbines. $C_{OM} = \pounds 13,000$ is the annual operation and maintenance cost per turbine. P is the energy output. 8760 is the total hours in a year. $r = 0.03$ interest rate. $y = 20$ denotes a wind farm lifespan of 20 years.

The difference between COE_1 (Eq. (4)) and GECCO's original model is that GECCO's model has one more component – farm size coefficient $\frac{0.1}{n}$ in its formula which is mainly used to prevent the situation of a search algorithm resulting with a solution producing an overall COE of 0 (at minimum) by providing the option of no turbine use.

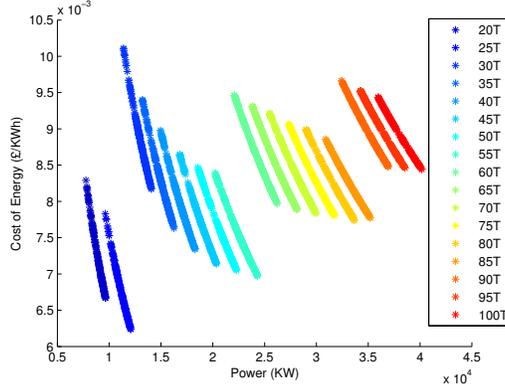
In our second COE model, we exclude the cost of substation as in Eq. (6).

$$COE_2 = \frac{C_t * n * ES + C_{OM} * n}{(1 - (1 + r)^{-y})/r} * \frac{1}{8760 * P} \quad (6)$$

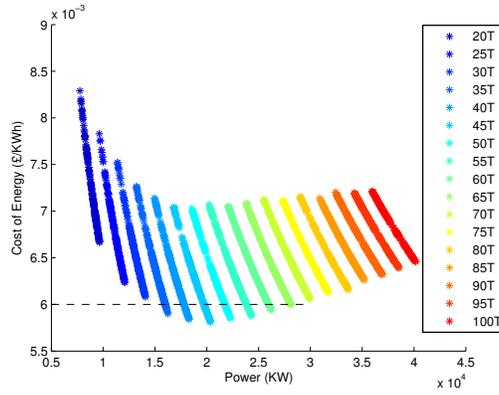
where ES is the same as Eq. (5)

Several main findings from Fig. 2 are as follows. Firstly, clear ‘jumps’ in the COE values considering substation are observed in Fig. 2(a). For every 30 turbine interval, the COE value is the highest (worst) at the beginning of this interval since a new substation is added, then it decreases because more power can be generated from more turbines. Secondly, Fig. 2(b) shows that the COE

¹The original cost is in USD dollars, we convert all the prices from USD dollars to British Pounds using the ratio \$1 = \pounds 0.65 from <http://www.usdollartopound.co.uk/> 10th August, 2015



(a) COE_1 against Power-with substation setting



(b) COE_2 against Power-without substation setting

Figure 2: (a) is the scatter of COE_1 (with substation setting) against power output obtained from optimising the positions of a serial number of turbine numbers. From left to right (colour from blue to red) is from 20T (turbines) to 100T (turbines) and (b) is the scatter of COE_2 (without substation setting) against power output.

values change with the increase of the energy production if no substation is considered in the COE model. In the beginning, the COE values are slowly reduced, since more energy is produced as the number of turbines increases. Then COE rises due to the more severe wake loss caused by more installed turbines. This finding is also consistent with the observation in a wind energy industry report [36].

Thirdly, both Fig. 2(a) and Fig. 2(b) suggest that there are indeed trade-offs among the following objectives: (i) minimising COE; (ii) maximising AEP and (iii) minimising the number

of turbines. For example, in Fig. 2(a), although 25 turbines' configuration gives the lowest COE (COE_1), the energy production is also relatively low which does not satisfy the goal of maximising AEP or minimising the number of turbines (which can be 20 turbines or less). The horizontal dash line in Fig. 2(b) illustrates a simple example of the trade-offs that for a given COE (COE_2) value, 35 turbines would be a more favourable choice if the decision maker(s) prefer to minimise the number of turbines. Otherwise, 55 turbines (which has the same level of COE) would be a better choice than say 35 turbines for the sole purpose of maximising the energy production.

Our analyses show two key findings. Firstly, COE, AEP and the number of turbines can be formulated into a single-objective formulation. However, the use of multi-objective optimisation approaches would be more suitable, since we can still observe the multi-objective or conflicting nature among these three objectives. Secondly, settings or modellings of COE influence the geometries of PFs, and thus pose various difficulties for different MOEAs considering that each algorithm makes use of different search components. For example, MOEAs without adequate diversification mechanisms can easily get trapped in a local optimum while searching a disconnected and multi-modal PF, such as illustrated in Fig. 2(a).

7. Conclusion and Future Work

This study investigated the application of three state-of-the-art multi-objective evolutionary algorithms, namely NSGA-II, SPEA2 and IBEA for solving a multi-objective wind farm layout optimisation problem. The objectives include maximisation of the annual energy production, minimisation of the cable length and minimising the land area. We then tried to solve this computationally difficult problem more effectively by mixing these three multi-objective evolutionary algorithms using nine different selection hyper-heuristics. The empirical results indicated that selection hyper-heuristics could indeed exploit the strengths of multiple multi-objective metaheuristics, and thus achieve statistically significant better performance than each constituent multi-objective metaheuristic used on its own with respect to different performance indicators, including hypervolume and uniform distribution. This phenomenon has been verified by further analysing the convergence and diversification properties of selection hyper-heuristics and the three underlying metaheuristics based on their resultant Pareto fronts.

This work also studied the conflicting nature of three other objectives: minimising cost of energy, maximising annual energy production and minimising the number of turbines. The motivation

behind this exploration is that the complexity of the wind farm layout optimisation problem calls for the balance of various conflicting objectives, even though these objectives are sometimes formulated into a single objective, such as cost of energy. Our analysis reveals that although annual energy production and the number of turbines are often modelled as components into the formulation of cost of energy, there are trade-offs among these three objectives and the modelling or setting of cost of energy can affect the geometries of final Pareto fronts. Further investigations and insights into the cost of energy models and the trade-offs among these three objectives would benefit decision makers for wind farm development.

In the future, we plan to design and test more intelligent selection mechanisms and adaptive move acceptance methods as components of multi-objective selection hyper-heuristics for solving new multi-objective wind farm layout optimisation problem instances. The new problem instances will be considered under different conflicting objectives subject to additional constraints, including geographical constraints with more realistic shapes of wind farms.

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