Wind farm maintenance scheduling model and solution approach

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Abstract

Wind energy has become an important source of energy in the last years, proven to be an alternative to fossil power production. The advances in technology have allowed to exploit this resource in new environments. While offshore wind farms projects are growing at important rates, onshore farms are still the main contributors of this energy source. However, challenges to make wind farms projects profitable are still prevailing. In this context, maintenance activities have an important impact on energy production and operational costs. A linear optimization model is proposed to solve a maintenance scheduling problem for onshore wind farms. The model includes classical key concepts such as availability and revenues. Moreover, it includes technicians crew costs which are relevant when the maintenance operator is not the farm responsible. Therefore, a multi objective scheme is used to solve the problem via the epsilon constraint method. Preliminary results on modified instances previously used in the literature show that an approximation to the pareto front can be found for small instances.

Keywords
Onshore wind farms, operations and maintenance, maintenance scheduling, multi objective optimization, epsilon constraint.

1. Introduction

The awareness of climate change, the variability of oil and gas prices, and their scarcity, have accelerated the use of energy alternatives, e.g. wind, solar, biomass, etc. Among these, wind energy has shown a remarkable development over the last decades. According to the Global Wind Energy Council (2016) the global installed wind capacity at the end of 2016 was of 486.8 Giga Watts (GW). This value implies an increase of 12.6% when compared to 2015, it corresponds to 54.6 GW installed during 2016. Moreover, according to the same organization projections, wind installed capacity will increase by almost 70% in the following five years. While offshore wind production has shown an important augmentation in the last years, onshore production remains the main source wind energy with nearly 97.5% of the total worldwide capacity according to the Global Wind Energy Council (2015).

As the use of wind energy rise globally, it comes with new challenges. Indeed, wind farm projects costs and their profitability represent a main driven force for their development. Wind energy prices have already shown to be competitive. For example, in Mexico during 2016 this energy source (as well as the solar one) have beat conventional technologies (Global Wind Energy Council, 2016). Moreover, wind energy is immune to fluctuations in fossil fuel prices, making it an interesting alternative from an economic viewpoint. Still, there exists opportunities to improve the projects, thus deriving in a more appealing future for wind energy. According to Ding et al. (2013) the Operation and Maintenance (O&M) of wind power systems account for as much as 25-30% of the total energy production costs. Other works in the offshore context such as the ones of Shafiee (2015) and Raknes et al. (2017), state that O&M costs range from 25-33% of the total life cycle cost. O&M costs include transportation costs, technician salaries and cost of repair actions and spare parts, as well as loss of revenue caused by production stops according to Raknes et al. (2017). Thus, maintenance scheduling plays a major role in the turbines availability and costs, as pointed out by Kovàcs et al. (2011).

Additionally, wind farms have an interesting particularity since they involve the interaction of multiple actors. Markard and Petersen (2009) recognize five stakeholders on wind farms projects, namely: turbine manufacturer, project developer, investor, operator, and load management and power distributor. The presence of different actors can derive in conflicting objectives, e.g. when the O&M operator and investor are different actors (Froger et al. 2017). Consequently, multi-objective optimization is an interesting paradigm to approach the problem.

This paper introduces a model to deal with the multi objective maintenance scheduling in the context of onshore wind farms. The model reflects the case when multiple objectives are simultaneously considered, usually due to the presence of different stakeholders. The paper is organized as follows, section 2 presents the literature review. The problem statement is reported in section 3. Section 4 presents the mathematical integer model proposed to solve the problem. Numerical results are discussed in section 5 and the paper is concluded in section 6.

2. Literature Review

Maintenance activities are performed to keep systems working, and to prevent or fix possible failures. In this context, maintenance scheduling and planning has been widely studied in the literature. For a review with applications in the industry, the reader is referred to Budai et al. (2008). In the context of wind farm Ding et al. (2013) present a survey of the different maintenance methodologies, applications, and limitations. Moreover, a recent overview of maintenance logistics for offshore wind energy can be found at Shafiee (2015). Besnard et al. (2011) propose a stochastic model for the maintenance planning of offshore wind farms. Stochasticity is incorporated through scenarios in which the wind, waves and production take different values. The model is based on a rolling horizon, i.e. it is reoptimized every day with the updated tasks and weather forecasts, and aims to minimize production losses and transportation costs. Stålhane et al. (2015) propose arc-flow and path-flow formulations for the routing and scheduling of vessels that perform maintenance tasks at offshore wind farms. The models consider as objective the minimization of transportation, downtime, and penalties costs. Instances considering a workday and at most eight tasks and five vessels are solved to optimality. A similar problem is tackled in Dai et al. (2015). The authors use a four index Mixed Integer Linear Problem (MILP) where vessels availability to work on a given day depends on the type of vessel. Numerical results are presented for instances with eight turbines and three days planning horizon, aiming to minimize the costs and production loss.

Although most of the related wind farm maintenance scheduling literature is devoted to the offshore version of the problem, there are some works that tackle the onshore version. Kovàcs et al. (2011) assume that crews formed by two technicians are used to perform the maintenance tasks. A MILP on a rolling horizon to minimize the total loss of production due to stopping the turbines and the degradation due to failures. Two types of degradations are considered, *general* and *peak*, the first one diminishes the power output by a percentage in any operation condition while the second one reduces the production during high speed winds, but not on lower speed ones. Although no detailed computational results are given, the authors claim to solve instances with up to 50 maintenance tasks, 4 teams and 7 wind farms. Froger et al. (2017) also consider the onshore windfarm maintenance scheduling. The authors consider multiple technician skills, different types of execution modes for the tasks as well as different farm locations. Moreover, the objective in the proposed model is to maximize electricity production over a short horizon. To solve the problem, two formulations based on Integer Linear Programming (ILP) are proposed. A constraint programming large neighborhood approach is devised to solve the problem. Froger et al. (2017b) study the problem introduced by Froger et al. (2017). The authors propose a branch-and-check approach to efficiently solve the problem. This method can consistently produce optimal or near optimal solution to instances with up to 80 tasks, several modes, skills, and farms locations.

Nevertheless, to the best of our knowledge, the works on maintenance scheduling for wind farms have been only focused on single objective problems. Moreover, while some works have considered aspects such as production losses, and operational costs at the same time, they are mixed on single expressions. Thus, such objectives skip the presence of multiple conflicting objectives, due for example, to the presence of several stakeholders (Markard and Petersen, 2009). A comprehensive review of multi-objective optimization and multi-criteria analysis in the energy sector can be found in Antunes and Henriques (2016). The authors review around 300 references in the sector and devise the importance of multi-objective optimization to balance the multiple, conflicting, and incommensurate evaluation aspects. An example of the importance of multi-objective optimization in the wind farm context can be found in Irawan et al. (2017b). The authors address a bi-objective version model for the installation scheduling in offshore wind farms. The objectives are set to minimize the costs and the completion period of the installation. The problem is solved through both exact and metaheuristic methods, using a compromise programming approach.

3. Problem statement

In this section, we present a multi-objective maintenance scheduling problem for onshore wind farms along with the necessary notation to describe it. A wind farm is defined as a collection of wind turbines used to produce energy. The problem can be summarized as the assignment of resources to perform maintenance tasks on the turbines located at one or several wind farms. Maintenance activities are carried on by a O&M operator. Although the inherent stochasticity of the problem due to weather conditions, it is assumed that precise forecasts for the planning horizon are available. Therefore, the maintenance schedule is developed for short horizon times, that is, at most a week. During this time, the amount of energy produced by the turbines, or the periods when safety conditions are respected are known in advance.

A set of J turbines indexed by j are considered. Turbines might be distributed among different wind farms but it is assumed that they are close enough to be reached in despicable times. Furthermore, turbines might require more than one type of maintenance. In this work, we consider periodic, corrective, and predictive maintenance tasks. Periodic activities include changing oil, general revision of the turbines, anchor bolts revision, etc. Corrective actions are those performed to repair failures in the turbine that already took place. Although these are uncommon they must bear in mind during maintenance scheduling. Predictive tasks are scheduled based on prognostics, aiming to prevent future failures and their impacts.

Each task $i \in I$ represents a maintenance activity, whether it is periodic, corrective, or predictive. It is assumed that the ensemble of tasks is specified prior to solving the problem. Also, each task is associated with a turbine $j \in J$, we define I_j as the subset of tasks to be performed in turbine j. To execute each task i a χ_{is} number of technicians with the skill s are necessary. Indeed, each task requires one or different skills held by technicians to perform the maintenance, e.g. mechanical, electrical, electro-mechanical, etc. The set S defines the considered ensemble of skills. Besides, an execution time β_i characterizes every task i. This time, considers the whole time for performing the task. That is, from stopping the turbine until it is restarted and verified again. We consider in this study that all maintenance activities stop the associated turbine during the task execution. Additionally, every started task is performed until finished, and all tasks must be performed during the horizon plan.

Furthermore, every task has a time window $[a_i, b_i]$, where the maintenance should take place. The opening time window is a hard constraint, so the task must start at a_i or latter. The enforcement of this condition accounts for the necessity of spare parts or any special equipment (e.g. cranes) to perform the task. Other spare parts or consumables are assumed to be available at a_i. The time window closure is a soft constraint; therefore, the task should preferably be finished at most at b_i. In the case it finishes later, a penalization cost α is considered per day of delay. Usually, periodic tasks can be performed all along the planning horizon, while corrective or predictive maintenance can be constrained for special equipment or special considerations based on their impacts.

Time is discretized in equally length periods $t \in T$ as commonly done in the literature (see for example Dai et al., 2015; Froger et al., 2017; Irawan et al., 2017). Every time period stands for the same amount of time, e.g. one minute, two hours, etc. During each time period t, a turbine j generates an amount of energy or utility per production denoted as Θ_{jt}. Moreover, we follow an additional representation of time as done by Froger et al. (2017). In this one, a set D defines the ensemble of days in the planning horizon. Every day $d \in D$ has a number of workable t periods called τ_d. Furthermore, the time intervals within a day are divided as normal working and extra working periods. The subset of time periods representing extra working periods is defined as T_e. At the end of each working day in the horizon plan, turbines continue to produce an amount of energy or utility per production $\Upsilon_{jd}\ \forall\ j \in J$ until the next day. Besides, for safety reasons, maintenance task can be only carried out during certain periods of time when weather allows it, e.g. wind speeds are below a value. To address this fact, the parameter ρ_{it} takes value one if the safety conditions are met or zero otherwise. If a task i was being performed during time $t-1$ and $\rho_{it}=0$, the technicians must stop until the safety conditions are met again.

A limited set of technicians is defined by P. Technicians mobilize to the turbines to perform their assigned maintenance tasks. All technicians perceive a fixed salary w_p, which is linearly dependent on the amount of skills they possess. Furthermore, a technician receives an extra wage ew_p for each extra working hour. It is assumed that a worker with a higher salary will enjoy a higher extra payment, i.e. $w_p > w_{p'}$ then $ew_p > ew_{p'}\ \forall p, p' \in P$. Besides, the parameter π_{ps} takes value one if the technician p has the skill s and zero otherwise. Let us also define l_s as the minimum wage among the workers $p \in P \mid \pi_{ps} = 1\ \forall\ s \in S$. That is, the less costly wage for a technician with the skill s. When a technician is assigned to perform a task, he must be present at the turbine until it is finished. Moreover, technicians can only work at one task in each time period.

In this paper, we consider that O&M operator and investors are the two parts involved in the maintenance scheduling. Indeed, O&M operator is paid to perform the maintenance activities, and it is assumed that he seeks to minimize its costs. Meanwhile, the investors expect to maximize the energy production/utility. O&M operator costs comprise the spare parts, the special equipment to perform tasks and the technician's wages. We focus our attention on three main components. The first one is the difference of wages perceived by technicians assigned to tasks that can be performed by less costly ones. The second one, is the extra hour wages paid to technicians, and the third one, the penalization due to maintenance tasks outside the time window. Spare parts and special equipment costs are disregarded since they are assumed to be unavoidable by the O&M operator. Hence, the objective is to minimize the costs of the O&M operator while maximizing the amount/profit of energy production.

4. Mathematical model

The problem described in section 3 is now formalized as an Integer Linear Problem (ILP). The following variables are thus defined:

$$x_{it}: \begin{cases} 1 \ \textit{If task i is scheduled to begin at time t} \\ 0 \ \textit{otherwise} \end{cases}$$
$$z_{it}: \begin{cases} 1 \ \textit{If task i is scheduled at time t} \\ 0 \ \textit{otherwise} \end{cases}$$
$$e_{it}: \begin{cases} 1 \ \textit{If task i is finished at time t} \\ 0 \ \textit{otherwise} \end{cases}$$
$$y_{pi}: \begin{cases} 1 \ \textit{If resource p is assigned to task i} \\ 0 \ \textit{otherwise} \end{cases}$$
$$v_{pti}: \begin{cases} 1 \ \textit{If resource p is scheduled at time t to task i} \\ 0 \ \textit{otherwise} \end{cases}$$
$$u_{id}: \begin{cases} 1 \ \textit{If task i is scheduled in day d} \\ 0 \ \textit{otherwise} \end{cases}$$
$$\gamma_{jt}: \begin{cases} 1 \ \textit{If turbine j is able to produce energy at period t} \\ 0 \ \textit{otherwise} \end{cases}$$

$\eta_{jd}: \begin{cases} 1\ If\ turbine\ j\ is\ able\ to\ produce\ at\ the\ end\ of\ day\ d \\ 0\ otherwise \end{cases}$
$\zeta_i: The\ number\ of\ days\ task\ i\ is\ delayed\ with\ respect\ to\ b_i$

Using the abovementioned variables and the characteristics described in section 3, the ILP is defined as follows:

$$Max\ Z_1 = \sum_{j\in J}\sum_{t\in T}\Theta_{jt}\gamma_{jt} + \sum_{j\in J}\sum_{d\in D}\Upsilon_{jd}\eta_{jd} \quad (1)$$
$$Min\ Z_2 = \sum_{i\in I}\sum_{p\in P}\sum_{s\in S}\kappa_i y_{pi}(w_p - l_s) + \sum_{p\in P0}\sum_{t\in T_e}\sum_{i\in I} ew_p v_{pti} + \sum_{i\in I}\alpha\zeta_i$$

$$\sum_{t\in T} x_{it} = 1 \quad \forall\ i \in I \quad (2)$$

$$\sum_{t\in T} e_{it} = 1 \quad \forall\ i \in I \quad (3)$$

$$z_{it} = x_{it} + x_{it-1} - e_{it-1} \quad \forall\ i \in I, t \in T \quad (4)$$
$$x_{i0} + e_{i0} + z_{i0} = 0 \quad \forall i \in I \quad (5)$$
$$\sum_{t\in T}\pi_{ps} y_{pi} \geq \chi_{is} \quad \forall i \in I, s \in S \quad (6)$$
$$\sum_{t\in T} z_{it}\rho_{it} = \beta_{\mathrm{i}} \quad \forall i \in I \quad (7)$$
$$\sum_{t=1+(d-1)\tau_d}^{d\tau_d} z_{it} \leq \tau_d u_{id} \quad \forall\ i \in I, d \in D \quad (8)$$
$$u_{id} = 0 \quad \forall\ i \in I,\ \ d \in D \mid d < a_i \quad (9)$$
$$\zeta_i \geq d u_{id} - b_i \quad \forall\ i \in I, d \in D \quad (10)$$
$$z_{it} + y_{pi} \leq 1 + v_{pti} \quad \forall\ p \in P.t \in T, i \in I \quad (11)$$
$$v_{pti} \leq z_{it} \quad \forall\ p \in P.t \in T, i \in I \quad (12)$$
$$\sum_{t\in T} v_{pit} \leq M y_{pi} \quad \forall\ p \in\ P, i \in I \quad (13)$$
$$\gamma_{jt} \leq (1 - z_{it}) \quad \forall j \in J, t \in T, i \in I_j \quad (14)$$
$$\eta_{jd} \leq 2 - (u_{id} + u_{id+1}) \quad \forall\ j \in J, d \in D, i \in I_j \quad (15)$$
$$x_{it} \in \{0,1\} \quad \forall i \in I, t \in T \quad (16)$$
$$z_{it} \in \{0,1\} \quad \forall i \in I, t \in T \quad (17)$$
$$e_{it} \in \{0,1\} \quad \forall i \in I, t \in T \quad (18)$$
$$y_{pi} \in \{0,1\} \quad \forall\ p \in P, i \in I \quad (19)$$
$$v_{pti} \in \{0.1\} \quad \forall\ p \in P, t \in T, i \in I \quad (20)$$
$$u_{id} \in \{0,1\} \quad \forall\ i \in I.d \in D \quad (21)$$
$$\gamma_{jt} \in \{0,1\} \quad \forall\ j \in J.t \in T \quad (22)$$
$$\eta_{jd} \in \{0,1\} \quad \forall\ j \in J.d \in D \quad (23)$$
$$\zeta_i \in \mathcal{Z}^+ \cup \{0\} \quad \forall\ i \in I \quad (24)$$

The objectives in equation (1) state that the amount/utility of energy produced is sought to be maximized while cost must be minimized. These last are composed by three parts, the difference between the salaries of a technician assigned to a task i and the minimum wage of a technician offering the same skill. The second part accounts for the extra time periods wages, and the third one is the penalization for not finishing the task within the time window. Constraints (2) and (3) ensure that all tasks are started and finished within the time horizon. The coherence between the start, the execution, and the end of a task is guaranteed by constraint (4), moreover, it ensures that tasks are executed until finished once they been have started. Constraint (5) states the initial conditions by considering that no task starts, finishes, or is assigned during time period zero. The number of technicians with the required skills to perform each task is imposed in constraint (6). The former equation has a sense of greater or equal for some special cases, e.g. consider a task i which requires two skills s_1, s_2 with a number of technicians of two and one respectively. If the equation is set to equality two technicians p_1, p_2 both with skills s_1, s_2 cannot be simultaneously assigned to the task since it will violate the equation for skill s_2. Still, this scenario where p_1 and p_2 are assigned to perform task i is valid and therefore we choose to keep the constraint sense. Constraint (7) ensures that the amount of time periods expended on a task will be sufficient to finish it, the parameter ρ_{it} guarantees that the weather allows to execute the task during these periods. The coupling between tasks executed during a day and the actual scheduled time periods is considered in constraint (8). Time windows are defined in constraints (9) and the (10), the first one safeguards that tasks must start after their associated opening time window, and the second one, keeps track of the number of days a task is delayed with respect to its time window closure. Equations (11) to (13) couple the technicians' assignment to a task with its execution times. The parameter M in constraint (13) is used as a big M value. Moreover, constraints (14) and

(15) determine if a turbine can produce energy at normal time periods, and at the end of the days respectively. Finally, equations (16) to (24) stand the decision variables.

4.1 The Epsilon constraint approach

Multi-Objective Optimization Problems (MOOP) are defined as problems where multiple, often conflicting objectives are to be optimized at the same time. Multi-objective optimization methods differ from single objective ones where only one solution is found to minimize/maximize the problem at hand. Indeed, in MOOP more than one solution can be found, especially when the method used deals with Pareto-optimization. Thus, solving MOOP is a process of finding the ensemble of solutions called Pareto efficient or non-dominated. These solutions are those for which no objective can be improved without worsen at least another objective. The whole set of non-dominated solutions is called Pareto Front (Luc 2016).

Several approaches are discussed in the literature to solve MOOP, e.g. weighted global criterion (Marler and Arora (2004)), goal programming (Tamiz et al. (1998)), epsilon constraints (Mavrotas (2009)), etc. To address our model, we use the epsilon constraint method. This approach is used to construct an ensemble of Pareto Efficient Solutions (PES). In general terms, the epsilon constraint works by iteratively solving single objective problems. Consider the following multi objective problem $Max\ F(x) = f_1(x), f_2(x), \dots, f_n(x) |\ x \in \Omega$. Each $f_i\ \forall\ i = 1 \dots n$ represents an objective, and the condition $x \in \Omega$ stands for feasible set of solutions. Epsilon constraint method solves a group of problems $Max\ f_j(x)\ |\ f_i(x) \geq e_i\ \ \forall\ i\ = 1..n\ \wedge\ i \neq j, x \in \Omega$ by changing the values of e_i. Each solution found is efficient and kept devising (partially) the Pareto Front. Although simpler approaches can be used such as the *Weighting Method* in which the different objectives are reduced to a simple objective using weights for each component, the epsilon constraint is preferred for the following reasons. First, epsilon constraint can find non-supported solutions, i.e. solutions not in the convex envelope of the Pareto Front. Second, there is no need to scale the objectives. Third, epsilon constraint iterations can be coded so new efficient points are found at each iteration, this can avoid unnecessary iterations which need considerable amounts of time for solving the ILPs.

Algorithm 1: Epsilon Constraints method

1: Solutions = {}
2: $\{z_1^*, z_2\} = \max Z_1$
3: $\{z_1^*, z_2^*\} = \min Z_2 \mid (Z_1 = z_1^*)$
4: Solutions = Solutions $\cup \{z_1^*, z_2^*\}$
5: $\{z_1, z_2^{**}\} = \min Z_2$
6: stepSize = $(z_2^* - z_2^{**})$/(numSteps)
7: i <- 1
8:   **while**$(z_2^* - i * stepSize) > \ z_2^{**})$
9:       $\{z_1^*, z_2\} = \max Z_1 \mid (Z_2 \leq\ z_2^* - i * stepSize)$
10:      $\{z_1^*, z_2^{***}\} = \min Z_2 \mid (Z_1 = z_1^*)$
11:      Solutions = Solutions $\cup \{z_1^*, z_2^{***}\}$
12:      i = i+1
13:   **end while**
14:   Sort and Check (Solutions)
15:   **return** Solutions

Algorithm 1 shows the general steps of our implementation of the epsilon constraint method. Maximizing and minimizing procedures make calls to a linear solver and retrieve the value of Z_1 and Z_2 after performing the optimization. These optimizations are carried out for a single objective using the model presented in section 4, adding the pertinent epsilon-constraints. Line 1 starts by initializing an empty array where the solutions will be kept. In line 2, the quantity/utility of the energy production is maximized, while line 3 minimizes the costs with the additional constraint that energy production must match the one found in line 2. The solution is then saved in the proper array of efficient solutions. It shall be noticed that it is necessary to solve both problems (energy and costs), to retrieve an efficient point. Indeed, preliminary tests show that solving only the problem $\max Z_1$ gives suboptimal solutions in terms of costs. The algorithm continues solving the problem $\min Z_2$ in line 5, this is done to define the interval within the objective Z_2 is comprised, i.e. z_2^*, z_2^{**}. In line 6, a step size is calculated to use it for the epsilon constraint method. This value depends on the minimum and maximum value attained by Z_2 as well as a parameter called numSteps. This last allows to control the number of iterations performed during the loop. Indeed, higher values for the number of steps permit to better determine the Pareto Front at the expense of higher computational times. Nevertheless, the value for this parameter does not guarantee that a different efficient point will be found for each possible step value, it works as an upper bound. Between lines 8 and 13 the main loop iteratively solves the ILPs for energy and costs using the proper constraints, while saving the efficient solutions. Finally, in line 14 the ensemble of solutions is sorted and solutions are checked for dominance. Indeed, if solutions are optimal, they are efficient, nevertheless, if optimality is not guarantee, solutions are only potentially efficient.

5. Numerical Results

To test the proposed model, we use the instances proposed by Froger et al. (2017). For the sake of completeness, we recall their main characteristics. The testbed is composed by 160 instances with different characteristics. Indeed, instances vary according to core characteristics such as: time horizon lengths (10, 20 or 40), time periods per day (2 or 4), number of tasks (20, 40 or 80), number of skills (1 or 3), and the technician-to-work-ratio (A and B). Among these, we concentrate only in a subset of 40 instances with at most 20 tasks, and 20-time periods. Moreover, for instances with two-time periods per day we add an additionally period to stand for extra hours. This extra time period has an implicit duration of four hours. The same procedure is performed for instances with four-time periods, unless, for these, two extra time periods are added per day (each one representing 2 hours). To assign an energy utility to these time periods, the following procedure is employed. We use the original η_{jd} for each day and turbine, and divide it by 16 (number of hours between workable days). Then, extra periods use this coefficient multiplied by the number of hours they stand for, to determine the amount/utility of energy production. It is assumed that weather conditions are safe to perform maintenance tasks during extra time periods, i.e. $\rho_{it} = 1$. Additionally, since original instances consider multiple modes or ways to perform each task, a single mode is randomly selected. This picked mode include the information of the number of technician per skill required to perform the task, and its duration (number of periods). Besides, it is assumed that transport times between every pair of turbines are negligible. Tasks' time windows are not considered in Froger et al. (2017) instances, thus, we set $a_i = 0, b_i = |D|\ \forall i \in I$.

To constraint the computational effort required to solve the problems, we limit the amount of time that epsilon constraint method expends on the ILPs. For problems in lines 2, 3 and, 5 in Algorithm 1, the time limit is set to 2000 seconds. ILPs in lines 9 and 10 are limited to 500 seconds. The first problems are led to run for more time since they are used to create the interval in which epsilon constraints will be defined. Moreover, the parameter associated to the number of steps is set to 50. This value guarantees a good trade-off between the approximation of the Pareto Front and the running times. Both time limits and the number of steps were selected after several preliminary tests. Since times are constrained, optimal solutions are not guaranteed, therefore, we keep track of the GAP metric for each single objective problem.

All runs are conducted on a Dell Latitude E6420 personal computer with Intel® Core™ i7-2760QM @2.4 GHz, running Windows 7 Professional 64 bits. The algorithms were coded on Java and compiled with JavaSE-1.8_45, with maximum allocated memory of 1 Gb. To solve linear problems, we use the Java interface with Gurobi 7 (2017) optimizer.

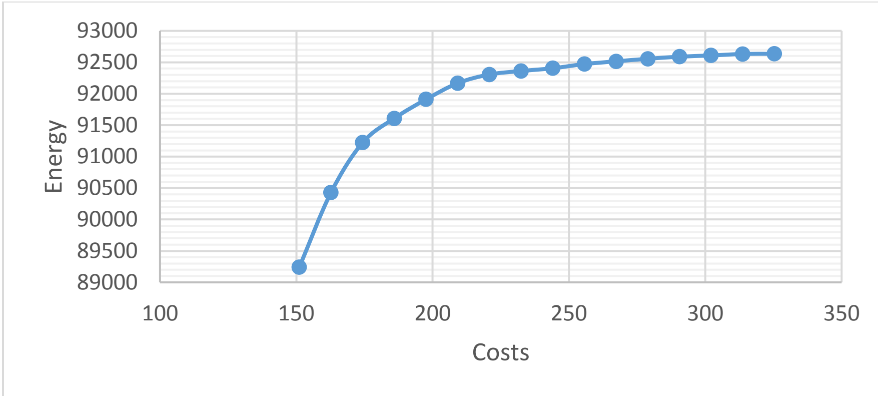

Figure 1 – Approximate Pareto Front for Froger et al. (2017) instance 10_2_1_20_B_5

Figure 1 presents an example of the solutions found. The instance originally contains 10 period times but this value was increased to consider extra time periods. Three periods are defined for each day and only one skill is considered. Moreover, the instance contains 20 tasks with a regular technician-to-work-ratio, that is, technicians can perform all the tasks during the planning horizon. 16 non-dominated points (solutions) are found, although only two are proven optimal, thus efficient. Indeed, 12 points present a small gap in the energy component. Still, this gap is on average of 0.03%. The other two points present an average gap of 0.04% in the cost component. The graphic shows an overall concave behavior, displaying a smaller energy utility/production when costs are small and bigger production at the expense of higher costs. However, it shall be noticed that not all points rely on the convex hull, e.g. point nine, counting from the left-below part of the graph, showing the conflicting nature of the objectives. All the tested instances present a similar behavior in terms of shape. Furthermore, it shall be noticed that for figure 1, an increase of 115% in the minimum cost can have an impact of almost 4% in the energy utility/production.

Table 1 summarizes the results found for testbed instances. Results are grouped by families of instances, in here we follow the original notation of Froger et al. (2017) “a_b_c_d_e” where a, b, c, d, and e refer to the original number of time periods in the planning horizon, the original number of periods per day, the number of skills considered, the number of tasks and technician-to-work ratio, respectively. Five instances compose each family, thus, the eight families account for the 40 tested instances. For each one is reported, the average time (Avg. Time) per solved instance, the average number of non-dominated solutions found (Avg. Solutions), the average number of solutions proven to be efficient (Avg. E. Solutions), the average gap for non-optimal solutions in terms of costs (Avg. Gap C), the average gap for non-optimal solutions for the energy objective (Avg. Gap E), the average number of solutions in which costs are not optimal (Avg. CNOP), and the number of solutions in which energy is not optimal (Avg. ENOP).

Table 1. Epsilon Constraints summary results for Froger et al. (2017) instances

Family	Avg. Time (h)	Avg. Solutions	Avg. E. Solutions	Avg. Gap C	Avg. Gap E	Avg. CNOP	Avg. ENOP
10_2_1_20_A	1.85	12.2	4.4	4.7%	0.7%	2	7.2
10_2_1_20_B	1.22	10.2	4	0%	0.3%	0	6
10_2_3_20_A	1.96	10.8	5	5.7%	0.6%	2	4.6
10_2_3_20_B	2.39	13.4	6.2	9.5%	0.3%	1.2	6
20_4_1_20_A	2.81	12.8	4.2	16.2%	0.5%	4.6	7.6
20_4_1_20_B	3.41	15.2	3	12.1%	0.1%	5.2	10.8
20_4_3_20_A	2.65	8.4	1	28.4%	1.6%	5.0	5.1
20_4_3_20_B	2.70	7.8	1	34.6%	1.4%	5.4	4.6
Total	2.37	11.35	3.6	13.9%	0.6%	3.2	6.5

Table 1 shows that on average, instances take around 2.37 hours to be solved. A significant increase in computational times is seen when the number of periods is incremented. The reason for this behavior is the increase in the size of the ILP models. In terms of the number of solutions, a very limited number is found for the whole set of instances, averaging 11.35 points. A reasonable explication to this limited number of potentially non-dominated solutions is that space solution for the problems is highly constrained. Therefore, the number of solutions, and more important, efficient solutions is limited.

Among the solutions found by the epsilon-constraint method, nearly one third are proven to be efficient. Indeed, as little as this number might be seen, the reason is the complexity in solving the single objective ILP. One can see that the cost objective is by much the one with the higher gaps, averaging 13.9%. Furthermore, the gaps on cost component show a considerable rise when more skill are considered in the problems. This is especially important in instances with higher number of time periods, where family 20_4_3_20_B reaches a maximum of 34.6%.

Energy objective contrary to costs objective, show an excellent performance. Through the 40 instances, the average gap is only 0.6%. Type B instances (regular technician-to-work-ratio) consistently outperform type A (tight technician-to-work-ratio) instances in this metric. Despite the better performance in terms of energy gaps, results show that the number of solutions not proven efficient is mostly due to energy objective function. The average number of solutions for which energy presents a positive gap doubles the same metric for costs objective. Therefore, it is safe to say that single objective Z_2 is solved to optimally more consistently than Z_1. However, when dealing with sub-optimal solutions, the average costs (Z_1) gap is over 20 times bigger than the energy (Z_2) average gap.

6. Conclusions

This paper introduces a new model to solve the wind farm maintenance scheduling problem in the onshore context. The proposed model considers the multi objective nature of the problem, taking account of both costs as well as the energy production/utility. The problem is solved using an ILP embedded in an epsilon constraint algorithm. Results show that an approximation to the pareto front can be found to small instances previously used in the literature. Still, the complexity of ILP problems make that most of the solutions found by the algorithm cannot be proven to be Pareto Efficient. Improvement in the computational times and performance of the ILP considering the cost objective must be conducted in our future work. Nevertheless, as shown in a detailed example, one can see the importance of considering multiple objectives. In fact, the augmentation of costs can have significant consequences in the amount/utility of energy produced. Our solution approach can thus give the decision makers an important source of information to plan and perform the maintenance activities.
Undergoing work considers new variants of objectives as well as approximation methods to deal with bigger instances. Indeed, the stochastic nature of the problem makes a daily roll-over approach suitable, thus, faster approaches are necessary to apply this type of models. Moreover, we are currently considering the inherent stochasticity in task times. Certainly, times to perform a task might not be completely known prior to the problem solution, therefore, solution methods must consider this aspect to create robust and reliable solutions.

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