Simulation and Optimization of Offshore Renewable Energy Arrays for Minimal Life-Cycle Costs

Second Year Report

Robin Kuipers

Supervisors:
Kerem Akartunali
Euan Barlow

University of Strathclyde
Strathclyde Business School
Glasgow, Scotland

October, 2020

Abstract

This report aims to give a detailed overview of the research progress I made between January 2020 and September 2020, which is the time between the completion of the first yearly review and the start of the second yearly review of this PhD project into logistical decisions regarding offshore wind farms. It will quickly recap the progress made in the first year, and then detail the progress made in the second year, which primarily focused on developing and implementing models for optimization problems related to topic. The report also discusses future work, and what the next steps are.

Contents

1 Introduction **4**

1.1 Problem description . . . 5

1.2 Research questions . . . 7

2 Closing knowledge gaps **9**

2.1 The maintenance phase . . . 9

2.2 Other new knowledge . . . 13

2.3 Closing thoughts . . . 14

3 Developing models **15**

3.1 Initial models . . . 15

3.2 More sophisticated models . . . 20

4 Implementation **21**

5 Additional activities **22**

6 Next steps **24**

6.1 Timeline . . . 24

1 Introduction

For the past two years, I have been researching logistics related to offshore windfarm projects; the installation, maintenance, and decommissioning of windfarms in various seas and oceans, primarily the North Sea. The installation and decommissioning projects (at the start and end of the windfarm's lifespan respectively) can often take up to several years, and the lifespan of such farms is usually between 20 and 30 years, over which maintenance has to be done. For these projects, expensive vessels have to be used, the rent of which is often upwards of £100.000 per day (Barlow et al. 2014), hence a project with multiple vessels over many months can cost upwards of £100 million (Kaiser & Snyder 2010). Therefore, even small improvements to the schedules can save significant amounts of money.

The complexity with these logistics comes from various factors, the first being the severe impact that weather conditions can have on when operational tasks can be completed. These projects take place on open sea, where weather can often be rougher than on land. In addition, the high-tech vessels are performing operations on large industrial constructions, hence there is a limited range of allowed wind speeds and wave heights. Another factor which can further limit possible schedules is the inflexibility involved in vessel chartering (renting), since vessels of the required caliber cannot be chartered on short notice, making adaptive in-the-moment scheduling is impossible. This means we will have to make decisions significantly in advance, and run the risk of chartering vessels in periods where they might not be able to complete their tasks due to the weather conditions.

This report will detail the research progress I have made since the completion of my first yearly review, which (due to scheduling issues and delays) was only completed in January 2020. Further on in this section, I will recap the specific parts of this problem that I am looking at (Section 1.1), and which research questions I initially posed (Section 1.2). Then Section 2 through Section 5 will talk about the work I have been doing since the last review. Respectively, these sections are about the knowledge gaps I closed, the models I have developed, how I have implemented them, and all additional activities I have taken part in. Finally, Section 6 will discuss the next steps for this project.

1.1 Problem description

This research looks at offshore windfarms (OWFs) and the scheduling decisions made over the entire life-cycle of such an OWF. I will focus on the type of windfarms currently being build in the North Sea (RenewableUK 2017, Barlow et al. 2018). These windfarms generally consist of up to 150 Wind Turbine Generators (WTGs) and the farms we focus on are located in roughly 50+ kilometers off the coast. The specific duration of each phase of the life-cycle depends on the specific windfarm, but to give the reader some idea of the timescales involved: A typical life-cycle would consist of roughly 2-3 yeas of installation, 20-30 years in which the WTGs generate energy and need to be maintained, and then another 2-3 years in which the turbines are decommissioned. These turbines are large structures that will need to be transported and installed by specialized and expensive vessels, leading to large costs over these years.

In the literature these three phases are commonly treated separately. Both the installation and decommission phases have similar structures; a fixed set of tasks that needs to be completed as quickly or as profitably as possible. Focusing on cost over speed might lead to a different schedule, as some decisions might slow down the overall project but lead to individual turbines being operational earlier, from which point it can start generating energy and income. Commonly there will be contractual or legal deadlines on installation and decommission, setting dates at which the OWF should be fully or partially operational, or completely decommissioned. A key difference between the installation and decommission phase are that in the installation phase minimizing cost will help reach the deadlines; ideally the installation is completed as soon as possible, as income will be generated by each completed turbine. For decommission this is not the case; if decommission starts later turbines will generate income for longer, but it will be harder to reach the deadlines.

The maintenance phase has an entirely different structure from the other two phases. There will be a small set of fixed tasks, since there are legal requirements on minimum amount of maintenance that needs to be done, but this will not be the bulk of the work performed during this phase. A maintenance strategy will need to be formed that determines when turbines will be visited. These visits can be at predetermined moments, or after a turbine fails, or sometimes even right before a turbine is predicted to fail (based on sensor data). An optimal strategy will often use a combination of these types of visits in order to minimize cost, accounting for both the cost of repairs and the amount of income missed due to failures and downtime during maintenance. An additional difference during the maintenance phase is that tasks will often be smaller than the tasks in the other phases. During installation and decommission entire turbines need to be transported and worked on, often requiring very specific and expensive vessels. Conversely during maintenance many smaller repairs can often be done by simply sending engineers over and all you need is a crew transport vessel. This is not the case for every maintenance task as larger repairs and replacements will sometimes need to happen, but it will still hold for many small tasks.

Each of these three phases is subject to stochastic elements, the weather conditions being a major factor to take into account. In addition to the weather possibly restricting which tasks can be performed at any given time, it plays another factor during the maintenance phase. Strong winds also increase the energy output of the turbines, making it extra beneficial to have all turbines up and running before periods of strong winds. Other than the weather, task durations have an inherently uncertain factor, and turbine failures are also difficult to predict. All this together means that uncertain factors can have an immense impact on the overall costs of the project. For this reason robustness is often a metric to be taken into account as well. It might be in the operators best interest to work a less intensive schedule if it reduces the chances of large delays.

1.2 Research questions

In this PhD project my goal is to look at scheduling during the entire life-cycle of an OWF. As far as we are aware, this has not been done in the literature, which indicated there may be optimizations and new insights to be found here. Therefore my primary research question is:

Question. *Can considering the entirety of the life-cycle of an Offshore Wind Farm, and how each of the phases interact, improve logistical decision making on these projects?*

It is clear that a primary reason for splitting the project into phases is that the problem becomes more manageable, and there is generally no need to make all scheduling decisions at the start of the project. There is no point in scheduling the entire decommission phase at the time of installation, as over the 20-30 year lifespan of the windfarm the available vessels will likely change. However, treating the phases entirely separately misses the interactions between the phases. This interaction exists within the real world, and if the literature ignores it this creates a divide between academia and the real world. For that reason I want to investigate these interactions.

The first type of interaction takes place when two phases are active at the same time; after the first turbines have completed installation they potentially need maintenance, while installation continues on the rest of the turbines. The reverse effect takes place when decommission starts, as it does not start at the same time for every turbine. During this time, the phases share resources and could potentially hinder each other (when the same port is used for different vessels servicing different phases). On the other hand, if attention is payed this sharing of resources could be beneficial. Some installation tasks require smaller vessels that can also be used for maintenance operations, and some maintenance operations use larger vessels more commonly used for installation tasks. Therefore paying attention to this overlap period could both help reduce obstacles and create new benefits from this interaction.

The second type of interaction is the long-term effect scheduling decisions might have. If the installation is looked at in isolation a schedule might be produced in which the completion time of the first and the last turbine is years apart; this might have an affect on their wear and chance to fail over the course of the maintenance phase. This in turn might also lead to those first-installed turbines being decommissioned first as well. Since decisions made during the installation phase might still influence events long after installation is complete, these long term effects might also influence the decision in the first place. For that reason this interaction can be looked at from two perspectives; early decisions that are influenced by their long-term effects, and later decisions that are influenced by decisions made in earlier phases.

These interactions bring me to the sub-questions of my research:

Sub-Question 1. *Can considering how phases in the life-cycle of a windfarm overlap and share resources improve logistical decision making on these projects?*

Sub-Question 2. *Can simulating the entire life-cycle of a windfarm provide useful data to base logistical decisions on in the later phases of these projects?*

Sub-Question 3. *Can considering the long-term effects of logistical decisions early on in the life-cycle of a windfarm improve these decisions?*

2 Closing knowledge gaps

During my first yearly review it was remarked that most of my reading up to that point focused on either methodology or installation projects, and there were gaps concerning the other two phases, primarily maintenance. Over the past months I have worked to close these gaps, and I consistently updated the literature review as I gained knowledge. This section will show the highlights of that updated literature review, and I will give some closing thoughts on these new insights at the end.

2.1 The maintenance phase

In (Shafiee 2015) the different topics that fall under maintenance are divided into three timescales (echelons):

1. Strategic: Long term, over the lifespan of an OWF
    - Wind farm design for reliability
    - Location/Capacity of maintenance accommodations
    - Maintenance strategy selection
    - Outsourcing decisions
2. Tactical: Medium term, between 1 and 5 years
    - Spare parts management
    - Maintenance support organization
    - Purchasing/leasing decisions
3. Operational: Short term, day to day
    - Maintenance scheduling
    - Routing of maintenance vessels
    - Performance measurement

Decisions within the strategic echelon are found to have the biggest impact on the costs of operations, which makes sense as they affect the largest amount of time. However each of these echelons include important decisions that will have to be made for the maintenance of the sites. Besides providing this framework to categorize research, they also highlight which areas appear most thoroughly researched, and identify some unexplored areas. Potentially due to their large impact, the topics within the strategic echelon have received most attention, while the topics in the operational echelon received least. The writers indicate they these shorter term areas might hold unexplored potential for future research.

In (Dinwoodie et al. 2012) an attempt is made to analyse the availability of OWFs. It is observed that the availability of offshore farms is much lower than that of onshore farms; currently offshore availability is around 80%, while onshore this is 97%. Various future scenarios are simulated to investigate which measures are likely to improve availability. It is found that increasing vessel operability to allow a higher significant wave height will greatly increase availablity, but realistically it will remain significantly below onshore availability. It is posited this can only be improved with improvement of the components to lower their failure rates, but an 8-fold improvement is required to achieve the same level of availability as onshore.

In another paper (Dinwoodie & McMillan 2014) the same researchers focus on comparing operational strategies. They consider 4 approaches:

- Annual charter, where maintenance operations take place at predetermined times
- Fix on fail, where repairs are made as soon as any failures are detected
- Batch repair, where repairs are done after a fixed number of failures is detected
- Purchase, where a vessel is purchased rather than rented

In their research they find the latter three strategies to be close together in costs while the Annual charter strategy lags behind. Which of these three strategies performs best depends on scenario specifics such as fluctuations in vessel costs, the value of energy, and specific failure rates. Each of the strategies also has inherent characteristics that the operator might have preferences in, such as the purchase strategy having much higher costs up front, but lower operational costs.

An issue with this paper is that mixing of strategies is only very briefly discussed, while this is often beneficial and commonly discussed in the literature. For example, in batch repair, if the batch size is set to 5 failures and for an extended period of time there are 4 failures, it might be beneficial to repair it if this situation goes on for long enough. One way to do this is to mix the annual charter strategy with the batch repair strategy, having a set time to do maintenance even if the required number of failures is not reached. Since this combination of preventive and corrective maintenance is a common strategy within the literature its absence in this paper is surprising.

In (Dinwoodie et al. 2015) this same group of researchers proposes a reference case for maintenance models. Their idea is for various maintenance models to optimise a constructed scenario a fictional windfarm, as a benchmark to compare these models. This allows us to see which models perform better in various scenarios, as they constructed a base case and a set of variants. In the paper they compare four models, and compare various metrics of the results. For availability of the windfarms all results are extremely close, apart from three scenarios. It is explained that these differences result from previously unknown assumptions in the different models, such as whether parallel maintenance tasks are possible on the same turbine, and the moment at which tasks should be assigned to vessels.

This uncovering of assumptions is a strong benefit of using a standardised reference case to verify a model. Seeing that a new model performs similarly to other models apart from certain scenarios can give insight into how this new model handles these scenarios in ways that might otherwise have gone unnoticed, as demonstrated in this paper.

In (Besnard et al. 2011) a stochasitc optimisation model is constructed for short-term maintenance planning. The primary goal is to utilize times when energy production is expected to be low for maintenance, in order to minimise production losses. An interesting aspect of this model is the build-in uncertainty of weather forecasts. The stochastic element of the model is realized by having a small set of scenarios, and the average cost over all scenarios is minimised. The first time step is assumed to have the correct forecast, hence the idea behind the model is for the optimisation to be recomputed regularly. A rolling horizon approach such as this seems like a good method to deal with these uncertain forecasts, although it can be computationally expensive to recalculate regularly.

Another optimisation model focused on maintenance is given in (Stålhane et al. 2019), where the problem of fleet composition is investigated through a two-stage stochastic programming model. The problem is decomposed using a variant of a Dantzig-Wolfe decomposition. In the first stage the set of vessels to be chartered for each active base is decided, while in the second stage the maintenance tasks are divided over the available vessels. The first stage has an objective function minimising costs, which has one term representing the expected costs from the second stage. This cost depends on the stochastic variables in the second stage (failures, energy generated based on weather conditions, availability of vessels based on weather conditions). In order to solve it, a set of scenarios is generated, each of which represent a realisation of this set of variables. The weighted average costs of all scenarios (weighted on their probability) is used to represent the expected costs, after which the first stage of the problem can be solved.

This sort of decomposition is potentially useful for my models, to handle the stochastic aspects of the problem. In this paper the model is verified by comparing it to reference cases constructed in (Dinwoodie et al. 2015) which was discussed earlier in this section. The computations are shown to run in feasible time, and when the fleet composition is fixed it is shown to give comparable results to what is expected.

2.2 Other new knowledge

While there is not much research relating specifically to decommission projects, some recent work has still been done in this field. In (Irawan et al. 2019) an attempt to optimise the decommissioning is made using an ILP. The model created focuses on minimising total costs, and takes many factors into account, such as both offshore and onshore logistics, components that can be sold and components that can be recycled. This broadness means the model is more accurate, but it also means they were not able to solve the exact problem. For this reason they tried various relaxations, and proposed a matheuristic method in which some integer constraints are relaxed. They use this method to create feasible and well-performing solutions in a short time.

In the last two decades the the installation time has generally decreased, as analysed in (Lacal-Arántegui et al. 2018). This work looks at the installation times of the foundations of a windfarm, the installation times of the turbines, and the overall installation times. It observes a 22% time decrease per turbine between the periods of 2000 to 2003, and 2016 to 2017. This improvement is more impressive when you consider the distance from the shore has increased in that time. However, the true scale of the improvement only becomes clear when you look at the time per megawatt; this reveals a 71% time reduction within this timeframe. This is a very substantial reduction, and one that shows the potential of large windfarms with many turbines that are located far off the shore. The specific causes of this improvement are not investigated much, so it is unclear whether this improvement mainly comes from the components used, or the logistics of installation, or some other cause. Investigating this is noted as future research.

An overview of the state of robust optimisation is given in (Gabrel et al.

2014). This study looks at 130 papers, 45 PhD dissertations, and selected other works published between 2007 and 2013 which discussed robust optimisation. The sheer amount of research done reflects the strength of this method. Both the theory and applications of robust optimisation are discussed. The applications include classical logistics problems such as inventory management and scheduling, problems related to finance and revenue management, queueing networks, energy systems and public good (decisions that will benefit the general public). This shows the wide variety of possible applications that RO methods can have. They conclude by highlighting four key developments in RO between 2007 and 2013; (1) the extensive amount of research regarding robustifying stochastic optimization, (2) a link between uncertainty sets and risk theory allows for a connection with decision sciences, (3) new results in the area of sequential decision-making and multi-stage models, and (4) new areas of applications.

2.3 Closing thoughts

As is hopefully evident from this section, I have worked hard to improve my knowledge where it was lacking before. A key insight I gained from the maintenance papers discussed is how different this phase is, not only in the work that need to be done, but also from a modeling perspective. When scheduling the installation phase which will take roughly 3 years you could (roughly) plan which tasks are performed in which weeks, for the entire project. And each week the project will get closer to completion. With the maintenance phase spanning 20-30 years this approach is infeasible, and there is no one goal that you progressively move closer to. Instead it has a more cyclic nature where you aim to mitigate the degradation of the windfarm over time, and the tasks that need to be performed cannot be known *a priory*. Therefore smaller timescales, such as rolling horizons covering weeks rather than years, are much more appropriate for this phase. This is an insight that needs to be considered in a model aiming to combine this phase with the other phases.

3 Developing models

In the past year I have started developing optimisation models for various scheduling decisions that come up during an OWFs life-cycle. I developed the theory of these models, and implemented and tested them with simple test-cases. This implementation will be discussed in Section 4 and this section will talk about the models and the process of creating and improving them.

I started with very simple models that had a small scope and many assumptions, and progressively added complexity while relaxing the assumptions. This provided me with practice and insights in optimization modeling, a technique I had previously extensively read about but not used myself on any large scale. Therefore this start with simple models was needed, and this approach has made me learn a lot about the nuances in creating these models.

All models I created are Mixed-Integer Linear Programming (MILP) models, meaning the variables can both be continuous or integer variables, and every variable has a linear relation with the objective and the constraints (i.e. no variables are multiplied by other variables). This is the type of models most commonly used in the scheduling literature I have come across, indicating they are generally well-suited for these this type of problem.

3.1 Initial models

The first models I worked on were three simple models, one for each of the three phases. My idea behind this was to create a basis for each of the phases, which I could then combine into models where multiple phases are considered. To give the reader an idea of how these models work I will show some of the models I created.

I first started work on an installation model. I tried a handful of models that did not work or had major flaws, until I came to the following model that works under some heavy assumptions:

$$\max_{\substack{O_p, N_{rp} \in \mathbb{Z}^* \\ s_{ait} \in \{0,1\}}} \sum_{p \in P} [O_p \cdot v_p - \sum_{r \in R} N_{rp} \cdot C_{rp}] \tag{1}$$

subject to:

$$s_{ait} \leq s_{ai(t+1)} \qquad \forall a \in A, \forall i \in I, \forall t \in T \tag{2}$$

$$s_{ai\sigma_{it_N}} \geq 1 \qquad \forall a \in A, \forall i \in I \tag{3}$$

$$s_{ajt} \leq s_{ai\sigma_{it}} \qquad \forall a \in A, \forall (i,j) \in IP, \forall t \in T \tag{4}$$

$$N_{rp} \geq \sum_{a \in A} \sum_{i \in I} (\rho_{ir} \cdot (s_{ait} - s_{ai\sigma_{it}})) \qquad \forall r \in R, \forall p \in P, \forall t \in T_p \tag{5}$$

$$O_p = \sum_{a \in A} s_{ai_N \sigma_{i_N} t_p} \qquad \forall p \in P \tag{6}$$

$$N_{rp} \leq m_{rp} \qquad \forall r \in R, \forall p \in P \tag{7}$$

In the problem for which this model is made there is a set of assets A that each have a set of I tasks that need to be completed within the timeframe. There are two timescales used; periods p which is the timescale at which turbines can be brought online and vessels can be chartered (a month within my artificial test cases) and timesteps t at which tasks are performed (an hour in my test cases).

There are three types of decision variables in this model:

- O_p: integer variable representing how many turbines are online in a given period p
- N_{rp}: integer variable representing how many resources of type r are used in period p
- s_{ait}: binary variable which takes a value of 1 if task i on asset a has start at (or before) time t

The primary decisions that need to be made are the start times of the tasks (the first time steps for each asset a and task i for which s_{ait} takes the value 1); from this the times the turbines come online and the resources required follow.

Equation (1) is the objective; the goal is maximizing the total value of the project. Therefore, per period, we add up the energy value generated ($O_p \cdot v_p$ where v_p is the value of energy that a single turbine generates in that timeframe) and subtract the costs of vessels used ($N_{rp} \cdot C_{rp}$ where C_{rp} is the cost of that type of vessel).

Equation (2) enforces that if a task is started it remains started for every later timestep. Equation 3 uses the time indicator σ_{it} which treated as a parameter; it indicates the timestep at which task i should have been started, for it to have finished at time t; it is calculated using the duration of task i, taking into account all timesteps in which the weather restricts task i from being worked on. Since this is a highly simplified model, the weather is assumed to be perfectly predicted, hence σ_{it} is a deterministic value. In equation (3) it uses the value t_N which is the final timestep, hence this equation enforces that every task is started early enough for it to be finished by the final timestep.

Equation (4) enforces a specific task order; IP is the set of pairs of tasks (i, j) which require task i to be finished before task j is started. In equation (5) the number of vessels needed in a specific period is calculated; ρ_{ir} is the amount of resources of type r task i needs. It uses T_p which is simply the set of timesteps within period p. Equation (6) counts how many assets have finished installation (completed task i_N) in time to be active in period p (before time step t_p). Finally equation (7) puts a maximum on the number of vessels of a specific type used in a given period.

The above model can be used to optimize the installation project, under some severe assumptions. It is assumed that the precise weather is known for the entire project (which can often span years), assumes no delay in tasks other than that based on weather, and assumes every turbine is active at full strength without any failures from the moment it is completed. This said, creating this model was valuable practice for me, as even getting to this model took some tries and each failed attempt taught me more aspects to pay attention to.

The initial decommission model is nearly identical to the above model, other than turbines going offline when work is started instead going online when work is completed. The maintenance model I made is very similar in structure as well; it assumes that an asset will fail if it is not maintained for some predetermined time. This is clearly a significant simplification from stochastic failures which is the more common and realistic approach, but for my initial models I assumed determinism. Under these assumptions the maintenance models had a set amount of minimum maintenance tasks that should be performed, and a set of optional tasks that can be performed to increase uptime. These models will not be shown here, but they can be found in the appendix.

After creating these models I combined them into one model spanning the entire life-cycle, planning every single task (under the same deterministic assumptions).

$$\max_{\substack{N_{rp}\in\mathbb{Z}^* \\ s_{ait},o_{at}\in\{0,1\}}} \sum_{p\in P}[DIS^p(\sum_{t\in T_p}\sum_{a\in A}(o_{at}\cdot v_t) - \sum_{r\in R}(N_{rp}\cdot C_{rp}))] \tag{8}$$

subject to:

$$s_{ait} \leq s_{ai(t+1)} \qquad \forall a\in A, \forall i\in\mathcal{I}, \forall t\in T \tag{9}$$

$$s_{ai\sigma_{it_N}} \geq 1 \qquad \forall a\in A, \forall i\in\mathcal{I}-M^O \tag{10}$$

$$s_{ai_0^D t} - 1 \leq s_{ai\sigma_{it}} - s_{ait} \qquad \forall a\in A, \forall i\in\mathcal{I}-D, \forall t\in T \tag{11}$$

$$s_{ajt} \leq s_{ai\sigma_{it}} \qquad \forall a\in A, \forall (i,j)\in IP, \forall t\in T \tag{12}$$

$$m_{rp} \geq N_{rp} \geq \sum_{a\in A}\sum_{i\in\mathcal{I}}(\rho_{ir}\cdot(s_{ait} - s_{ai\sigma_{it}})) \qquad \forall r\in R, \forall p\in P, \forall t\in T_p \tag{13}$$

$$o_{at} \leq s_{ai_N^I\sigma_{i_N^I t}} - s_{ai_0^D t} \qquad \forall a\in A, \forall t\in T \tag{14}$$

$$o_{at} \leq \sum_{i\in M\cup\{i_N^I\}}(s_{ai\sigma_{it}} - s_{ai\sigma_{i(t-\lambda_a)}}) \qquad \forall a\in A, \forall t\in T \tag{15}$$

$$o_{at} \leq 1 + s_{ai\sigma_{it}} - s_{ait} \qquad \forall a\in A, \forall i\in M, \forall t\in T \tag{16}$$

I will not go over every detail of this model, but the full notes can be found in the appendix. The primary structure of having s_{ait} be the main variables and having variables for the required resources and online turbines remains the same as before. The largest difference is the replacement of variables O_p with o_{at}, which is a binary variable per asset and timestep indicating whether that asset is online at the given time. In order for it to be online that asset needs to be fully installed and not started decommission (equation (14)), have had recent maintenance (equation (15)) and no maintenance on at asset can be happening at this time (equation (16)).

This model still has very strong assumptions and for that reason would not be valuable in practice. But even if those assumptions were to be relaxed, a model such as this would not have much value in practice. Optimizing every single scheduling decision over the entire 20+ year life-cycle of an OWF at the start of the project is both infeasible and unnecessary. Infeasible because the size of this problem is too big for any optimizing solver to solve; if a timestep is an hour there are over 175.000 timesteps in a 20 year period, and with very conservative values of 40 tasks per asset and 80 assets that would lead to over half a billion s_{ait} variables. That is not to say another approach could not create a feasible model for the entire life-cycle, although it is an extrodinarily large problem that would normally be split into smaller problems. On top of being infeasible, there is no strong reason to plan all of this in advance in a single model; cost estimation is generally better done using simulation, and any solution found by this model is unlikely to be much better than solutions found by models for individual phases, as there is not much interaction other than resource sharing included in this model.

While this model is not usable in practice, it was still a good exercise for me to work on. I would not have some of the insights above if I had not created a (simplified) model spanning the entire life-cycle, and experimenting with the size of model (in number of variables and constraints) gave me a better idea of how quickly models such as this can grow in size.

3.2 More sophisticated models

After working my way up to the previously discussed life-cycle spanning model, I aimed to relax the assumptions in it, first and foremost the assumption that every aspect is deterministic. This proved difficult for various reasons. The model I started with is complicated, and I do not have much experience with Stochastic Programming models, which made starting with a complicated model such as this challenging. It also spans a large timescale, but still has a high fidelity (if a timestep is still assumed to be an hour).

In the models shown before the parameter σ_{it} was used to incorporate weather circumstances, and this parameter was used as a variable index. This approach is not well suited for Stochastic Programming, as this σ_{it} would be subject to uncertainty, which means the variables involved are also subject to uncertainty. I tried to handle this issue by introducing scenarios, a technique used in the literature (Besnard et al. 2011, de Matos & Finardi 2012). Each scenario represents a realization of all uncertain factors, and the model would be optimized over a set of (selected) scenarios. In this example a new index would be introduced to σ_{it}, say σ_{its}, where s is the scenario index. However this approach is more suited to shorter timescales than the ones I was using; only a handful of scenarios are needed to capture the possible weather conditions over the course of a week or a month, but over the course of 20 years many scenarios are needed to make the set representative of the possible options. Therefore I opted to scale down and introduce stochastic elements in a smaller model first.

For this I chose to focus on the maintenance phase, introducing stochastic failures, weather circumstances and energy values.

4 Implementation

Lorem Ipsum

5 Additional activities

In addition to the work directly related to my PhD project, I have participated in some courses.

I was supposed to take part in the NATCOR course Convex Optimization, to be held at the University of Edinburgh in June 2020. However, due to the Covid-19 pandemic this course was canceled. I was also enrolled in the NATCOR course Forecasting and Predictive Analytics, which was to be held in September 2020 at Lancaster University. This course, due the same pandemic, has been postponed to February 2021.

While those courses not taking place as planned was disappointing, another course I did not originally plan to go to had to move entirely online, making it possible for me to follow it. The course in question was CO@Work (Combinatorial Optimization at work), hosted by the University of Berlin. This two-week course offered lectures (via Youtube) on varying topics, and exercise and Q&A sessions (via Zoom). Since the Zoom sessions took place at inconvenient times (due to timezones), I primarily partook in the lectures. The course was aimed at a wide variety of students, ranging from undergraduates new to optimization, to PhD students like myself. This meant that some lectures went over material I am already familiar with, like the workings of the simplex algorithm. Other material focused on techniques to help with solving linear and mixed-integer programs, such as column generation and branch-and-bound techniques. While I had previously been taught how these methods work, this was years ago, and the refresher was quite helpful. The course also had more time to go into details on these techniques, so I certainly learned new aspects of these techniques. Finally there were some corporate talks, at which various companies within the optimization industry talked about what they do and what a career with them could look like. While some of these talks seemed very specific to the company hosting it and less interesting, some also simply talked about work and careers as optimizers in general, which I found very helpful and interesting.

Generally I am glad I got to follow this course, and the format of having a few hours of lectures to watch at my own pace helped lower the workload (compared to traveling to Berlin for two weeks). This allowed me to still work on my own project during this course, and since the lectures were recorded videos rather than live, I could rewatch the parts that were most interesting or most complex. That said, I did miss the social aspect of this course, as normally with courses such as this you get to spend a week or two with students from all over the world who all study subjects similar to my own. This dimension was entirely missing, which is of course a strong drawback.

Apart from following courses, I have also helped teach a course. The course, Information Access & Mining (CS412), was a 4th year Computer Science course focusing on data analysis through machine learning. This is fairly far removed from the topic of my own project, but I was still fairly able to teach the course because of my Computer Science background. The main thing that was new for me was the Python language used in the course, with which I was previously unfamiliar. However, this simply meant that in addition to the teaching experience I got from teaching this course, I also made myself acquainted with Python, which turned out to be a relatively easy language to learn. I lead the labs, which meant I had to answer students questions regarding their exercises. Since I prepared the labs well, answering these questions was fairly straightforward. Additionally I had to mark the exercises, which took the majority of my time spend. But since I was provided with an decently detailed answer key, this was not very difficult either. After the labs stopped (due to the Covid-19 pandemic) my work solely consisted of the marking, lowering the workload.

This was my first real teaching experience, and I think it went very well. I enjoyed helping the students, and I enjoyed expanding my own knowledge of both the programming language and the subject matter. If I get another chance to help out with a course that interests me during my PhD, I will likely take it.

6 Next steps

Lorem Ipsum

6.1 Timeline

Lorem Ipsum

References

Barlow, E., Öztürk, D. T., Revie, M., Akartunalı, K., Day, A. H. & Boulougouris, E. (2018), 'A mixed-method optimisation and simulation framework for supporting logistical decisions during offshore wind farm installations', *European Journal of Operational Research* **264**(3), 894–906.

Barlow, E., Tezcaner Öztürk, D., Day, A., Boulougouris, E., Revie, M. & Akartunalı, K. (2014), 'A support tool for assessing the risks of heavy lift vessel logistics in the installation of offshore wind farms', *Marine Heavy Transport & Lift IV* .

Besnard, F., Patriksson, M., Strömberg, A.-B., Wojciechowski, A., Fischer, K. & Bertling, L. (2011), A stochastic model for opportunistic maintenance planning of offshore wind farms, *in* '2011 IEEE Trondheim PowerTech', IEEE, pp. 1–8.

de Matos, V. L. & Finardi, E. C. (2012), 'A computational study of a stochastic optimization model for long term hydrothermal scheduling', *International Journal of Electrical Power & Energy Systems* **43**(1), 1443–1452.

Dinwoodie, I. A. & McMillan, D. (2014), 'Operational strategies for offshore wind turbines to mitigate failure rate uncertainty on operational costs and revenue', *IET Renewable Power Generation* **8**(4), 359–366.

Dinwoodie, I., Endrerud, O.-E. V., Hofmann, M., Martin, R. & Sperstad, I. B. (2015), 'Reference cases for verification of operation and maintenance simulation models for offshore wind farms', *Wind Engineering* **39**(1), 1–14.

Dinwoodie, I., Quail, F. & McMillan, D. (2012), Analysis of offshore wind turbine operation and maintenance using a novel time domain meteo-ocean modeling approach, *in* 'ASME Turbo Expo 2012: Turbine Technical Conference and Exposition', American Society of Mechanical Engineers, pp. 847–857.

Gabrel, V., Murat, C. & Thiele, A. (2014), 'Recent advances in robust optimization: An overview', *European Journal of Operational Research* **235**(3), 471–483.

Irawan, C. A., Wall, G. & Jones, D. (2019), 'An optimisation model for scheduling the decommissioning of an offshore wind farm', *OR Spectrum* **41**(2), 513–548.

Kaiser, M. J. & Snyder, B. (2010), 'Offshore wind energy installation and decommissioning cost estimation in the us outer continental shelf', *US Dept. of the Interior, Bureau of Ocean Energy Management, Regulation and Enforcement, Herndon, VA TA&R* **648**.

Lacal-Arántegui, R., Yusta, J. M. & Domínguez-Navarro, J. A. (2018), 'Offshore wind installation: Analysing the evidence behind improvements in installation time', *Renewable and Sustainable Energy Reviews* **92**, 133–145.

Renewable-UK (2017), 'Offshore wind project timelines', *https://www.renewableuk.com/news/294516/Offshore-Wind-Project-Timelines.htm* . Accessed: 2019-03-24.

Shafiee, M. (2015), 'Maintenance logistics organization for offshore wind energy: Current progress and future perspectives', *Renewable Energy* **77**, 182–193.

Stålhane, M., Halvorsen-Weare, E. E., Nonås, L. M. & Pantuso, G. (2019), 'Optimizing vessel fleet size and mix to support maintenance operations at offshore wind farms', *European Journal of Operational Research* **276**(2), 495–509.