European Journal of Operational Research 264 (2018) 894–906

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

A mixed-method optimisation and simulation framework for supporting logistical decisions during offshore wind farm installations

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ARTICLE INFO

Article history:
Received 30 November 2015
Accepted 21 May 2017
Available online 26 May 2017

Keywords:
OR in energy
Mixed methods
Action research
Offshore wind farms
Installation logistics

ABSTRACT

With a typical investment in excess of £100 million for each project, the installation phase of offshore wind farms (OWFs) is an area where substantial cost-reductions can be achieved; however, to-date there have been relatively few studies exploring this. In this paper, we develop a mixed-method framework which exploits the complementary strengths of two decision-support methods: discrete-event simulation and robust optimisation. The simulation component allows developers to estimate the impact of user-defined asset selections on the likely cost and duration of the full or partial completion of the installation process. The optimisation component provides developers with an installation schedule that is robust to changes in operation durations due to weather uncertainties. The combined framework provides a decision-support tool which enhances the individual capability of both models by feedback channels between the two, and provides a mechanism to address current OWF installation projects. The combined framework, verified and validated by external experts, was applied to an installation case study to illustrate the application of the combined approach. An installation schedule was identified which accounted for seasonal uncertainties and optimised the ordering of activities.

1. Introduction

Offshore wind farms (OWFs) in Europe are progressing towards larger sites further offshore in deeper water, as typified by the UK round 3 sites which are to be developed over the coming years (Renewable UK, 2014). These sites will typically consist of 100–400 turbines and will be located up to 190 kilometres from shore in water depths up to 55 metres (Renewable UK, 2014), and the installation of these sites will typically span several years. Information on expected costs of installation is sparse for these larger sites but for existing smaller sites closer to shore, costs are typically upwards of £100 million (Kaiser & Synder, 2010). In comparison with existing OWFs, these new sites are typically increased distances from shore with larger turbines that lead to increased periods of installation spanning several years (Renewable UK, 2014). Improved management of installation logistics was identified as offering substantial cost-reductions to the lifetime cost of an OWF (Offshore Wind Cost Reduction Task Force, 2012; European Wind Energy Technology Platform, 2014). Deeper water on-site will add to the increases in operational durations, and will increase the complexity of the offshore operations and sensitivity to weather conditions in comparison with coastal installations. As these sites will be exposed to harsher weather conditions, the combination of more weather-sensitive installation operations carried out over a longer time period increases the uncertainty in predictions of cost and duration for the installation. One mechanism for achieving the desired cost-reductions is to pursue the most cost-effective logistical decisions, and these can be identified by improving the understanding of how cost and duration are affected by logistical decisions during the installation.

Several studies present applications of decision support to OWF installations. Scholz-Reiter, Lütjen, Heger, and Schweizer (2010) and Ait-Alla, Quandt, and Lutjen (2013) look at short-term vessel planning for the installation of an offshore wind farm. Mixed-integer linear programming models are employed to identify the optimal configuration of vessel schedules to minimise installation duration and cost, respectively. Weather data are represented in categorical states and supplied to the models as deterministic inputs. In Lutjen and Karimi (2012), a two-level discrete event simulation which couples a port inventory control system with a reactive scheduling component is used to determine the effect that different levels of inventory have on the progress

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http://dx.doi.org/10.1016/j.ejor.2017.05.043
0377-2217/

of the installation. Appropriate vessel loads and operations are determined using forecast weather conditions with five categorical weather states considered. Each of these studies demonstrates the application of the respective decision support tools to small-scale OWF installations, and in practice these tools would struggle to cope with the demands of a realistic OWF installation problem. Lange, Rinne, and Haasis (2012) present a simulation tool which models the construction of an OWF from the manufacturing of components through to final installation, providing a high-level view of the entire installation process. Key stages in the manufacture and supply network which could lead to bottlenecks can be identified; however, the wide scope of this tool necessitates a relatively simplistic model of the offshore installation operations. Stempinski et al. (2014) consider the scheduling of installation operations for tripods for turbine foundations. They present two simulation methods: one method utilises a probabilistic assessment of weather downtime to generate the schedule, the second method employs a discrete-event simulation with historical weather time-series. In each case weather limits for the offshore installation operation are obtained using a numerical simulation of this process. This tool considers the installation of a single category of asset using a single installation vessel, and it is unclear how this tool could handle the full complexity of an OWF installation schedule.

In a more general context, decision support models have been developed for various other types of offshore installation projects. For example, Morandeau, Walker, Argall, and Nicholls-Lee (2013) present a tool designed to support installation operations for marine energy sites. This tool employs summary statistics to simulate the expected impact of weather on the installation, and the tool is applied to the installation of an array of 10 tidal turbines. Li, Li, Yang, and Zhou (2014) describe the application of an agent-based simulation model to evaluate scheduling decisions for the installation of an offshore oil and gas platform. Iyer, Grossmann, Vasantharajan, and Cullick (1998) present a mixed-integer linear programming model for the planning and scheduling of offshore oil field facilities, including platform installations. Shyshou, Gribkovskaia, and Barcelo (2010) employ a discrete-event simulation to model the impact of spot-rates and vessel allocations on the total vessel hiring costs in a fleet-sizing problem arising in the scheduling of anchor-handling vessels supporting offshore oil and gas drilling operations.

During the planning and assessment stage of an OWF project, a consortium of utilities, vessel operators, installers and original equipment manufacturers work collaboratively to identify an installation strategy that will minimise the cost and duration of the installation project. An installation strategy will include decisions such as the selection and use of installation vessels, the selection and use of ports, and the scheduling of the installation operation, such as when to begin an installation project and when to begin certain tasks. To do this, the consortium uses their individual expertise to identify potential bottlenecks, trade-off vessel characteristics and assess the impact of different decisions. These decisions are typically taken after a mixture of qualitative and quantitative analysis and to date lack any form of rigour or evaluation.

In order to address the challenges of larger installation projects and increasing uncertainties, two models have been developed in a collaborative project between industry experts and academics to support logistical decision making at the planning or bidding stage of an OWF installation. These models have been presented previously by the authors (Barlow et al., 2015, 2016). Action research (Lewin, 1946) was the chosen methodology to ensure the models developed were grounded in the challenges facing the OWF developers. Action research is a research methodology whereby theory informs practice and practice helps to subsequently refine and develop more theoretical developments (Winter & Burroughs, 1989).

Barlow et al. (2015, 2016) developed a simulation model which enables a detailed understanding of the cost and duration of an installation scenario to be obtained. This allows alternative logistical decisions to be evaluated and compared, so that a realistic understanding of good practice on a given OWF site can be developed and pursued. Tezcaner Öztürk et al. (2016) developed an optimisation model identifying installation schedules that are robust against weather uncertainties. The model provides a worst-case upper bound on the project duration determining an installation schedule by assigning the task durations. Both models are capable of handling realistic large-scale installation projects.

The contribution of this paper is to integrate these modelling approaches to yield a mixed-method framework and decision support tool that improves logistical decision-making at the planning stage of an OWF installation. This framework exploits the complementary strengths of each technique: the simulation model provides accurate scenario evaluations, enabling the most favourable time of the year to start operations to be identified, and the optimisation model identifies optimal task schedules that are robust to weather disruptions. Using the models in combination has provided OWF developers with a mechanism to obtain a realistic understanding of the impact of uncertain weather conditions, and to identify appropriate logistical installation decisions. The remainder of this paper is structured as follows: Section 2 introduces the OWF installation model used, Section 3 introduces the simulation and optimisation models, and presents the mixed-method framework, Section 4 describes the application to a case study OWF installation, Section 5 describes the verification and validation steps undertaken by one of the industry collaborators, and Section 6 concludes the research.

2. Logical model of an offshore wind farm installation

This paper employs the OWF installation model presented in Barlow et al. (2015, 2016), and additional technical information on this model is provided in these references. The model considers the installation of the key offshore assets for generation and export: wind turbine generators (WTGs) and their subsea foundations, offshore substation platforms (OSPs) that collect and convert the generated power prior to transmission to shore, the subsea OSP foundations, the inter-array cables that connect the WTGs to the OSPs, and the export cables that carry the generated power from the OSP to shore. In the remainder of this paper we will refer to these collectively as the assets. Fig. 1 shows part of the Sheringham Shoal OWF located off the South East coast of the UK, with 80 metres tall 3.6 megawatts WTGs and two 1000 tons OSPs. This

Fig. 1. Wind turbines and offshore substation platforms at the Sheringham Shoal wind farm. ©NHD-INFO/CC-BY-2.0.

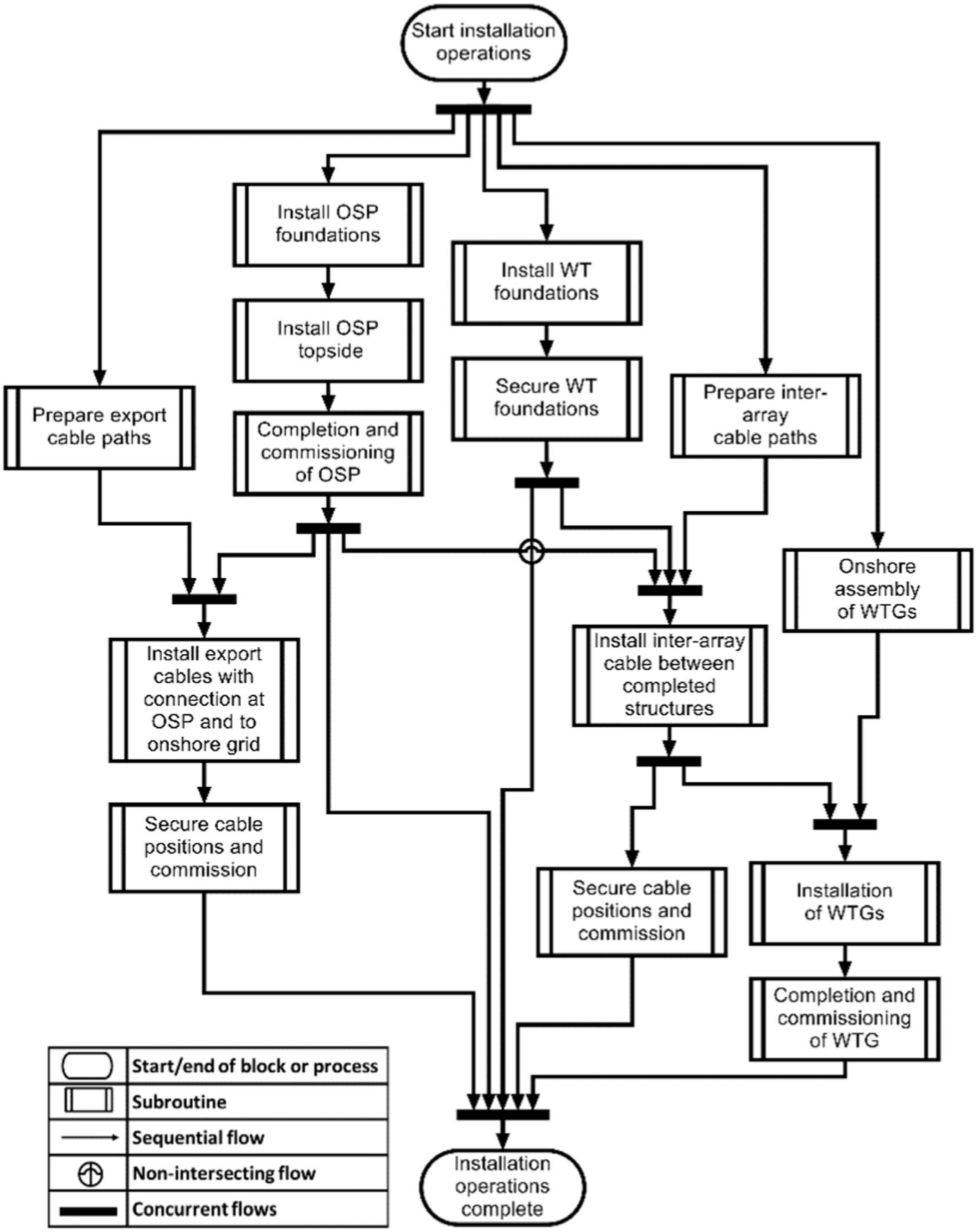

Fig. 2. High-level schematic of the offshore wind farm installation process (Barlow et al., 2016).

OWF is smaller in scale and more coastal than the current phase of OWF developments, and had installation costs of approximately £1.1 billion.

This installation model was developed in collaboration with industry partners spanning multiple interviews, workshops and validation sessions. The model captures the operations required to install each asset and the relationships between these operations in terms of precedence and sequencing. The model is designed to support logistical decisions related to the installation vessels and the ports which these use. These decision include, but are not limited to: which ports should be used for the loading of each type of asset, whether or not aspects of a particular port should be developed (for example, increasing the capacity of the port or improving the crane facilities), the number of vessels which are used to install each type of asset, the specific vessels which are chosen to install each type of asset and the benefits of choosing one vessel over another, if a single vessel should be used to install more than one type of asset, whether installation vessels are self-supplying or supported by supply barges and the number of supply barges used, whether vessels should operate over winter months or not, and the scheduling of start-dates for every set of installation tasks.

A high-level overview of the installation model is shown in Fig. 2. This figure shows the overall sequence in which operations are carried out during an installation project; for example, the installation of OSP foundations will start before and finish before the start and finish dates, respectively, for the installation of OSP

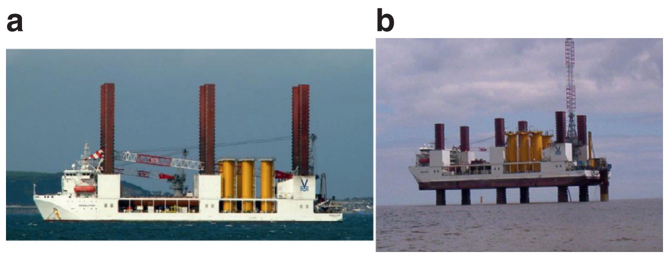

Fig. 3. Jack-up installation vessel (a) in transit in jacked-down position (©Ross/CC-BY-SA-2.0) and (b) on-site in jacked-up position (©Ian Simons/CC-BY-SA-2.0).

topsides. Operations are shown as subroutines to indicate that these consist of multiple operations. For example, the installation of OSP foundations will consist of a series of operations which must be completed on an OSP, and this series of operations must then be completed on each OSP. The operations carried out on a single OSP are carried out in series, whereas operations between different OSPs can be completed in parallel where there is sufficient resource for this (such as multiple installation vessels being available and suitable for use). A similar discussion can be presented for each subroutine. At each turbine location on-site, a turbine foundation is installed first, followed by laying of the inter-array cables with connection at the foundation structures, followed by the installation of the WTG. Where there is sufficient resource, this sequence of operations at the turbine can be completed in parallel at different turbine locations. At each OSP location, the OSP foundations must be completed prior to connection with the export cables; however, it is possible that preparatory operations on the export cable paths will begin first due to the time required for these, and the OSP installation will then begin after a suitable time-lag. The OSP foundations are also installed prior to pull-in of the inter-array cables. With sufficient resource, this sequence of operations can be completed in parallel at different OSP locations.

Each asset is considered from delivery to the port used to load the installation vessels until installation is complete. Multiple installation vessels can be used for the installation of each category of asset, and installation can be supported by supply barges for some assets. Operations are grouped practically, with groupings representative of the series of tasks which must be completed in the same weather window in practice. Tasks such as the installation of the WTG components, jacking operations, release of sea-fastenings and cranes, lowering and retrieval of pile templates and cable pull-ins and jointing works can each be included as appropriate. Following mobilisation, each installation vessel loads-out the number of WTGs to be carried and transits to site. The vessel proceeds with installations until the cargo is empty, at which point it returns to port and reloads as appropriate. Specialised jack-up vessels are utilised for the installation of WTGs as shown in Fig. 3; these vessels employ retractable legs which raise the vessel above the sea-surface and provide a stable platform to complete the installation operations. Additionally, the supporting operations for WTG installation are shown in Fig. 4, which provides a high-level view of the model structure for the installation of WTGs. Operations displayed as sub-processes indicate that the operation is applied to all WTGs, and the sequencing shown in Fig. 4 applies to a single WTG. Onshore assembly of turbines is carried out prior to loading onto an installation vessel, with the degree of assembly largely driven by the turbine manufacturers. The degree of onshore assembly will dictate the number and complexity of offshore operations, and any combinations of these onshore and offshore operations can be supported by the model. Once the WTG is installed a number of supporting operations are required prior to the activation of the turbine. Mechanical and electrical completion operations complete the installation, followed by commissioning of the WTG. Once commissioned, final testing and acceptance are carried out, after which the turbine can be activated and begin to generate power as required.

The general structure of the model for each asset installation is similar to that shown in Fig. 4, with the main differences arising in the modelling of the on-site offshore installation operations. Fig. 2 indicates the support operations which are required with the installation of the other key assets. These include boulder clearance, pre-lay surveys and trenching of cable paths, post-lay cable burial, mechanical and electrical completion operations on OSPs, grouting of foundations and the commissioning of various assets.

Each operation modelled is described in terms of the operational limits and the required duration to complete the operation. Factors such as contingency time required for each operation and random vessel failures can also be considered. A large number of operational decisions can be defined, which provide the flexibility to model many real-world installation scenarios. Pile-driven jacket foundations can be installed through a pre- or post-piling approach, each support operation for the cable laying can be included as required for a given set of site conditions, and various decisions dictate the use of supply barges where appropriate. There are typically up to two OSPs on a given wind farm, and these assets are substantially heavier than other assets installed above sea-level. As such, OSPS are typically installed using highly sought after and expensive vessels from the oil and gas industry equipped with suitable cranes for lifting. Due to these factors, the installation of OSPs can follow a larger number of installation scenarios than is typical of other assets. For example, a single vessel may fully install each OSP in turn, or may partially complete the installation of each OSP, before returning to each OSP to complete the installation. Some of these decisions are investigated in Barlow et al. (2014b).

3. Mixed-method offshore wind farm installation logistics framework

As the problem was being structured, different methodologies to model the installation project were considered. Two models emerged as potential candidates for development; discrete event simulation and optimisation, however both have different strengths and weaknesses with regard to the scheduling of OWF installation logistics. A simulation model would be capable of providing a realistic assessment of the duration of installation operations subject to uncertain weather conditions; however, a large number of simulation runs (for example 1000 simulations) may be required to ensure that robust estimates on the durations can be obtained. The computing time to evaluate a single installation scenario could therefore be in the order of hours, and investigating many installation scenarios could become infeasible.

Alternatively, an optimisation model could comfortably explore large decision-spaces to identify the optimal scheduling of operations; however, each operation duration is defined as a specific value within its range by a robust model. The result is that the assigned durations may not be representative of their actual durations, so that schedules may be insensitive to seasonality, and the benefits of operating during months with more favourable weather conditions cannot be exploited.

Instead of developing a single model or two models in isolation, a mixed-methods approach was adopted where the complementary strengths of the simulation and optimisation models were combined (see Clausen, Goedicke, Mest, Wohlgemuth, 2012; Glover, Kelly, & Laguna, 1996) for examples of simulation and optimisation mixed method approaches). A simulation model was developed in order to explore the impact of starting operations at different months throughout the year. This would enable the seasonality of the weather conditions to be fully considered in an installation schedule, and with a relatively focused decision problem

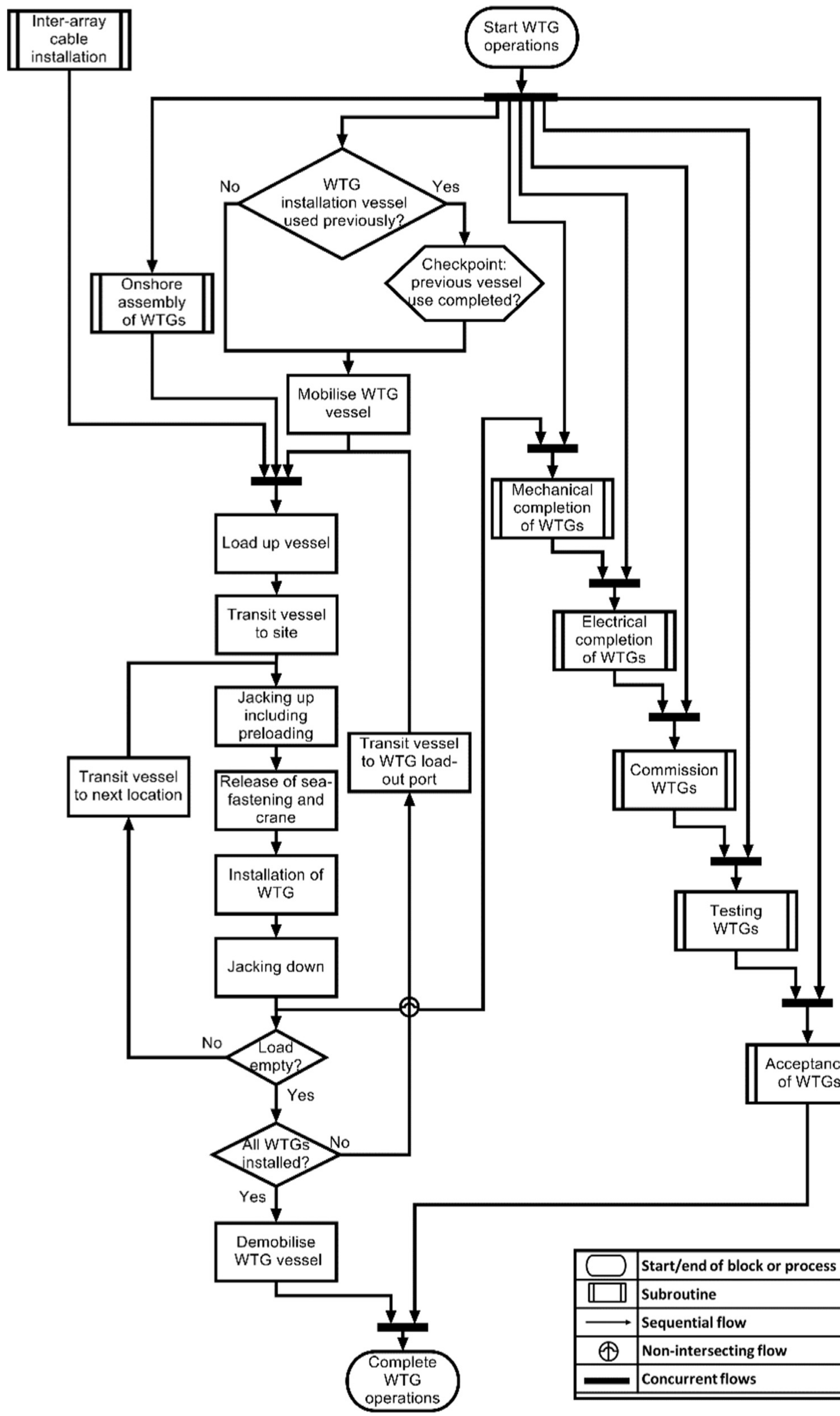

Fig. 4. Flowchart depicting the scheduling of tasks during the installation of a WTG.

computing times would not be overly restrictive. An optimisation model was developed to identify the optimal scheduling of operations from this starting-point, with full exploration of the potential start-times for each set of operations possible; a task that would be infeasible using the simulation model alone. The output of the optimisation model would then be used by the simulation model to model the overall uncertainty and cost of the installation project using a more detailed weather model. Both models were developed in Matlab, and run off an Excel interface for user inputs. The remainder of this section describes the two models.

3.1. Offshore wind farm installation logistics simulation model

The simulation model employs a synthetic weather time-series model to provide a realistic estimation of how the installation operations will progress. A fuller description of the weather model employed here is provided in Dinwoodie and McMillan (2014), in which the weather model is used to analyse the effectiveness of maintenance operations for an OWF; however, the model is summarised here for clarity. Synthetic weather time-series are generated from statistical analysis of hindcast (historical) weather data sets. The method used here to generate synthetic weather time-series is a correlated autoregression model. Autoregression identifies the underlying trends as a data-set changes over time, and exploits these trends to predict future behaviour of the data-set. An autoregression model expresses a given data-point as a linear combination of the previous data-points. The general form of an autoregressive model of data-set X at time-step t is

$$X_t = \mu + \sum_{i=1}^{p} \varphi_i (X_{t-i} - \mu) + \epsilon_t, \tag{1}$$

where μ is the mean of the data-set, ϵ_t is a random variation influencing the tth data-point, φ_i is a multiplicative factor acting on the ith data-point before X_t, and p is the order of the model. The extent of the dependency of a data-point on previous data-points is controlled by the model order p and the multiplicative factors $\{\varphi_i\}_{i=1}^{p}$; these define how far back in time has an influence on the current data-point and the extent of this influence. The existing hindcast data-set is analysed to define the extent of the dependency on previous data-points such that the closest fit to the existing data-set is produced. Future data-points are then generated iteratively using the same dependency relationships.

The weather properties included here are significant wave height and wind speed. As discussed in Dinwoodie and McMillan (2014), wind and wave time series require pre-processing such that the mean and variance are stationary and the data approximates a normal distribution prior to the application of autoregressive modelling. Eq. (1) can then be applied to the transformed wind and wave time-series to generate synthetic hourly weather series. Correlations between the wind and wave data can be incorporated by correlating the random variations, ϵ_t, at each time-step across both time-series.

The variability of the historical data-set influences the degree of uncertainty surrounding the accuracy of predicted conditions. Consistently stable weather conditions can be predicted with a relatively high level of certainty, whereas the accuracy for a prediction of highly transient weather conditions is more uncertain. Each synthetic weather series generated through the autoregression model is one prediction of future weather conditions at a particular location, and by taking many predictions an accurate representation of the uncertainty associated with the predictions can be obtained. The weather model is coupled with the logical installation model described in Section 2 in the framework of a discrete-event simulation model. Discrete-event simulation is a widely used OR technique for the analysis of complex systems. Recent examples of applications of discrete-event simulation to dynamic systems in a renewable energy context include: managing electric vehicle charging (Palensky, Widl, Stifter, & Elsheikh, 2013; Darabi & Ferdowsi, 2014), design and analysis of wood pellet supply chains (Mobini, Sowlati, & Sokhansanj, 2013), design and analysis of the supply chain for biocrude production (Ekşioğlu, Palak, Mondala, & Greenwood, 2013), evaluation and management of smart grids (Al-Agtash, 2013; Brown and Khan 2013), scheduling and control of distribution circuits with photo-voltaic generators (Jung et al., 2015), and operation and maintenance of OWFs (Endrerud & Liyanage, 2015; Dinwoodie & McMillan, 2014).

The discrete-event simulation model is a multi-threaded implementation, where each thread can operate in parallel to other threads subject to specific logical constraints. The threads represent each installation vessel, supply barge and support operation, and the constraints in each case are defined by the logical installation model. Each thread maintains a clock which records the time transpired since the global start of the installation project. The state of the model represents the current clock for each thread, the current progress of the installation for each WTG, OSP, and cable, the location of each vessel and barge (in-port or on-site), and the current number of assets carried by each vessel and barge. Events are characterised as pre-installation support operations, in-port installation vessel or barge operations, on-site installation vessel or barge operations, and post-installation support operations, and each event results in some change to the state of the model. The first stage of the simulation completes all pre-installation support operations for all assets, as these can be grouped according to asset-type and each group is then completed independently. The main loop of the simulation maintains a priority queue of the threads associated with installation vessels and barges, where the level of priority is determined from the time of the thread clock and the satisfaction of various constraints to ensure the logical structure of the installation model is adhered to. Furthermore, priority is given to earlier operations in the sequence displayed in Fig. 2 and installation vessels are prioritised over supply barges, in order to reduce the computational burden of processing constraint violations. The selection of each thread within the main simulation loop triggers a sequence of events, with the particular sequence dependent on the selected vessel or barge and the associated type of asset, its current location and current cargo. Upon the completion of events characterised as on-site operations, a sequence of post-installation operations are triggered, dependent on the type of asset in question.

For a given installation scenario, the simulation model estimates the progress of the installation under each synthetic realisation of weather conditions through the discrete-event simulation model. Metrics such as task durations, costs, progression and delays can be recorded for each simulation, and the value recorded in each case will be dependent on the sensitivity of the metric to the weather conditions and to the severity of weather conditions in the particular synthetic time series. Repeating this process builds an uncertainty distribution for each metric, and by doing this across many synthetic weather series an accurate representation of the expected impact of the uncertain weather conditions is obtained. Fig. 6 from the case study in Section 4 provides a typical example of the uncertainty distributions for a particular metric; the metric in this case is the duration of use for the WTG installation vessels, and each box-plot in Fig. 6 shows the uncertainty distribution for this metric for a particular start-date of operations.

The number of simulations used will therefore have a substantial impact on the accuracy of the uncertainty distribution for each metric, and should be chosen to be sufficiently large so that an acceptable level of accuracy is obtained. The process for ensuring the accuracy of the uncertainty distribution for a given metric is discussed further in Barlow et al. (2016). For example, for the case study investigations presented in Section 4.1 the number of simulations is set to 1000.

In addition to historical weather data covering a suitable time-period, the simulation model requires input data on the various vessels utilised during the installation. In particular, the capability of each vessel to perform its designated tasks is required, including the operational weather and daylight limitations for each task and the associated durations, which may be uncertain. Additional information on the size and location of the site and all ports used is required. The nature of the model enables a detailed breakdown of the simulated installation scenario to be produced, with costs, durations, operational and weather delays, and progress/rate of operations each provided at a site-level as well as per category of asset. Standard industry measures such as the 50th percentile and the 90th percentile can be recorded for each output; however, these outputs are recorded for every simulation so that a more complete understanding of the variation of each output is also provided.

This simulation model can therefore be utilised to explore the impact of a wide variety of logistical decisions on the OWF installation. Considerations such as the number of vessels or barges used for each type of asset installation, the operational capability of the vessels and barges, the impact of the ports selected for use, and the scheduling of the various stages to the installation, can each be explored in detail and validated. Section 4 demonstrates the application of this model to the scheduling of multiple operations, and the model has been employed previously to explore the impact on the installation duration and costs of: the operational characteristics of the installation vessels (Barlow et al., 2014a), the use of the installation vessels and the selected installation strategy (Barlow et al., 2014b), the size and composition of the installation vessel fleet (Barlow et al., 2016), and technological and operational advances to the installation process (Barlow et al., 2015).

3.2. Offshore wind farm installation logistics optimisation model

Developing a schedule for the installation operations of an OWF will identify crucial aspects of the installation, including the expected progress of the installation, when critical operations are expected to start, when vessels are required, and when the installation of each type of asset begins. Key logistical installation decisions can then be supported, for example organising the delivery of assets to ports, determining the vessel hiring dates and durations, and estimating the time interval to hire crew for support installation operations. To correctly inform these decisions, the planned baseline schedule should accurately represent the actual (observed) schedule. The installation of large-scale OWFs is a long term process, during which many disruptions to the planned baseline schedule can be expected. For example, the task durations may be longer or shorter depending on the weather conditions and crew capability, assets may arrive at port later than expected, or vessels may become unavailable due to breakdowns, leading to delays in the tasks assigned to that vessel. A realistic baseline schedule must therefore account for these unexpected disruptions.

There are many studies that incorporate uncertainty in creating baseline schedules based on optimisation techniques; see Herroelen and Leus (2005) for a comprehensive survey. In this study, we employ robust optimisation techniques to find the estimated task start times which minimise the total project duration, subject to uncertain task durations. The resulting baseline schedule provides an upper bound on the total project duration. To create this baseline schedule, we first determine which tasks are assigned to each vessel, followed by the resulting durations and precedence relations between the tasks. Our solution approach is thus composed of two stages: the first stage is the initialization stage for the robust baseline schedule, in which we assign to each vessel the tasks required to complete the installation; the second stage finds the robust baseline schedule solving an optimisation model. The details of the first and second stages are explained in Sections 3.2.1 and 3.2.2, respectively.

3.2.1. Asset-vessel assignment algorithm

We develop an asset-vessel assignment algorithm to decide which tasks are performed by each vessel, given the vessel and asset configuration of the OWF. The planner selects the vessels to be used to install each type of asset, and the installation order of the assets in each case. The algorithm then assigns assets to the appropriate vessels based on the asset installation order. With all assets assigned, we structure the complete set of tasks to be performed by each vessel.

Consider, for example, an OWF with 100 turbines and two installation vessels with capacities of four turbines each. The first asset to be installed is assigned to the vessel which can complete this installation at the earliest time. We then update that vessel's expected installation finish time to account for all tasks required to install the first asset. The second asset to be installed is now assigned to the vessel which can complete this installation at the earliest time. Continuing in this fashion until all assets are assigned to vessels, we structure all tasks performed by each vessel, the precedence relations between tasks, and the task durations. In this example, the first three tasks are mobilisation, loading of four turbines, and transiting to site. The mobilisation task precedes the loading task, consisting of four turbines being loaded, which precedes the transiting task.

The steps of the asset-vessel assignment algorithm are given below.

Step 1. Find assets that are not yet assigned to any vessel.
Step 2. Find the expected time to complete installation of the next asset for each vessel, considering all tasks that have been assigned in each case.
Step 3. Assign the next asset to be installed to the vessel that has the shortest installation finish time. If all assets are assigned to a vessel, terminate the algorithm. Otherwise go to Step 2.

The detailed calculations for the installation finish times are given in Tezcaner Öztürk et al. (2016).

3.2.2. Generating a robust schedule

The second stage of our approach generates the baseline schedule for all tasks of the installation by utilizing robust optimisation methods. In their seminal paper, Bertsimas and Sim (2004) developed a robust model allowing a subset of constants, which are subject to uncertainty, change their values within an interval defined by minimum and maximum values. In a project scheduling context, Minoux (2009) solves program evaluation and review technique (PERT) scheduling problem with a two-stage robust linear programming model based on the approach developed by Bertsimas and Sim (2004). They consider only precedence relations between tasks as constraints. Our method is also based on Bertsimas and Sim (2004) approach, but we consider a more general case. For the OWF installation problem, we schedule a large number of tasks subject to three constraint sets: precedence relations, task ready times, and task deadlines. A precedence relation constraint is included if one task should be finished before another task can begin. An example is the installation task of a turbine that can start only if the asset is transported to the site, the installation vessel is present at the installation site and is idle, and the inter-array cable(s) for that turbine is (are) installed. These make three predecessor tasks for the installation task of this turbine. We should note that, in the meantime, installation of other turbines can be ongoing, and their installations do not affect the installation of other turbines. If some vessels begin operating after the start date of the project, or some operations cannot start before a specific date, we set ready times for the tasks of these vessels and operations. The ready times are conceptually different than the precedence relations between tasks, such that they determine the start time of the first task of a vessel. The ready times are user-defined parameters and they depend on the contracts for the vessels and ports rather than the progress of the installation operations.

A developer may commit to begin generation before the whole installation finishes, which is commonly agreed as a percentage of generating capacity available from an export generation date. We refer to these export generation dates as task deadlines. The model decides on the start times of the tasks to minimise the total duration of the installation project, subject to all constraints.

The mathematical programming model we develop has two levels. The inner level aims to find an overall schedule that minimises the total project duration with deterministic task durations. The outer level determines the sensitivity of the project duration to variations in durations of different tasks, and thus identifies which task variations have the greatest impact on the project duration. We combine both levels in a single mathematical programming model and solve them simultaneously.

Let T denote the set of tasks, $T_{dd} \subset T$ be the set of tasks with deadlines, and $T_r \subset T$ be the set of tasks with ready times. We introduce two dummy tasks to the task set: initial task 0 and the final task N. Let the set IP include all tasks pairs (i, j) for which task $i \in T$ precedes task $j \in T$, dd_i denote the deadline of task $i \in T_{dd}$, r_i denote the ready time of task $i \in T_r$, and d_i denote the duration of task $i \in T$. We include all tasks without an immediate predecessor to T_r and if they do not have ready times, we set their ready times to 0. We add $(0, i)$ to IP for tasks $i \in T_r$ and (i, N) to IP for tasks $i \in T$ that do not have any successor task. We assume $d_i \in [d_{i,min}, d_{i,max}]$, where $d_{i,min}$ is the nominal value (under no deviation) and $d_{i,max} = d_{i,min} + d_{i,inc}$, with $d_{i,inc}$ defining the range of duration values for task i. The model decides on the start times (t_i) of each task i, and minimises t_N, i.e., the start time of the final task. $\Gamma \in \mathbb{R}_+$ is a parameter representing the maximum number of tasks whose duration can deviate within their interval, and z_i denotes the extent to which the duration of task i deviates.

$$\begin{array}{ll} \text{Maximise} & \left\{ \begin{array}{lll} \text{Minimise } t_N & & \\ t_j - t_i \geq d_{i,min} + d_{i,inc} z_i & (i,j) \in IP,\ i > 0 & (2) \\ -t_i \geq d_{i,min} + d_{i,inc} z_i - dd_i & i \in T_{dd} & (3) \\ t_i - t_0 \geq r_i & i \in T_r & (4) \\ t_0 \geq 0 & & (5) \end{array} \right. \\ \sum_{i \in T} z_i \leq \Gamma & \\ 0 \leq z_i \leq 1 & \end{array}$$

The inner model finds an optimal schedule for a set of tasks by setting the task start times, the decision variables t_i for $i \in T$, that minimise the total duration of the project. The task durations are taken as $d_i = d_{i,min} + d_{i,inc} z_i$. Constraint (2) ensures that if task i precedes task j, task j cannot start before task i is completed. If task i has a deadline, constraint (3) ensures that task i should be completed before its deadline. Similarly, if task i has a ready time, constraint (4) ensures that task i cannot start before its ready time. Since task 0 is the initial task and all other tasks are preceded by it, setting the start time of this task greater than zero is enough in constraint (5). The outer model finds the maximum total duration of the project if Γ task durations are assumed to take values within their interval. The outer model decides on the values of z_i, $i \in T$ to obtain the highest possible increment in the total duration of the project. We remark that intermediate task completions are not necessarily estimated for their individual worst case scenarios in such a schedule, as only the total project duration is evaluated for its worst case, however, such completion times still provide an estimate to the user. The two models can be combined in a single-stage optimisation model by dualising the inner model. Since the z_i's are parameters to the inner model but decision variables for the overall model, we have the multiplication of two decision variables in the objective function of the combined model; the z_i variables and the dual variables corresponding to constraints (2) and (3). We linearize the resulting nonlinear model using additional binary variables. The details of these steps can be seen in Tezcaner Öztürk et al. (2016). The final linear model has as many binary variables as the number of immediate precedences between tasks, and this does not increase the computational burden of the model; installation projects with thousands of tasks can be solved in a few minutes.

The overall problem finds a robust schedule for Γ deviating tasks satisfying constraints (1)–(4), and an OWF planner can decide on the percentage of tasks that may vary from their nominal values. Γ can be obtained by multiplying the percentage of deviating tasks with the total number of tasks, and Γ can take any positive value. If $\Gamma = 0$, the model reduces to a deterministic LP: there is no need to solve the robust model as $z_i = 0\ \forall i \in T$ in the outer model, and it is sufficient to solve the inner model by setting the duration of each task i to $d_{i,min}$. If more than two schedules have the same project duration, we select the schedule with the least cost, as detailed in Tezcaner Öztürk et al. (2016). We make a remark regarding the range of task durations: the minimum value can be seen as the shortest duration with perfect weather conditions and crew capability, with the maximum value being the longest duration when the weather conditions do not permit the task to start immediately. Finally, we also make a technical remark that, unlike the models presented in Bertsimas and Sim (2004) and Minoux (2009), our model does not necessarily generate extreme case solutions with all z_i variables but one set to either 0 or 1, as it incorporates deadlines.

The model generates a robust schedule for a percentage of tasks deviating from their nominal durations, while satisfying the precedence, ready time, and deadline constraints. Solving only the inner model to obtain a schedule by setting the durations of the tasks to their expected values could potentially result in suboptimal or infeasible schedules when deviations are present. By contrast, the advantage of this robust schedule is that the project duration proposed by the model is guaranteed to be greater than or equal to the actual duration of a project with a given percentage of deviating tasks. Moreover, if the tasks with deviation are different to those proposed by the model, the schedule still remains feasible. Optimal project durations will be naturally increasing while the value of Γ increases.

The input for the optimisation model is taken through an Excel Interface, and the optimisation model is prepared to be solved by one of the following optimisation software packages: CPLEX, FICO Xpress, or MATLAB. The results of the model (the Gantt chart for the operations of the vessels, the total project duration and cost) are then reported in the same Excel sheet. Given that there are five distinct high-level vessel operations, followed by five support operations at each WTG, in addition to various vessel operations (such as transiting between port and site), the total number of tasks are around a few thousands for large OWFs. Presenting the Gantt chart for an OWF with hundreds of assets would not be practical and would provide little clarification to the reader, however, we present an example Gantt chart in Fig. 5 for the installation of 10 turbines using two installation vessels. Some tasks are grouped to provide a better understanding of the schedule. The vessels have different performances and thus their task durations vary, but both finalize their tasks by day 27.

We also developed a rolling horizon algorithm to optimise the scheduling of the remaining tasks to finalise installation. This algorithm can be used throughout the installation process, when the OWF planner sees substantial deviations from the baseline schedule, and there is a need to find new estimates for project completion time, activation dates for vessels, etc., or when new vessel options arise. The algorithm uses the two steps (asset-vessel assignment algorithm and generating a robust schedule) as we use in creating the baseline schedule, this time separating the planning

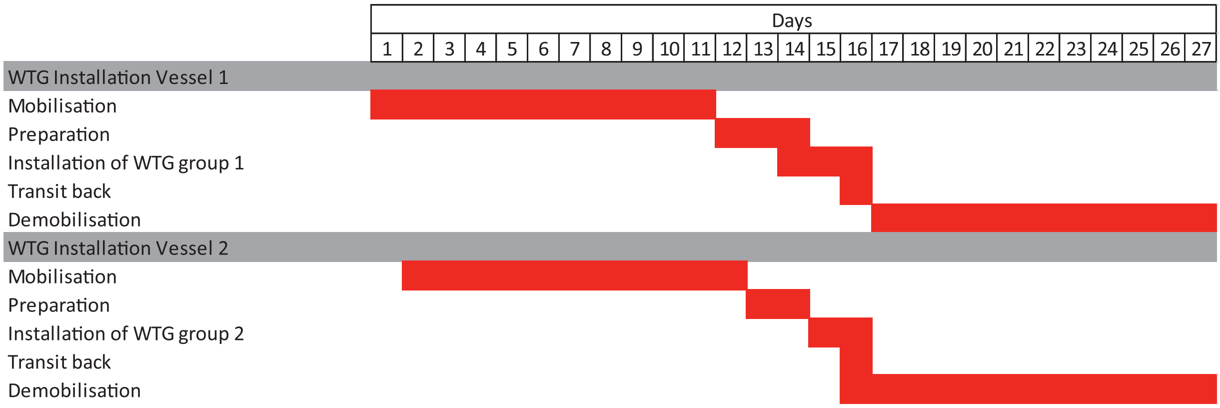

Fig. 5. An example Gantt chart for operations of two vessels for the installation of 10 turbines.

horizon into two: fixed period and planning period. Fixed period spans the duration of the tasks that are already assigned to the vessels, and we allocate the remaining tasks to the vessels during their planning periods. The details of this algorithm can be seen in Tezcaner Öztürk et al. (2016). In creating a robust baseline schedule, our aim is to provide a worst-case bound on the project duration; and the respective project cost and estimates for vessel/operation activation dates. The companies require estimates on these such that the arrangements for the installation project should be done before the installation starts. For example, some of the vessels need to be reserved in advance with high costs of lease as there is a competitive demand from various industries such as oil and gas, and hence changing such decisions often can be very costly. Although it is possible that the progress of the project is not going in line with the initial plan, the rolling horizon algorithm is capable of generating new schedules at different points in time, and to suggest updated bounds on the project duration, and updated vessel/operation activation dates.

4. Case study: supporting decision making throughout an offshore wind farm installation

To demonstrate the capability of the simulation and optimisation model discussed in Section 3, a case study of an offshore wind farm installation is investigated. This case study was developed in collaboration with industry partners and is designed to give a general representation of the next phase of OWF installations in Europe. The input parameter values were provided by the industry partners based on their combined experience from previous OWF installation projects; however, these inputs are entirely generic and do not correspond to any specific OWF installation.

The site studied here is shown in Fig. 6 and consists of 120 WTGs with 6 megawatts generating capacity and 2 OSPs connected through 127 inter-array cables. Each OSP has two parallel export cables, each consisting of four offshore sections and a single nearshore section. The site is located in the North Sea 80 Nautical Miles (NM) off the East coast of the UK with an average water depth of 50 metres.

To populate the weather model discussed in Section 3, high-quality time-series weather data is required. For the purposes of this study weather data from the FINO1 weather research station is used, which is located in the North Sea 50 kilometres off the coast of Germany (Bundesministerium fuer Umwelt, 2012). While the conditions recorded at FINO1 may differ from a particular site off the coast of the UK, this data enables the capability of the simulation and optimisation models to be demonstrated with realistic weather data.

Sections 4.1 and 4.2, respectively, present the application of the simulation and optimisation components of the holistic scheduling approach presented in Section 3 to the case study OWF. For the sake of brevity the analysis is restricted to the installation of the 120 WTGs of the case study. Two identical high-performance WTG installation vessels are utilised, which are capable of installing turbines up to wind speeds of 10 metres per second and transiting at 12 knots with a full load up to significant wave heights of 2 m. The installation operations are shown in Fig. 4, with support operations consisting of mechanical and electrical completion, commissioning, testing and acceptance.

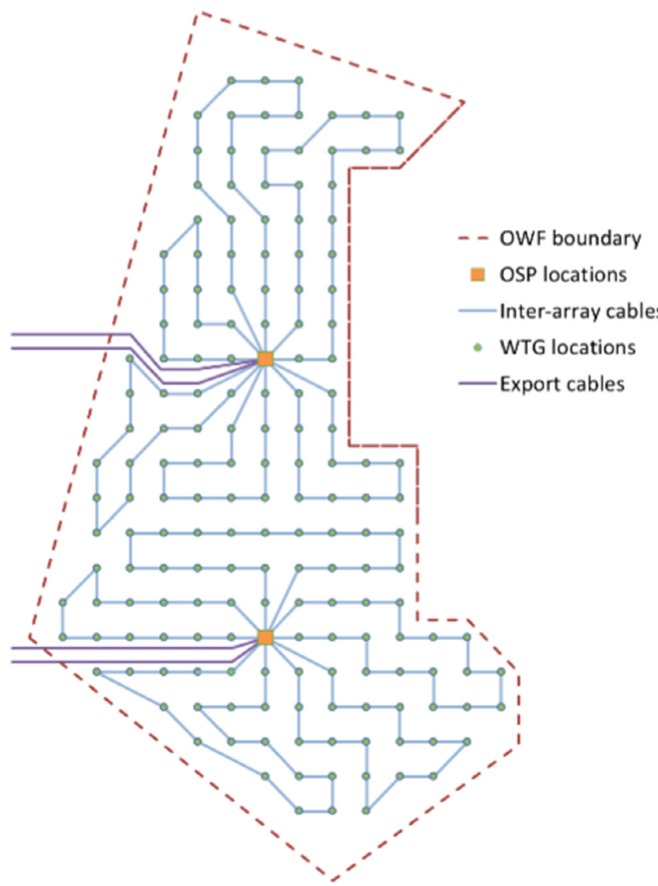

Fig. 6. Layout of the case study offshore wind farm site.

4.1. Scheduling installation operations with consideration of seasonality

For the investigations below, 1000 simulations are performed for each start-date considered, with 1000 simulations found

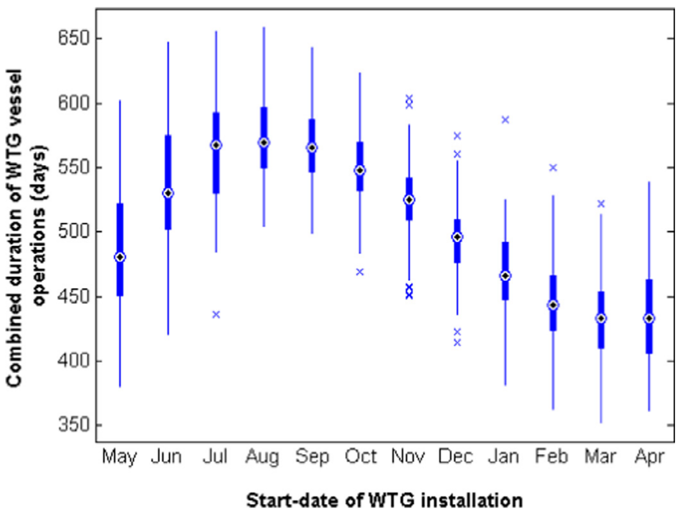

Fig. 7. The impact on the combined duration of both WTG installation vessels, as the vessel start-date is varied over the course of one year.

to provide an acceptable level of statistical accuracy; further information on this process can be found in Barlow et al. (2016).

For the sake of brevity, the starting date for the WTG installation is considered here in terms of the impact on the duration of vessel operations. The cost per day for the WTG installation vessels can be expected to be substantially more expensive than costs for the installation technicians required to complete the WTG support operations. Minimising the duration of the WTG vessel operations is therefore a reasonable approach; however, in practice a more sophisticated investigation could be performed, as is discussed in Section 4.3. Fig. 7 shows the variation in the combined duration of both installation vessels, as the vessel mobilisation dates are varied from an original date of 1st May over the course of one year. All preceding operations are assumed to be completed at times such that these will not delay the installation vessel operations. It is evident from Fig. 7 that appropriate selection of the start-date for installation vessel operations has a substantial impact on the resulting operation durations. A start-date in March produces the shortest vessel durations on average, with a combined total for both installation vessels of approximately 440 days. In contrast, a start-date in August produces the longest vessel durations on average, at approximately 570 days for both vessels combined. A single WTG installation vessel therefore operates for between approximately 7.5–9.5 months of the year. The duration is minimised by fully exploiting the summer months and more favourable weather conditions, and by minimising the exposure to the winter months and delays resulting from harsher weather conditions.

4.2. Scheduling installation operations with optimal staggering of operations

The case study is now solved using the robust optimisation model to obtain an understanding of how the tasks progress overall and to suggest activation dates for the support operations to the WTG installation. The base-case activation date for the installation vessels is 243 days after the start-date of the installation to allow for the delivery and onshore assembly of the WTGs. If different types of assets are to be installed, the optimisation model suggests activation dates for each vessel, which would be useful for planning vessel-hire contracts.

We apply the optimisation model for different percentages of deviating tasks, with findings shown in Table 1, where durations are adjusted relative to the start-date of the installation vessels. We recall that the robustness parameter Γ is obtained by multiplying the percentage of deviating tasks with the total number of tasks. The last five columns of Table 1 show the estimated activation dates for each support installation operation under the worst case scenario for total project duration. The results are obtained using CPLEX solver.

The total project duration is determined by the series of consecutive tasks that form the longest path, which is referred to as the critical path. The optimisation model sets the duration of the tasks on the critical path to their upper bounds and finds the longest possible project duration. For different percentages of deviating tasks, the resulting project duration will be the same if the number of tasks on the critical path is less than the number of deviating tasks. As more task durations are allowed to deviate from their nominal values, both project duration and project cost increase as expected; however, the resulting schedules become more robust to changes in the task durations, which is particularly crucial when weather conditions are volatile.

Before we discuss results regarding varying percentages of deviating tasks, we make a technical remark on the use of the robustness parameter Γ: this parameter can be seen as a bound on the sum of percentage deviations of all individual tasks. For example, if we set 10% of tasks to deviate for a system with 20 tasks (hence, setting $\Gamma = 2$) a feasible solution can have any combination of deviations for individual tasks (the variables z_i) as long as their sum is bounded by 2. This could therefore be achieved by 2 tasks deviating to their maximum possible duration while the remaining 18 tasks take their minimum duration values with no deviation (hence $\sum z_i = 1 + 1 \leq 2$), or by each of the 20 tasks having a deviation of 0.1 to their maximum possible duration (hence $\sum z_i = 20 \times 0.1 \leq 2$). We note that when we search the critical path in a robust network setting, the optimal solutions naturally tend to the extreme cases where deviations are equal to either one or zero, as indicated with the first solution to the numerical example above for the case of 20 tasks and $\Gamma = 2$. Although this observation is noted for models such as those presented in Bertsimas and Sim (2004) and Minoux (2009), we remark that our model does not necessarily generate such extreme case solutions, as it incorporates deadlines.

If 5% of the tasks are assumed to deviate from their nominal durations, the estimated time to start support operations is approximately 156 days after the installation start-date. This estimation might be valid for an installation project that spans mostly spring-summer months, where the tasks do not deviate much due to weather conditions. As the percentage of deviating tasks increases to 50%, the suggested activation dates increase to approximately 535 days after the installation start-date. This estimation, on the contrary, refers to a project that spans mostly winter months, and the task durations show considerable variability. The increase in the activation dates results from the increase to the critical paths from longer vessel operation durations. We also remark that this represents a relatively extreme case, resulting in half of the tasks hitting their longest expected durations. The activation dates of electrical completion and commissioning are marginally delayed from the mechanical completion start-date; however, there is a gap between the activation dates of commissioning and testing operations for all percentages of deviating tasks. Acting in conservative fashion, the optimisation model finds the latest start for all the support operations, guaranteeing that there is no delay from waiting for a preceding support operation to finalise. The assumed duration of testing is much shorter than the commissioning operation, leading to this gap between their activation times.

Determining the percentage of deviating tasks usually requires expert judgement to decide on the weather conditions for the total installation duration. The installation generally spans a few

Table 1
Project duration, project cost, and activation dates for different percentage of deviating tasks.

Percentage of deviating tasks (%)	Total project duration (days)	Total project cost (k£)	Activation dates (days after start date of installation vessels)				
			Mechanical completion	Electrical completion	Commissioning	Testing	Acceptance
5	555.28	111665.34	156.04	156.68	157.32	234.96	235.28
10	731.50	140829.44	332.26	332.90	333.54	411.18	411.50
25	949.54	182152.81	539.87	540.51	543.98	605.33	605.65
50	949.54	184575.30	535.24	538.70	539.35	614.13	615.41

years (the installation of 120 turbines takes 2–3 years as given in Table 1), and it is generally not straightforward to determine the variability of task durations. OWF developers need to test different Γ values based on their expert judgements and evaluate the schedules generated. If the installation is mostly carried out during summer months, a lower percentage of deviating tasks will be more representative of the installation. If the installation spans primarily winter months, the percentage of deviating tasks might be set to a larger value.

4.3. Discussion

Sections 4.1 and 4.2 illustrated the mixed-method scheduling approach presented in Section 3. This approach is one method of hybridising these models; however, there are various alternatives which could be explored. As indicated in Section 4.1, an alternative application is to give a more sophisticated consideration of the impact of varying the start-date. The optimisation model could be applied as a preliminary step to identify the optimal scheduling of the different sets of operations, as demonstrated in Section 4.2. This would provide a schedule which is optimal with respect to the average yearly weather conditions. The simulation model could then be used to explore this schedule of operations, and to investigate perturbations to the yearly average optimal schedule as the start-date is varied throughout the year. This would provide an optimal schedule for each month of the year. However, the approach presented in Section 4.1 was thought to provide a more concise and straightforward demonstration of these models.

An alternative hybridisation would be to use the simulation model to identify the tasks which are most susceptible to weather delays, or equivalently most susceptible to deviations from their nominal value. This information could be used to explicitly define the deviating tasks in the optimisation analysis, rather than using the deviation percentage defined through Γ and automating the selection of the deviating tasks. This additional information would provide an analysis which is more representative of the progress that would actually be observed in a real installation application.

The above investigations focus on the duration of operations, however, in reality this is only one factor for an OWF developer, and the date from which power can be generated and exported to the onshore grid would also be taken into consideration. Each of these factors has an economic impact on the viability of the OWF, and a balance between low installation costs (through low durations of vessel use) and early generation (through completing operations as quickly as possible) must be achieved.

5. Verification, validation and application

The models were developed to be used to inform installation strategies for upcoming OWFs by the industry partners involved in their development. Upon completion, the models were subjected to verification and validation by those within the project team and external experts. Due to the limited number of OWFs that have been installed and the lack of reliable data to benchmark the model output to, industry partners agreed that a pragmatic approach to validation was required. Phillips (1984) defines a requisite model as one such that “its form and content are sufficient to solve the problem”. Three different activities were carried out to verify and validate the model.

First, the model code was subjected to external verification from a mathematical software consultancy to review and interrogate the implementation of the logistical model and the logical structure of the code. They confirmed that the code was an accurate representation of the logical structure agreed by the industry collaborators. Second, the model was benchmarked against an industry-standard tool developed by a leading marine consultancy firm. Where differences where identified, these were discussed with industry experts. In particular, the weather model employed here provides improved accuracy in uncertainty quantification for durations and costs. Furthermore, the framework developed here enables flexible and reactive assignment of tasks when multiple vessels install the same asset, which is more representative of task assignment in practice. Finally, engineers within the two industry organisations explored multiple case studies to ensure that the model was fit for purpose. This included ensuring that the output was adequate to support the decisions necessary and that the output could be interrogated sufficiently to identify the cost and uncertainty drivers within the installation process. Based on these verification and validation steps, the models have now been adopted by industry partners to inform installation strategy development.

This framework is currently being used by SSE Renewables (one of our collaborating industry partners) to support decision making for the logistical planning of the Beatrice OWF installation project, a 600 megawatts wind farm located off the North-East coast of the UK which is scheduled for installation over 2017–2019. The framework has been fundamental to the decision-making process since the earliest stages of installation planning, and has enabled each stage of the installation to be interrogated. The capability to perform a detailed analysis, comparison and optimisation of alternative options to a variety of decisions has enabled in-depth exploration of these decisions, and the iterative development of the installation plan as decisions are fine-tuned, pursued or abandoned.

SSE Renewables estimate that the use of this framework has delivered a saving of approximately 14% (tens of millions of GBP) of the installation costs, compared with initial cost estimates. These savings have been brought about by improving the efficiency of the installation operations, primarily with respect to the installation of the turbine foundations, the inter-array cables and the OSPs. The framework presented here facilitated improvements by providing a mechanism to quantitatively analyse and optimise aspects of the installation, such as vessel selection and scheduling. An indicative example of this is applying the tools to investigate the efficiency of the available jacket installation techniques and how these can be deployed across the site. For each scenario considered, the most efficient scheduling approach for the jacket installation vessels and all follow-on operations is identified and compared, enabling informed decisions to be made. The same process is then applied to explore the available options for the pile installation, and for each subsequent installation operation.

6. Conclusions

The next phase of offshore wind farms (OWFs) to be developed in Europe in the coming years will typically consist of hundreds of turbines, and will be located further from shore in deeper water than has previously been encountered (Renewable UK, 2014). The installation of these sites will typically span several years and cost upwards of £100 million (Kaiser & Synder, 2010). Limited industry experience on projects of these scales and location characteristics motivates the need for decision-making support for developers, to ensure that operations are planned as efficiently as possible and that the vast installation costs are streamlined where possible.

This paper describes the integration of a pair of complementary decision support models for the installation of an OWF. Both models can be applied at the planning and bidding stages of an installation, with each model supporting specific aspects of installation scheduling. An OWF installation case study is investigated to demonstrate the potential capability of this integrated framework to provide decision support to an OWF developer planning an installation campaign. The scope is restricted here to the installation of the wind turbines for brevity; however, a similar approach to that outlined here could be applied to the installation of all OWF assets. The framework presented here could be adapted to model a variety of processes where operations are subject to uncertain weather conditions, including tasks during the operation and maintenance or decommissioning (removal of an asset from active status, including deconstruction of the structure) phases of an OWF, or similar tasks related to other forms of renewable energy such as wave or tidal.

Future developments of this mixed methods framework will explore more efficient interfacing between the simulation and optimisation components. Section 4.3 highlights an approach which would make explicit use of the simulation model to define the required robustness of the optimisation solution. This approach could be utilised even further by restructuring the optimisation model to handle specific ranges of task durations which are defined by the simulation model for a particular operation in a given timeframe. To utilise the simulation model in this way may require development of a meta-model for the simulation model, such that the many duration outputs can be generated in a tractable timescale within the optimisation run. The resulting model would implicitly combine the detailed weather sensitivity of the simulation model with the superior scheduling ability of the optimisation model, thus provide a powerful decision-support tool for OWF developers.

Acknowledgements

This study was funded through the University of Strathclyde Technology and Innovation Centre, grant reference TIC/LCPE/FI03. The authors thank industrial partners Scottish Power Renewables, SSE Renewables and Technip Offshore Wind Limited for their contribution to this work. Additionally, the authors thank the Bundesministerium fuer Umwelt (Federal Ministry for the Environment, Nature Conservation and Nuclear Safety) and the Projekttraeger Juelich (project executing organisation) for climate data from the FINO project.

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