Towards Efficiency: Declarative Modelling in Wind Farm Preventive Maintenance Strategies

Rasmus Dovnborg Frederiksen *[0009-0007-2799-1050]*
Aalborg University, Denmark rasmusdf@mp.aau.dk

Grzegorz Bocewicz *[0000-0002-5181-2872]*
Koszalin University of Technology, Poland grzegorz.bocewicz@tu.koszalin.pl

Peter Nielsen *[0000-0002-4882-7942]*
Aalborg University, Denmark peter@mp.aau.dk

Grzegorz Radzki *[0000-0002-0688-1764]*
Koszalin University of Technology, Poland grzegorz.radzki@tu.koszalin.pl

Robert Wójcik *[0000-0003-3860-7011]*
Wrocław University of Science and Technology, Poland robert.wojcik@pwr.edu.pl

Zbigniew Banaszak *[0000-0001-7219-3903]*
Koszalin University of Technology, Poland zbigniew.banaszak@tu.koszalin.pl

Abstract

Ensuring optimal functioning and efficiency of offshore wind farms requires effective performance maintenance strategies. The developed declarative reference model allows capturing the trade-off between the costs of losses incurred due to extending the servicing time of wind turbines and the expenditure incurred on the scale of the fleet of vessels used and the service teams employed to maintain them. The problem of meeting constraints formulated in this representation allows for identifying and mitigating potential problems before they occur.

Keywords: Offshore wind farm, Preventive maintenance, Performance evaluation.

1. Introduction

Among the primary maintenance processes for Offshore Wind Farms (OWFs) - including preventive maintenance, predictive (condition-based) maintenance, and corrective (reactive) maintenance - the first two assume paramount importance in mitigating Operation and Maintenance (O&M) costs [2], [12].

The influences of the selected maintenance processes on O&M, and particularly on the Levelized Cost of Energy (LCOE), are considered separately in the literature [2], [6]. Consequently, we advocate for adopting a reference modelling methodology as a comprehensive approach to enhance preventive-predictive maintenance in OWFs. Employing a declarative paradigm-based modelling framework, we aim to predict and evaluate the performance of maintenance strategies for OWFs. The adopted reference model facilitates a simplified assessment of wind farms' profitability, explicitly focusing on maintenance considerations and incorporating only selected O&M cost metrics. While this model may lack the precision of real-world scenarios, it offers better suitability for evaluating the cost-effectiveness of various iterations of predictive maintenance strategies. The declarative nature of the reference model renders it highly compatible for practical implementation within established constraint programming environments such as ILOG, ECLiPSe, and Gurobi. Our research objective is to develop a prototype system to assist decision-makers in optimizing preventive-proactive O&M and logistics strategies for OWF maintenance. This approach involves selecting a crew transfer vessel fleet, planning and scheduling vessel missions, and organizing service teams.

Besides the design, construction, and O&M of OWFs the research conducted in this area focuses mainly on assessing the effectiveness of OWF perceived in the context of maintenance strategies, primarily preventive and proactive ones [11].

In this context, there is a visible lack of publications dealing with a comprehensive approach that integrates the threads, as mentioned earlier, to determine the effective operations of OWFs. This situation is exacerbated by the lack of tools supporting operators' decisions to plan appropriate missions to maintain OWF performance at a given level. The presented research gap indicates the need to develop OWF maintenance models that enable planning and operational control of OWF maintenance processes through their implementation in DSS class tools. The modeling framework used for research in maintaining the performance of OWFs implementing preventive, proactive, and reactive maintenance processes covers a vast spectrum of methods and techniques. It is worth mentioning stochastic mixed-integer linear programming [9], generalized stochastic Petri nets [10], machine learning-based techniques [8], mixed integer linear programming [5], Ant Colony algorithms [1], numerical simulation [7], and the digital twin technology [13]. Unfortunately, among the mentioned representations, there are no solutions based on declarative modeling techniques that enable the use of widely available constraint programming environments [2]. The highlighted research gap underscores the necessity for developing models with an open structure, facilitating the incorporation of additional constraints, or replacing existing ones. These possibilities are provided by the declarative programming paradigm that allows for constraints of various nature (i.e., logical, algebraic, linear, and non-linear conditions, considering the crisp and/or fuzzy variables).

2. Problem formulation

In general the operational profit of OWF (for any period T) can be represented by the following equation [4]:

$$P_T = Rev_T - CoD_T - CS_T\ , \tag{1}$$

where Rev_T is the potential revenue from the produced power, and CoD_T is the cost of downtime, i.e., the revenue lost from suspended production. $Rev_T - CoD_T$ is thus the actual (for period T) revenue gained from the produced power. CS_T is the cost of service, constituting the overall cost of O&M. CS_T includes all costs related to preventive services during period T. While CS_T is highly specific to the individual cases and cannot be formulated clearly [4], CoD_T can be stated as:

$$CoD_T = \sum_{d\in D} \sum_{t\in T_d} MW \times p_t \times Wf_t \times 0.96\ \ , \tag{2}$$

where MW is the nominal power output of the WT, p_t is the price of energy, Wf_t is the wind factor, which is in percent how much of the nominal power output can be generated given the wind at time t. In fact, the costs of CoD_T downtime can be reduced by implementing preventive service missions. Servicing the WT early enough can prevent downtimes and the associated costs. To assess the impact of the service mission S_T on the value of CoD_T costs, the concept of **service effectiveness** $\boldsymbol{\varepsilon \in [0, 1]}$ is introduced. **Effectiveness of service** ε is defined as the ratio of omitted downtimes during the mission S_T service missions to the total number of expected downtimes.

The problem of planning S_T service missions assume that: they are decomposed into sub-missions: $S_T^1, \dots, S_T^q, \dots. S_T^{ld}$; each WT is serviced by one service team (service team number is limited to NW); service teams are transported to WTs using a fleet of vessels (vessels number is limited to NS); each WT is visited by vessels twice (the first time to deliver the team, the second time to pick up the team); the service time (st_i) of each WT is known, the transport times ($vt_{i,j}$) between WTs are also known; depending on the adopted strategy, the service team delivered to the WT by a given vessel must be collected by that vessel or may be collected by another one.

Considering that the costs $CoD_T(\varepsilon)$ and $CS_T(\varepsilon)$ (defined as functions dependent on ε) are dependent on the preventive strategy, the planning service missions comes down to minimizing the sum of these costs: $\min\{CoD_T(\varepsilon) + CS_T(\varepsilon)\}$, i.e., the answer to the following question is sought: Which plan of service mission (with effectiveness ε) guarantees (in a given T) the minimum cost value? This kind of problem can be formulated (in a simplified form) in terms of the Constraint Optimization Problem (COP) [2], [5]:

$$CO_q = \left(\left(\mathcal{V}_q, \mathcal{D}_q\right), \mathcal{C}_q, \mathcal{C}_{OPT}\right) \quad , \tag{3}$$

where $\mathcal{V}_q = \{x_{i,j}^s, y_i^s, aw_{\omega,i} |\ i,j = 1,..,NT, s = 1 \dots NS, \omega = 1,\dots,NW\}$ is a set of decision variables determining the service mission plan: routes of vessels ($x_{i,j}^s$- binary variable used to indicate if the vessel s travels to tubine j to i), schedules of the vessels (y_i^s - time at which vessel s arrives at the point i) and sewice teams assingmet ($aw_{\omega,i}$ - binary variable used to indicate if the team ω is assigned to turbine i); $\mathcal{D}_\mathrm{q}$ is a set of domains of decision variables: $x_{i,j}^s, aw_{\omega,i} \in \{0,1\}$, $y_i^s \in \mathbb{N}$; $\mathcal{C}_\mathrm{q}$ is a set of constraints describing the relationships between vessels, service teams and OWF (eg. [3]); $\mathcal{C}_{OPT}$ is an objective function describing tradeoff between the costs: $\min\{CoD_T(\varepsilon) + CS_T(\varepsilon)\}$.

To solve the CO_q problem, i.e., (3), it is necessary to determine the values of the decision variables $\mathcal{V}_q$ that meet all the constraints of the $\mathcal{C}_q$ set, and the objective function $\mathcal{C}_{OPT}$ reaches its minimum. The solution to the CO_q problem determines service missions S_T^q for each day of period T.

3. Computer-aided OWF Maintenance Planning

Depending on the assumptions made, the dispatcher can determine both the form of decision variables and the constraints binding them without changing the algorithm responsible for searching for a solution.

This method indicates the potential for adapting the model to meet specific expectations and requirements, which may arise from current needs, including various inquiries. In the case under consideration, the parameterized values of the characteristics describing OWF, fleet of vessels, and service teams allow for capturing the trade-off between the costs resulting from WTs not serviced on time (cost of downtimes $CoD_T(\varepsilon)$) and the expenses incurred in connection with the implementation of the service mission: fleet costs and employed service teams (cost of service $CS_T(\varepsilon)$). Examples of questions determining different configurations of (3) model are as follows:

- How many days will it take to service a subset of WTs counting NI turbines using the NS fleet of vessels carrying NW service teams, assuming that the time windows defining the individual service date of each WT are known?
- Is it possible to service a subset of WTs counting NI turbines in a given period (e.g., 2 days) using the NS $f$leet of vessels carrying NW service teams, with the service teams being delivered and picked up by the same vessel (constraint (22))?
- How does the large NS fleet of vessels carrying NW service teams guarantee to service a subset of NI turbines before all expected downtimes occur ($\varepsilon = 0$)? What is the cost of service $CS_T(\varepsilon)$ associated with such a mission plan?
- And others.

Fig. 1 shows a diagram of the proposed service mission planning system concept. When formulating a question, the user determines a set of parameters (decision variables) of the problem and the domains of their variability $\mathcal{V}_q$ for the considered CO_q problem. The adopted decision variables (their number and type), in turn, imply the structure of the set of constraints $\mathcal{C}_q, \mathcal{C}_{OPT}$. Solving the CO_q problem formulated in this way in the proactive OWF maintenance method, forces its implementation in a declarative programming environment IBM ILOG CPLEX. In other words, the structure of the question formulated by the user implies the structure of the CO_q problem, the solution of which determines the desired result. This approach means that the structure of the CO_q problem is parameterized by the user's question. In other words the open (declarative) structure of the proposed model allows for consideration of various cases of assessment/analysis of service missions characterized by different numbers of vessels, service teams, and delivery strategies.

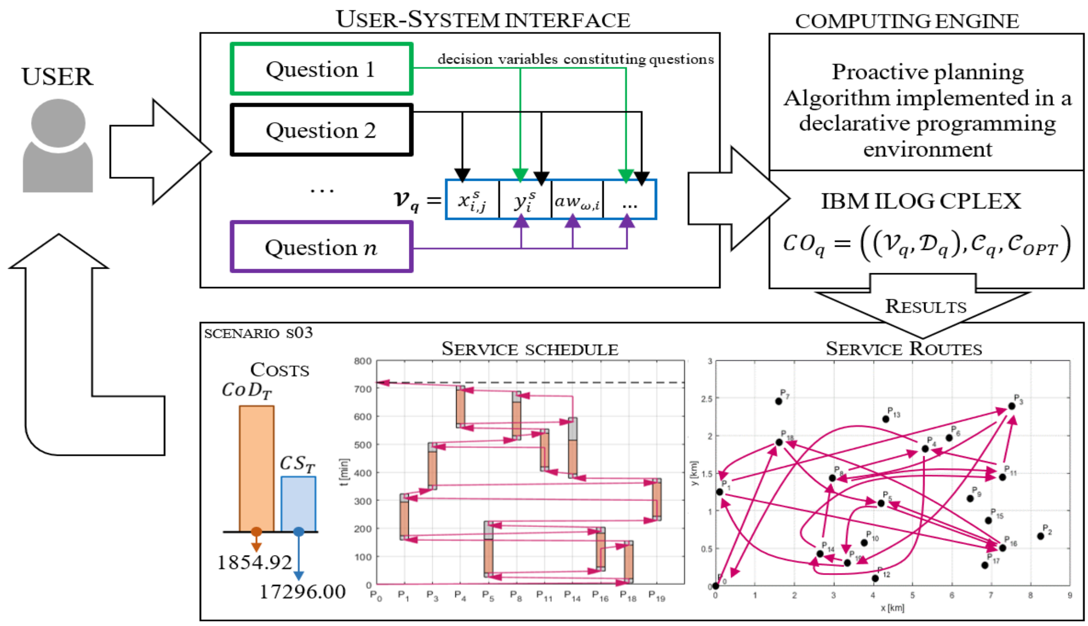

Fig. 1. Structure of interactive OWF Maintenance Planning

4. Scalability and Applicability Assessment

The OWF maintenance planning methodology described in Fig. 1 makes it possible to adapt the domains of decision variables, constraints, as well as the objective function of assumptions to the user's (dispatcher/planner) queries. The layout of the considered OWF includes a set of WFs located in an area of 9km×3km. Through experiments, diverse service mission scenarios were analyzed to identify the scenario with the lowest cost guarantee. The scope of the considered scenarios $s00 - s07$ includes various numbers of vessels: $NS = 1, \dots, 4$ and service teams: $NW = 1, \dots, 8$. The cheapest mission is selected for each of the considered scenarios. The obtained results are summarized in the table in Fig. 2a). Scenario $s00$ corresponds to a situation in which no preventive service takes place - the cost of downtimes $CoD_T = 53{,}922$ EUR. Subsequent scenarios $s01 - s07$ result in solutions requiring more and more service resources (vessels NS and service teams NW). It is easy to notice that as they increase, the mission time (DM variable) decreases from 4 to 1 day. This result also means an improvement in the effectiveness of service ε from 100% to 0%.

a)

scenarios	NS	NW	DM	ε[%]	$CS(\varepsilon)$	$CoD(\varepsilon)$	Total cost
s00	0	0	0	100	0.00	53921.97	53921.97
s01	1	1	4	27.77	22133.33	14972.75	37106.09
s02	1	2	3	8.15	18956.00	4393.00	23349.00
s03	1	3	2	3.44	17296.00	1854.92	19150.92
s04	2	4	2	2.93	20439.00	1577.94	22016.94
s05	2	5	2	2.46	22586.67	1325.49	23912.16
s06	2	6	2	1.99	24026.67	1073.04	25099.71
s07	4	8	1	0.00	28166.67	0	28166.67

b)

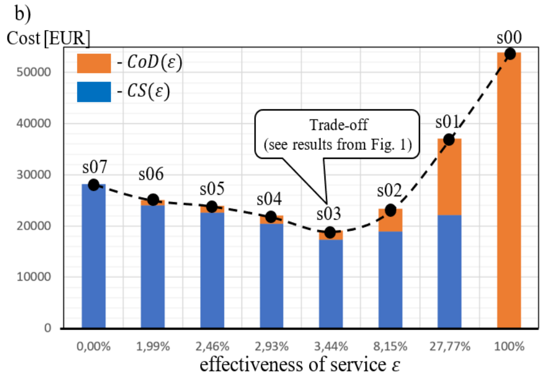

Fig. 2. Considered scenarios $s00 - s07$ a), maintenance cost function b)

It is worth noting that a better value of ε does not always lead to lower costs. Starting from scenario $s04$ (and beyond), the service costs $CS(\varepsilon)$ begin to dominate, which exceed the savings resulting from the reduction of downtime costs $CoD(\varepsilon)$. As a result, total costs start to increase - see Fig. 2b. Ultimately, the best solution turns out to be $s03$, leading to a compromise between the costs $CS(\varepsilon)$ and $CoD(\varepsilon)$. This scenario guarantees the lowest maintenance costs, 19,150.92 EUR, but requires one vessel and three service teams. The mission plan for this scenario is illustrated in Fig. 1 (results block). The experiments confirmed that achieving a service mission plan to protect all WTs against downtimes (a plan where ε = 0%) is too expensive. It turns out that the lowest maintenance costs are obtained for ε = 2%-3%.

5. Conclusions and Further Work

The primary objective of this study is to develop a comprehensive reference model enabling the simultaneous determination of preventive and proactive maintenance strategies for OWFs, thereby facilitating O&M decisions. Declarative in nature, this model has been carefully designed for practical implementation in established constrained programming environments such as ILOG, ECLiPSe, and Gurobi. Its notable feature is its flexible structure, allowing new relationships between decision variables to be included without compromising computational efficiency. It also enables the formulation and resolution of analysis problems (answering questions regarding what happens when) and synthesis problems (what parameters ensure its expected behavior).

Apart from investigating the applicability spectrum of the devised DSS, the primary focus can be on broadening the scope of problems it tackles. The challenges entailed in this expansion lie in amalgamating the existing declarative model representation with fuzzy sets and evolutionary algorithms. This integration accommodates imprecise parameter values encountered in practical scenarios, thus enhancing the tool's scalability.

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