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A Systematic Framework for Maintenance Scheduling and Routing for Off-Shore Wind Farms by Minimizing Predictive Production Loss

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Abstract. Maintenance scheduling and vessel routing are critical for the off-shore wind farm to reduce maintenance costs. In this research, a systematic framework that takes the advantage of predictive analysis for off-shore wind farm maintenance optimization is sketched and the optimization results are presented. The proposed framework consists of three different functional modules - the prognostic and diagnostic (P&D) module, the wind power prediction module, and the maintenance optimization module. The P&D module predicts and diagnoses the system failures based on the operational data of the wind turbine and generates the maintenance tasks for execution. The power prediction module predicts the weather conditions and the production of the wind turbine in the next 1-3 days, which will be helpful for maintenance task prioritization and scheduling. The optimization module absorbs information from the previous two modules as input and optimizes the overall maintenance costs. Comparing with the previous research works, this framework optimizes the maintenance cost in a more challenging situation by considering the predicted remaining useful life from the P&D module and also the future weather condition from the wind power prediction module. In the proposed framework, the maintenance scheduling and the vessel routing are optimized collaboratively with the consideration of real-time production loss. The result of the proposed framework is demonstrated on an off-shore wind farm and reduced maintenance cost is reported.

1 Introduction

Offshore wind farms have been rapidly developed over the last decade due to the reliable wind source and open space for installation[1, 2]. However, one limitation that impedes the development of offshore wind farms is its high operation and maintenance (O&M) cost caused by remoteness, rough environmental conditions, and logistic challenges[3]. It is reported in [4-6] that the maintenance cost for the offshore wind turbine takes as high as 20-35% of lifetime costs. Driven by the need for cost reduction, maintenance activity optimization plays a significant role in organizing maintenance activities for offshore wind farms. In the authors' opinion, the maintenance costs for offshore wind farm breakdown to the visible costs and invisible costs. The visible costs mainly consist of the maintenance-related costs, such as transportation, technician salary, price of spare parts, which have been extensively covered in the literature. The invisible cost, which essentially refers to the production loss (PL) introduced by turbine failures and degradation, is found equally important in practice due to the fact that wind turbines with higher power ratings are usually erected in offshore wind farms [7]. Therefore, this work aims to propose a novel optimization model for maintenance scheduling and vessel routing by accounting both the PL of offshore wind turbines and visible maintenance costs.

In the current literature, maintenance scheduling and vessel routing mainly optimize the visible maintenance cost[8-14]. Early investigations in [15-17] utilize Traveling Salesman Problem (TSP) and Travelling Repairman Problem (TRP) to optimize the transportation cost. It is argued in [18] that these models are over-simplistic to address real-world challenges. To account for the real situation for offshore wind farm maintenance, studies in [19, 20] estimate the cost based on simulation models and then suggest decisions accordingly. However, the use of these approaches needs human involvement and expert knowledge, and they are unable to schedule the maintenance tasks based on turbine operation conditions. To address this concern, the preventive and opportunistic maintenance strategies are utilized in [21-23] to schedule the maintenance tasks and to optimize the cost as well. To better prioritize the maintenance tasks, the use of predictive PL of wind turbines or equivalent penalty terms are highlighted in a number of recent researches [24-31] and report reduced overall cost. Kovács et al. [26, 30] utilize a simplified PL model for maintenance scheduling for the first time. However, the vessel return route optimization is not considered in their investigation and the correctness of the PL model is not justified based on

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real-world data. Irawan et al. [28] consider the vessel routing problems but the PL term in their optimization model is not considered. Instead of it, a simple penalty term is introduced for the delayed tasks.

Summarizing these research works, it is found that the production loss (PL) is still less investigated when optimizing the maintenance cost. Provided that the PL is a dynamic value that accumulates over time if the turbine degradation or failure is left unattended, the maintenance scheduling and vessel routing become a coupled problem that cannot be optimized separately. To fill in these gaps, the contributions of this research are summarized as follows. (1) A systematic methodology for the off-shore wind farm maintenance optimization is proposed. The PL is utilized in the proposed method to prioritize the maintenance tasks and to optimize the vessel route collaboratively. (2) The integration of PL term in the optimization model is well justified in this work and the computation of the production loss is clearly stated. (4) The effectiveness and the superiority of the proposed method are validated on the dataset from an off-shore wind farm with 27 4MW wind turbines. Reduced maintenance costs are reported.

The rest of this paper is organized as follows. The engineering problems are formally stated in Section 2. The proposed methodology is detailed in Section 3. The results and related discussions are presented in Section 4. The concluding remarks are given in Section 5.

2 Problem Statement

The main aim of this work is to reduce the maintenance cost for the off-shore wind farm by optimizing the maintenance activities. In the framework of this research, the maintenance cost for the off-shore wind farm is divided into a visible part and an invisible part. Visible cost for maintenance activities breaks down to the transportation cost, labor costs, price of spare parts, wind turbine downtime, etc. The invisible cost mainly refers to the Production Loss (PL) caused by wind turbine degradation and failure. To account for this portion of the cost in optimization, the power curving monitoring technology and weather forecast in future 1~3 days are needed. Power curving monitoring reflects the most recent performance of the wind turbine against the baseline or design expectations. The weather forecast tells the future wind speed distribution that is required to compute the future PL within the targeted maintenance time window. In this study, the future 1 to 3 days are mainly considered.

The inclusion of PL provides evidence to prioritize the maintenance tasks and brings new challenges to the optimization problem. In previous researches, the cost optimization for off-shores wind farms mainly considers the cost related to spare parts, service vessels, and maintenance technicians [28]. Some papers consider adding a penalty rule to quantify the risk of unexpected failures [31] or delayed maintenance timing [21, 28]. However, by considering PL in the optimization model, the previous static optimization problem becomes a dynamic scheduling problem, and the vessel routing and maintenance schedules need to be optimized collaboratively.

To tackle these challenges, this research aims to address following engineering problems: (1) the necessity to include wind turbine PL in maintenance optimization needs to be justified and quantified based on both simulation data and on-site data; (2) A feasible optimization model is required to optimize the vessel routing and maintenance scheduling collaboratively, so that the overall maintenance cost can be reduced.

3 Technical Approach

3.1. Systematic framework

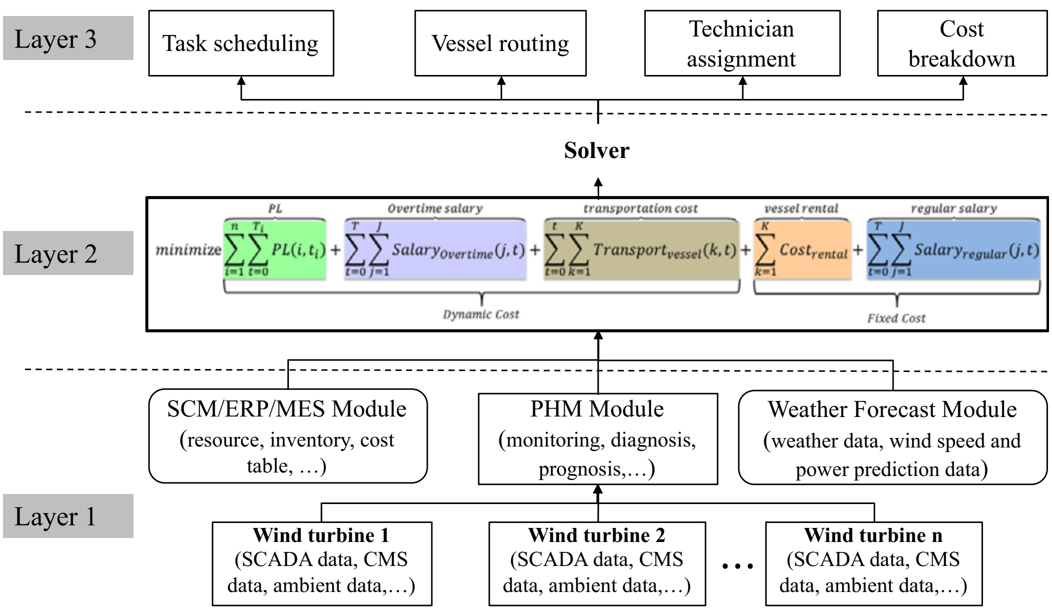

Fig. 1 Systematic framework of maintenance scheduling optimization for wind farms

An overview of the proposed framework is described in Fig. 1. The input layer of the methodology includes three different modules. (1) the PHM module monitors, diagnoses, and predicts the failure or degradation of wind turbines, and then generates a list of maintenance tasks for execution [32-34]. According to a number of recent work, the SCADA (Supervisory Control And Data Acquisition) system is widely utilized for wind turbine power curving monitoring and CMS (Condition Monitoring System) data is commonly utilized for the drive train diagnosis. (2) The weather forecast module predicts several ambient parameters, like wind speed, humidity, pressure, etc. These variables, especially the wind speed, provides necessary inputs to compute the production loss of wind turbines. (3) The SCM (Supplier Chain Management) / ERP (Enterprise Resource Planning) / MES (Manufacturing Execution System) provides useful information for the optimization, such as the cost for spare parts, availability of technicians, inventory readiness, etc. All this information will be utilized as input to the optimization model for optimal planning.

The core part of the methodology is the optimization model and solver in the second layer of Fig. 1. In the second layer, the overall maintenance cost comprises five different parts. The regular time salary and the vessel rental cost forms the fixed cost for any maintenance activity and has very little space for optimization. However, the overtime cost, transportation cost, and PL of the wind farm are closely related to the maintenance scheduling and vessel routing. These three cost terms constitute the dynamic cost that needs to be optimized in this research. It is also important to note that the overtime salary refers to labor costs caused by working overtime and the transportation cost is mainly contributed by the fuel cost for the vessel.

The expected outcome includes the optimized vessel route and maintenance task schedule, the technician assignments, and the cost breakdown, as shown in the third layer of Fig. 1. The optimized schedule will be given in the form of a Gantt Chart and the optimized vessel route will be visualized directly on the map. Other details of the model output will be demonstrated in results and discussions.

3.2 Model for Prognostics-based Maintenance Scheduling and Vessel Routing

The optimization model for routing and maintenance scheduling of vessels and technicians with a rolling horizon in future 1~3 days is proposed in this section. The notations in this paper are shown in Table 1 The model is to solve a scheduling problem where I geographically distributed maintenance tasks are to be performed by M types of technicians with K available vessels in a time period T.

Table 1 Notations

Parameters	
v_t	Electricity price at time t
c_f	Vessel fuel price per unit time
$\tau_{k,t}$	Whether the vessel k is permitted at time t
$\theta_{i,t}$	Whether task i can be start at time t
$d_{i,i'}$	Travel time between task i and task i'
TTR_i	Time to repair (TTR) of task i
$PL^0_{i,t}$	PL of turbine i at time t caused by degradation
$PL^1_{i,t}$	PL of turbine i at time t during maintenance
Variables	
$x_{k,i,t}$	Whether technicians are delivered or picked at node i at time t by vessel k
$a_{i,t}$	Whether task i is under maintenance at time t
$b_{i,t}$	Whether technicians are at task i at time t
$p_{i,m}$	Number of technician m required by task i
$P_{k,i,m}$	Number of technician m on vessel k after task i
$e_{k,i,i'}$	Whether the vessel k travels from turbine i to turbine i'
$z_{i,t}$	Production loss on task i at time t
$\varsigma_{i,t}$	Overtime salary cost of technicians art task i at time t

The objective in the proposed model is to minimize total maintenance cost Z that is written as below:

$$Z = \underbrace{\overbrace{\sum_i\sum_t z_{i,t} v_t}^{PL} + \overbrace{\sum_i\sum_t \varsigma_{i,t}}^{overtime\ salary} + \overbrace{\sum_k\sum_i\sum_{i'} e_{k,i,i'} d_{i,i'} c_f}^{transportation\ cost}}_{dynamic\ cost} + \underbrace{\overbrace{\sum_{k=1}^{K} Cost_{rental}}^{vessel\ rental} + \overbrace{\sum_{t=0}^{T}\sum_{k=1}^{J} Salary_{regular}(k,t)}^{regular\ salary}}_{fixed\ cost} \quad (1)$$

The overall cost can breakdown to dynamic cost and fixed cost. Dynamic cost refers to the portion of cost in Eq.(1) that will worth the optimization efforts. This portion of cost, which consists of the PL of wind turbine, overtime salary for technicians and the transportation cost for vessels, is directly related to the initiated maintenance scheduling and vessel routing plans. In comparison, the fixed cost refers to the cost that will not be affected by the maintenance schedule or vessel routes, such as the price of spare parts and the regular salary for technicians. Since the fixed cost is only a constant term adding to dynamic cost, it is omitted in the final objective function that is described in Eq. (2).

$$Min \overbrace{\sum_i\sum_t z_{i,t} v_t}^{PL} + \overbrace{\sum_i\sum_t \varsigma_{i,t}}^{overtime\ salary} + \overbrace{\sum_k\sum_i\sum_{i'} e_{k,i,i'} d_{i,i'} c_f}^{transportation\ cost} \quad (2)$$

The constraints for the optimization problem in this study are given as follows.

$$z_{i,t} \geq \left(1 - \sum_{k=1}^{K}\sum_{t'=1}^{t} x_{k,i,t'}\right) * PL^0_{i,t'} \quad (3)$$

$$z_{i,t} \geq \left(\sum_{k=1}^{K}\sum_{t'=t-TTR_i}^{t} x_{k,i,t'}\right) * PL^1_{i,t'} \quad (4)$$

$$\varsigma_{i,t} \geq \left[\sum_{k=1}^{K} \sum_{t'=t-TTR_i+1}^{t} \left(x_{k,i,t'} \sum_{m=1}^{M} P_{k,i,m}\right) * \delta_t\right] * C_{ot} \; \forall\, i,t \quad (5)$$

$$\sum_{k=1}^{K} x_{k,i,t} = 0, b_{i,t} = 0, a_{i,t} = 0 \; \forall i,t\colon \theta_{i,t} = 0 \; \forall\, i,t \quad (6)$$

$$\sum_{k=1}^{K} \sum_{t=1}^{T} x_{k,i,t} \leq 1 \; \forall\, i \leq I \quad (7)$$

$$\sum_{k=1}^{K} \sum_{t'=1}^{T} x_{k,i+I,t'} - \sum_{k=1}^{K} \sum_{t=1}^{T} x_{k,i,t} = 0 \; \forall\, 1 \leq i \leq I \quad (8)$$

$$a_{i,t} = \sum_{k=1}^{K} \sum_{t'=t-TTR_i}^{t} x_{k,i,t'} \; \forall\, i,t \quad (9)$$

$$\sum_{t'=1}^{t-1} b_{i,t'} = 0 \;\; \forall t\colon \; \sum_{k=1}^{K} x_{k,i,t} = 1 \quad (10)$$

$$a_{i,t} \leq b_{i,t} \; \forall\, i,t \quad (11)$$

$$\sum_{i'\colon d_{i,i'} > t'-t} x_{k,i',t'} = 0, \; if \; x_{k,i,t} = 1, \;\; \forall k, t, \; t' > t \quad (12)$$

$$e_{k,i,i'}\left(P_{k,i,m} - p_{i',m} - P_{k,i^{i},m}\right) = 0 \; \forall\, k,m \quad (13)$$

$$\sum_{i=1}^{I} e_{k,0,i} = 1 \; \forall\, k \quad (14)$$

$$\sum_{i=I+1}^{2I} e_{k,i,2I+1} = 1 \; \forall\, k \quad (15)$$

$$\sum_{k=1}^{K} \sum_{i=1}^{2I+1} e_{k,i,i'} = \sum_{k=1}^{K} \sum_{i''=1}^{2I+1} e_{k,i',i''} \;\; \forall\, i' \quad (16)$$

Eq. (3) and (4) restrict the lower bound of the PL based on mathematical treatments that decide whether $\boldsymbol{PL^0_{i,t}}$ or $\boldsymbol{PL^1_{i,t}}$ should be accounted in the optimization model at current time $\boldsymbol{t}$. Eq. (5) restricts the lower bound of technicians' overtime salary. Eq. (6) ensure that all the maintenance activities only take place in the allowed working time. Eq. (7) ensures that each task can only be performed once by one vessel. Eq. (8) guarantees that the technicians dropped off for maintenance can always be picked up. what is worth mentioning is that it doesn't have to be the same vessel to perform both technician delivery and pickup for one maintenance task. Eq. (10) confines that the task $\boldsymbol{i}$ will be under maintenance in a time length of $\boldsymbol{TTR_i}$ once the maintenance starts. Eq. (11) ensures that technicians will not be at the task if the maintenance doesn't start. Eq. (12) guarantees that the technicians will not leave before the maintenance is finished. Eq. (13) guarantees the travel time from one task to another one is no less than the given travel time. Eq. (14) updates the number of technicians on the vessel after every delivery or pickup visit. Eq. (15) and (16) ensure each vessel leaves from and returns to the harbor only once. Eq. (16) ensures flow conservation at each task.

In the proposed optimization model, the predictive PL is essentially used as evidence to prioritize the maintenance tasks. The PL related cost is computed in currency unit by multiplying the PL (in kWh) with the electricity price in the market. This PL cost term considers both the PL introduced by turbine the degradation ($\boldsymbol{PL^0_{i.t}}$) before maintenance and the PL is contributed by the turbine downtime ($\boldsymbol{PL^1_{i.t}}$) during the maintenance. The term $\boldsymbol{PL^0}$ is computed following Eq.

$$PL^0_{i,t} = f\left(WS_{i,t}, Cd_i\right) - f\left(WS_{i,t}, Cr_i\right) \quad (17)$$

Where $f(\cdot)$ is a function that maps the input wind speed to the expected power output, $WS_{i,t}$ denotes the wind speed at time $\boldsymbol{t}$ Cd_i denotes the design power curve of turbine $\boldsymbol{i}$ provided by the OEM, Cr_i denotes the estimated power curve based on the most recent real time data points.

And the $\boldsymbol{PL^1}$ term caused by turbine downtime can be written as:

$$PL^1_{i.t} = f(WS_p, C_{est}) \quad (18)$$

The constraints of PL are stated in Eq. (3) and (4). When assigning maintenance tasks to personnel, the present model is defined a more practical situation comparing with the previous works in [18, 26, 30]. The present model considers the expertise of technicians into M different types in Eq. (5) and (13). The total number for each type of technicians is regarded as limited in the present model and this number is adjustable by users on the real situation day from day. Treatment of these two practical constraints in optimization is rather challenge, since the consideration of these two terms may expand the total search space for optimization exponentially and intricate the numerical computation significantly.

4 Case Study

In this section, the proposed method is implemented on an offshore wind farm with 27 4MW wind turbines. In one typical maintenance scenario, 11 wind turbines need to be repaired within future 1~3 days based on the prognosis results. 2 vessels and 19 technicians are available in the O&M base to execute the maintenance activities. The main goal is to obtain a maintenance solution by optimizing the maintenance scheduling and routing of 2 vessels, such that the overall maintenance cost can be reduced.

The maintenance scheduling and vessel routing results obtained from the proposed model can be found in Fig. 2 and Fig. 3. The geographical distribution of wind turbines can be found in Fig. 2, where the turbines need to be maintained are highlighted as red. The vessel assignment and routing solution is also illustrated in Fig. 2. In previous research, it is either one vessel is involved in the maintenance scheduling, or the whole wind farm are divided into several sub-areas that each vessel only executes the maintenance tasks in one sub-area, which still can be seen as one vessel routing optimization problem. One disadvantage of these approaches is the lack of the consideration of resource sharing among different vessels. Compared with previous researches, the optimal routing solution obtained by proposed model is capable to share the resources perform the maintenance tasks jointly among different vessels. One good example for illustration is the maintenance task on wind turbine 2. As shown in Fig. 2, the vessel 1 is assigned to drop technicians to the turbine to perform the maintenance, but vessel 2 is assigned to pick up the technicians when the maintenance activity is done. The Gantt chart in Fig. 3 is used for maintenance activities scheduling. The maintenance tasks are prioritized by the proposed method, provided that the PL of different wind turbines could have significant differences caused by different performance degradation and wind speed change. These results clearly indicate that the proposed method can effectively provide an optimal maintenance scheduling and routing solution to obtain a good cost-benefit.

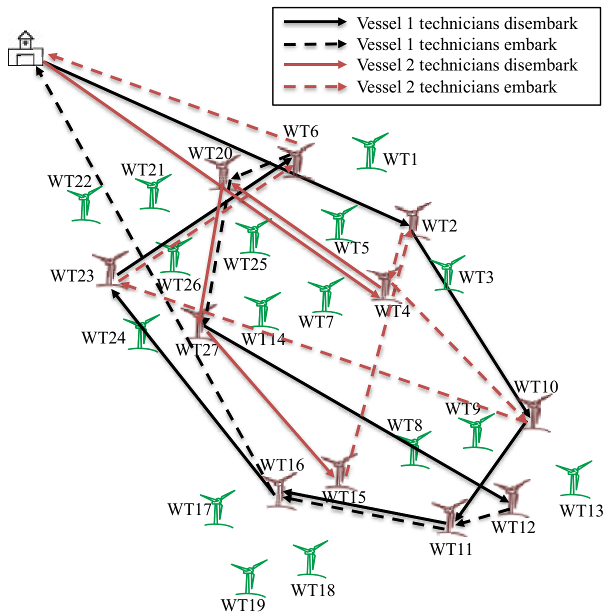

Fig. 2 The maintenance vessel route solution

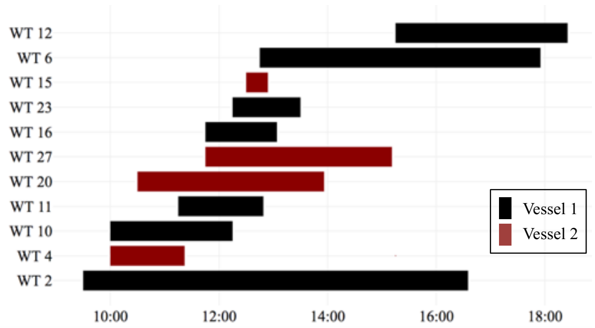

Fig. 3 Gantt Chart of maintenance activities scheduling

To illustrate the superiority of this proposed method, we benchmark the overall cost from proposed model with other 2 methods. In model 1, the optimization model doesn't consider the PL but all the terms and constraints are kept the same with the proposed model in this work except the PL constraint in Eq. (3) and (4) are set to 0 manually, which can be seen as a representative of the methods presented recently without employment of turbine prognosis information. In model 2, the optimization model considers the PL, but divide the entire maintenance tasks into 2 clusters that each vessel is assigned to perform the maintenance in one cluster individually. This method employed for benchmarking is similar to the method proposed by Irawan et al. (2017). The proposed work in this paper is denoted as model 3.

Based the fixed maintenance costs, it is shown in Table 2 that the invisible cost for wind turbine maintenance, a.k.a. the PL of wind turbines take a significant portion of overall dynamic maintenance cost. The overall maintenance cost is optimized by accounting for the PL of wind turbines. Table 2 also demonstrates that the overall maintenance cost based on the proposed model is 510.4 less than model 3, and 1023.6 less than model 2, and the saved PL cost is as high as 793 and 1280.5. This validates the superiority of the proposed model in terms of PL cost optimization and overall cost optimization.

Table 2 Cost comparison among 3 models

	Trans. cost	PL	Fixed cost	Total cost
Proposed method	809.4	**2815.7**	4800	**8425.0**
Method 1	603.1	4018.3	4800	9421.4
Method 2	715.2	3254.6	4800	8769.7

5 Conclusion

A systematic framework for the off-shore wind farm maintenance scheduling and routing is proposed in this paper. The effectiveness of the proposed model is validated based on the real data from an off-shore wind farm with 27 4MW wind turbines. The validation results show that, (1) PL of wind turbine takes a large portion of the maintenance cost due to the large power capacity of the off-shore wind turbine. Therefore, it is necessary to consider this portion of invisible cost during the maintenance activities optimization; (2) The proposed method can effectively prioritize the maintenance order based on wind turbine with different real time PL, so that a feasible and optimal maintenance schedule and vessel routes can be properly planned. This proposed methodology has been integrated into a software platform to provide maintenance optimization and planning services for the off-shore wind farms.

Future work will consider the model performance validation on a larger scale such as multiple wind farms or more maintenance tasks, motivated by the ever-increasing demand for wind energy. A novel optimization solver, which is designed for this optimization model specifically, will also be considered in future work.

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