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A Stochastic Model for Opportunistic Maintenance Planning of Offshore Wind Farms

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Abstract-- **A sound maintenance planning is of crucial importance for wind power farms, and especially for offshore locations. This paper presents a stochastic optimization model for opportunistic service maintenance of offshore wind farms. The model takes advantage of 7 days wind production ensemble forecast and opportunities at corrective maintenance activities in order to perform the service maintenance tasks at the lowest cost. The model is based on a rolling horizon, i.e. the optimization is performed on a daily basis to update the maintenance planning based on the updated production and weather forecasts. An example based on real wind data is used to demonstrate the value of the proposed approach. In this example, it is shown that 32% of the cost for production losses and transportation could be saved.**

***Index Terms*— Maintenance optimization, offshore wind power, opportunistic maintenance, stochastic optimization**

I. Nomenclature

A. Sets and indexes

T_1	First time step
T_{short}	Set of short horizon time steps
T_{long}	Set of long horizon time steps
S	Set of wind and production forecasting scenarios
WT	Set of wind turbines
PM	Set of preventive maintenance tasks
CM	Set of wind turbines requiring corrective maintenance

B. Indexes

$t \in T_{short} \cup T_{long}$	Index of time steps
$i \in WT$	Index of the wind turbines
$j \in PM$	Index of the preventive maintenance tasks
$s \in S$	Index of the wind/production forecasting scenarios
$k \in \{1,...,L\}$	Index of power loss levels for the long horizon

C. Costs, wind, wave and production parameters

C_{el}	Electricity cost [Euro/kWh]
C_{boat}	Daily cost for travel with the boat [Euro]
C_{hel}	Daily cost for travel with the helicopter [Euro]
C_{pen}	Penalty for supplementary maintenance hours [Euro/h]
P_{ts}	Expected hourly power loss during the short horizon if maintenance is performed, $t \in T_{short}$, $s \in S$ [kW]
P_k^{lev}	Power loss levels for the long horizon, $k \in \{1,...,L\}$ [kW]
E_{ts}^{CM}	Energy loss if a corrective maintenance task is done at time step t, and scenario s, $t \in T_{short}$, $s \in S$ [kWh]
W_{ts}^{d}	Average wind speed in time step t and scenario s, $t \in T_{short}$, $s \in S$ [km/h]
W_{ts}^{v}	Significant wave height in time step t and scenario s, $t \in T_{short}$, $s \in S$ [m]

D. Parameters

N_S	Number of scenarios for the wind, waves and production
w_{ij0}	Number of time steps before preventive maintenance task in wind turbine should be performed, $j \in PM$, $i \in CM$
τ_i^{CM}	Time to do corrective maintenance in wind turbine i [h]
τ_j^{PM}	Time to do preventive maintenance task j, $j \in PM$ [h]
τ_w	Time to access the nacelle of a wind turbine [h]
h	Available maintenance hours during the short horizon [h]
$h_{kts}^{\max}$	Available working hours at power loss level in step t the scenario s, $k \in \{1,...,L\}$, $t \in T_{long}$, $s \in S$ [h]
$W_{boat}^{d,\max}$	Maximum average wind speed for safe access [km/h]
$W_{boat}^{v,\max}$	Maximum significant wave height for safe access [m]

II. Introduction

A sound maintenance planning is of crucial importance for wind power farms, and especially for offshore locations. Maintenance of wind power plants, especially offshore, is known to be extensive and costly. The reasons behind this problem are related to frequent and unforeseen outages, spare part and equipment availability, and weather conditions that may lead to long downtimes. At the end of 2010, a rated capacity of 84 GW of wind power was installed in the European Union [1]. The target of the European Wind Energy Association is to reach 230 GW of installed wind power in Europe by the end of 2020, of which 40 GW shall be generated by offshore wind power plants [2]. However, the uncertainties of maintenance costs add an additional aspect to

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the risk of the projects related to incentives, regulatory issues and wind resources. These uncertainties may slow down the investment rate necessary to reach this target.

A failure in a wind turbine leads to direct costs for the spare part, maintenance equipment, transportation and maintenance staff required for correcting the failures, as well as indirect costs due to production losses. In order to reduce the present high maintenance costs, the maintenance strategies and organization need to be clearly defined, implemented and optimized. The maintenance optimization can be separated into interconnected tasks:

- Definition of suitable maintenance strategies for the components of the system according to their failure modes, probabilities, and consequences; [3], [4], [5], [6], [7], [8],
- Maintenance planning; [9], [10],
- Build a support organization, i.e. spare part and staff management, as well as investment decisions for transportation and maintenance equipment; [11], [12].

The focus of this paper is the maintenance planning for service maintenance activities. Yearly service maintenance takes 2-3 days per wind turbine and includes e.g. [14], [15]:

- Changes lubrication systems and oil filters,
- Check brushes and slip ring of DFIG,
- Inspection with respect to leakage,
- Test of safety systems, change pad brake,
- Retightening of bolts
- Oil sampling & analysis for the gearbox
- Visual inspection of the blades
- Possible infrared thermography for the electrical components (transformer, circuit breaker)

The objective of this paper is to develop an approach for optimizing the planning of service maintenance activities by taking advantage of opportunities at failure and low production forecasts to reduce costs for transportation and production losses. This work is a continuation of the work published in [8] that was inspired by an opportunistic maintenance optimization model proposed for the aircraft industry [13]. The model is improved in the present paper by considering ensemble wind production forecasting instead of point forecasting. Moreover, constraints on the accessibility to the wind turbines were added, as well as transportation decision on using the helicopter in case of bad weather. The example case is based on wind data from Lillgrund, an offshore wind farm located in the south west of Sweden.

The paper is structured as follows. Section III gives a description of the system and underlying assumptions of the model. The mathematical model is described in Section IV. The model is then illustrated with an example application described in Section V, and the results from the optimization are presented in Section VI. Conclusions and future works are discussed in Section VIII.

III. Model Description

A. Time framework

Wind power forecasting received a great focus during the last years for wind turbine control and operation scheduling. Forecasting models have been developed to predict wind power production up till 7 days using ensemble input from numerical weather prediction as available from the European Centre for Medium Range Weather Forecasts in Europe, see more details in [16]. Chaos theory was used in [10] to show that the limit of weather predictability is around two weeks. Longer horizons are of interest for the purpose of maintenance planning. An option is to use seasonal forecasts based on wind power historical data for the horizon above the 7 days.

In the proposed model, the time framework is separated into short and long horizon intervals according to the forecasting information available for each horizon. It is assumed that N_S scenarios are available for wind speed and production forecasts for the short horizon interval (SH) as well as seasonal forecasts for the long horizon interval (LH). Moreover, it is assumed that the uncertainty in the first time step is negligible, i.e. the expected wind, wave and production are the same for each scenario for T_1. This assumption enables to build to a stochastic optimization model with one recourse stage; see [18] for an introduction to stochastic programming. The planning decisions at the first time step in the short horizon are common to each scenario.

- The short horizon interval is discretized into N_{Tshort} time steps, each consisting of one day. The set of time steps in this interval is defined as $T_{short} = \{1,...,N_{Tshort}\}$ and the first time step is $T_1 = \{1\}$. Ex: $N_{Tshort} = 7$.
- The expected average hourly power production during one time step t and scenario s is P_{ts} , $t \in T_{short}$, $s \in S$. The wind speed and wave height are denoted $wind_{ts}$ and $wave_{ts}$ respectively.
- It is assumed that there is little uncertainty in the production, wind speed and wave height for the time step T_1, i.e. $P_{1s} = P_1$, $W_{1s}^d = W_1^d$, $W_{1s}^v = W_1^v, \forall s \in S$.
- The long horizon interval is discretized into N_{Tlong} time steps, consisting of one week steps except for the last step which is one month. The set of time steps in this interval is defined as $T_{long} = \{1,...,N_{Tlong}\}$ Ex: $N_{Tlong} = 4$
- The expected power production during maintenance hours is estimated by a discretized distribution with L levels of production. For each level $k \in \{1,...,L\}$, a power production is associated, denoted P_k^{lev} , as well as a number of maximum available working hours for each time step $t \in T_{long}$ and scenario $s \in S$, denoted $h_{kts}^{\max}$. An example is shown in Fig. 1.

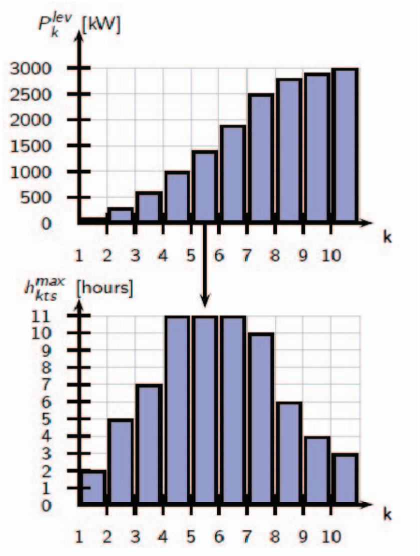

Fig. 1: For a given power loss level $k \in \{1,...,L\}$, time step $t \in T_{long}$ and scenario $s \in S$ corresponds a number $h_{kts}^{\max}$ of available maintenance hours at power loss P_k^{lev}.

B. System description

The system consists of a set WT of N_{WT} wind turbines. All the scheduled preventive maintenance tasks within the time horizon as well as corrective maintenance tasks required have to be defined. A set PM of preventive maintenance tasks that have to be performed within the horizon is defined. It includes subtasks of at least one hour. For each task $j \in PM$ the time to perform the activity is τ_j^{PM} hours. At the beginning of the optimization, the preventive maintenance task j in wind turbine i should be performed within the next w_{ij0} time steps.

A subset $CM \subset WT$ is defined for the wind turbines requiring corrective maintenance. The expected time to perform the corrective maintenance activity $i \in CM$ is τ_i^{CM}. It is assumed that there is at most one corrective maintenance activity per wind turbine at a time and it can be performed in at most a day. All the corrective maintenance activities are forced to be performed during the short horizon interval. The production losses if corrective maintenance is done at time step $t \in T_{short}$ in scenario $s \in S$ is E_{ts}^{CM}. Note that $E_{1s}^{CM} = E_1^{CM}$ since the expected production is the same in time step 1 for each scenario. Note that inspection after a failure occurs is modeled as a corrective maintenance task.

C. Costs and time constraints

The costs assumed in the model are production losses (when the wind turbine is stopped due to a failure or maintenance) and transportation costs. The costs for production losses are given by the product of the electricity market price C_{el} and the production losses, i.e the product of the duration of the maintenance activity τ_j^{PM} and the power production P_{ts} (in kW) for the short horizon interval and P_k^{lev} (in kW) for the long horizon interval. The cost for performing a corrective maintenance task in step $t \in T_{short}$ is the product of the induced production losses E_{ts}^{CM} (in kWh) with the electricity price. The transportation costs consist of a fixed cost C_{tr} each day when transportation is required. This cost may include fuel, sailing crew and boat/helicopter location costs depending on the type of service contracted with the transport company.

The maintenance team works normally h hours per day during the short horizon. The working time includes the time to perform the maintenance tasks as well as the time for accessing the nacelle of one wind turbine, denoted τ_w. A penalty cost C_{pen} is to be paid for each supplementary working hour. During the long horizon, the available number of working hours is defined by $h_{kts}^{\max}$ and no supplementary hours are considered. An example is depicted in Fig. 1. Moreover, it is assumed that in average a maintenance team visits two wind turbines for each travel to the wind farm.

D. Transportation constraints

Maintenance can be performed only if the weather condition, i.e. wind and significant wave height, allows safe access to the wind turbines. The maximum wind and significant wave height for safe access are denoted $W_{boat}^{d,\max}$, $W_{boat}^{v,\max}$, $W_{hel}^{d,\max}$, $W_{hel}^{v,\max}$ for the boat and the helicopter respectively.

IV. Mathematical Model

A. Decision Variables

$$nx_{ij} = \begin{cases} 1 & \text{if preventive maintenance task } j \text{ in wind turbine } i \\ & \text{is performed in time step 1,} \\ 0 & \text{otherwise,} \end{cases}$$

$j \in PM, i \in WT$

$$ny_i = \begin{cases} 1 & \text{if corrective maintenance task in wind turbine } i \\ & \text{is performed in time step 1,} \\ 0 & \text{otherwise,} \end{cases}$$

$i \in WT$

$$nd = \begin{cases} 1 & \text{if the helicopter is used in time step 1} \\ 0 & \text{otherwise.} \end{cases}$$

$$x_{ijts} = \begin{cases} 1 & \text{if preventive maintenance task } j \text{ in wind turbine } i \\ & \text{is performed in time step } t \text{ in scenario } s, \\ 0 & \text{otherwise,} \end{cases}$$

$j \in PM, i \in WT, t \in T_{short} \cup T_{long}, s \in S$

$$y_{its} = \begin{cases} 1 & \text{if corrective maintenance task in wind turbine } i \\ & \text{is performed in time step t in scenario } s, \\ 0 & \text{otherwise,} \end{cases}$$

$i \in WT, t \in T_{short}, s \in S$

$$d_{ts} = \begin{cases} 1 & \text{if the helicopter is used in time step t} \\ & \text{in scenario s} \\ 0 & \text{otherwise.} \end{cases}$$

$t \in T_{short}, s \in S$

$$\min \overbrace{\underbrace{nz \cdot C_{boat}}_{\text{Cost Boat}} + \underbrace{nd \cdot (C_{hel} - C_{boat})}_{\text{Cost Helicopter}} + \underbrace{ne \cdot C_{pen}}_{\text{Penalty Cost}} + \left[\underbrace{\sum_{i \in CM} ny_i \cdot E_1^{CM}}_{\substack{\text{Production losses}\\ \text{Corrective Maintenance}}} + \underbrace{\sum_{i,j} nx_{ij} \cdot \tau_i^{PM} \cdot P_1}_{\substack{\text{Production losses}\\ \text{Preventive Maintenance}}} \right] \cdot C_{el}}^{\text{Cost for the initial time step}} +$$

$$\frac{1}{N_S} \sum_{s \in S} \left[\overbrace{\sum_{t \in T_{short} \setminus T_1} z_{ts} \cdot C_{tr} + d_{ts} \cdot (C_{hel} - C_{boat}) + e_{ts} \cdot C_{pen} + \left[\sum_{i \in CM} y_{its} \cdot E_{ts}^{CM} + \sum_{i,j} x_{ijs} \cdot P_{ts} \right] \cdot C_{el}}^{\text{Costs for the short horizon}} + \overbrace{\sum_{t \in T_{long}} \left[\sum_k h_{tks} \cdot \left(P_k^{lev} \cdot C_{el} + \frac{C_{tr}}{h - 2 \cdot \tau_w} \right) \right]}^{\text{Cost for the long horizon}} \right]$$

Eq. 1: Objective function of the optimization model

B. Auxiliary Variables

$nz = \begin{cases} 1 & \text{if the wind park is visited at time step 1} \\ 0 & \text{otherwise,} \end{cases}$

$j \in PM, i \in WT, t \in T_{short} \cup T_{long}, s \in S$

$nv_i = \begin{cases} 1 & \text{if the wind turbine } i \text{ is visited at time step 1} \\ 0 & \text{otherwise,} \end{cases}$

$i \in WT$

ne Supplementary maintenance hours at time step 1

h_{tks} Maintenance hours used at production level k at step t in scenario s,

$k \in \{1,...,L\}, t \in T_{long}, s \in S$

$z_{ts} = \begin{cases} 1 & \text{if the wind park is visited at time step } t \text{ in scenario } s \\ 0 & \text{otherwise,} \end{cases}$

$t \in T_{short}, s \in S$

$v_{its} = \begin{cases} 1 & \text{if the wind turbine } i \text{ is visited at time step } t \text{ in scenario } s \\ 0 & \text{otherwise,} \end{cases}$

$i \in WT, t \in T_{short}, s \in S$

e_{ts} Supplementary maintenance hours at time step t in scenario s

$t \in T_{short}, s \in S$

C. Objective function

See Eq. 1.

D. Constraints

Constraints to force the corrective and preventive maintenance tasks to be performed in the short horizon:

$$ny_i + \sum_{t \in T_{short}} y_{its} = 1,\ i \in CM, s \in S$$

$$nx_{ij} + \sum_{t=1}^{w_{ij0}} x_{ijts} = 1,\ i \in CM, j \in PM, s \in S$$

Constraints on the auxiliary variable modeling travel to the wind farm and to the wind turbines:

$nz \ge nv_i,\ i \in WT,$

$nv_i \ge nx_{ij},\ i \in WT, j \in PM$

$nv_i \ge ny_i,\ i \in CM,$

$z_{ts} \ge v_{its},\ i \in WT, t \in T_{short}, s \in S$

$v_{its} \ge x_{ijts},\ i \in WT, j \in PM, t \in T_{short}, s \in S$

$v_{its} \ge y_{its},\ i \in CM, t \in T_{short}, s \in S$

Constraints on the number of working hours during the short horizon:

$$\sum_{ij} nx_{ij} \cdot \tau_j^{PM} + \sum_j ny_i \cdot \tau_i^{CM} + \sum_i nv_i \cdot \tau_w \le h + ne$$

$$\sum_{ij} x_{ijts} \cdot \tau_j^{PM} + \sum_j y_{its} \cdot \tau_i^{CM} + \sum_i v_{its} \cdot \tau_w \le h + e_{ts},\ t \in T_{short}, s \in S$$

$$h_{tks} \le h_{tks}^{\max},\ t \in T_{long}, k \in \{1,...,L\}$$

Accessibility constraints for transportation:

$$nz \cdot W_1^d \le W_{boat}^{d,\max} + (W_{hel}^{d,\max} - W_{boat}^{d,\max}) \cdot nd$$

$$nz \cdot W_1^v \le W_{boat}^{v,\max} + (W_{hel}^{v,\max} - W_{boat}^{v,\max}) \cdot nd$$

$$z_{ts} \cdot W_{ts}^d \le W_{boat}^{d,\max} + (W_{hel}^{d,\max} - W_{boat}^{d,\max}) \cdot d_{ts},\ t \in T_{short}, s \in S$$

$$z_{ts} \cdot W_{ts}^v \le W_{boat}^{v,\max} + (W_{hel}^{v,\max} - W_{boat}^{v,\max}) \cdot d_{ts},\ t \in T_{short}, s \in S$$

V. Example Application

This example consists of five 3MW wind turbines with four preventive maintenance tasks to be performed on each turbine. In total this corresponds to two days of work, e.g. the major service maintenance during the summer in an offshore wind farm. The tasks 1 and 3 take 4 hours per turbine and the tasks 2 and 4 take 3 hours. A scenario of 60 days is used, which means that 60 maintenance planning optimizations are performed using the model previously. It is assumed that the preventive maintenance tasks 1 and 2 have to be performed within the first 20 days and the preventive maintenance tasks 3 and 4 should be performed during the first 50 days:

$$N_{Tshort} = 7, N_{Tlong} = 4$$

$$\tau_{10} = \tau_{30} = 4\text{ h}, \tau_{20} = \tau_{40} = 3\text{ h}$$

$$w_{i10} = w_{i20} = 20\text{ days}, w_{i30} = w_{i40} = 50\text{ days}$$

The failure scenario was generated randomly assuming a failure rate of 5 failures per turbine per year. The failure scenario is depicted in Fig. 3. The repair time was assumed to be 4 hours for each failure.

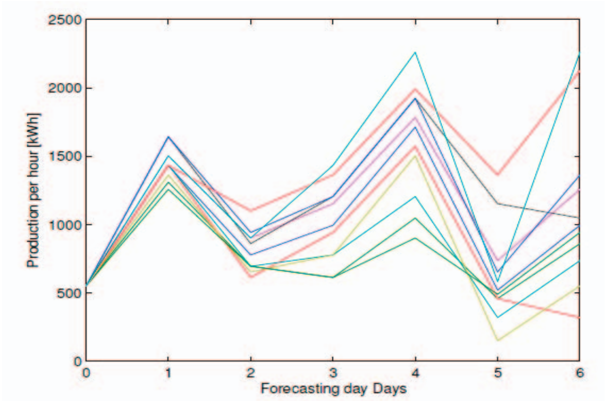

Fig. 2: Example of wind power production scenarios for the example case.

7 days forecasting scenarios were considered for the example case. The wind forecast for each scenario was generated randomly assuming a normal distribution of the forecasting error with increasing variance. The production forecasts were based on the wind forecasts scenarios, using a simple power curve of the Vestas V90-3 MW wind turbine [21]. An example of the power production scenarios is shown in Fig. 2. The power losses for corrective maintenance P_{ts}^{CM} were calculated using the production scenarios and repair times τ_i^{CM} .

For the long horizon, the number of power levels was L = 10, and the power production levels P_k^{lev} are shown in the upper part of Fig. 1. The maximum number of hours available at each power production level, $h_{kts}^{\max}$ was generated based on historical data with three possible scenarios, good, average and bad production, each scenario having equal probability.

The electricity price has been assumed to be 60€ per MWh (average electricity plus green certificate price in Sweden in 2009). The daily cost for the boat is assumed to be 500 € and would include the fuel and possible daily crew costs. The penalty cost for supplementary maintenance hours is 200 € per hour for a team of two maintenance technicians.

$$\mathrm{C_{el}} = 60\,€/\mathrm{MWh},\, \mathrm{C_{boat}} = 500\,€,\ \mathrm{C_{pen}} = 200\,€$$

The maximum wind speed and wave height for accessing the wind turbine with vessel boat is assumed to be $Wd_{boat}^{\max} = 12$ km/h and $Wa_{baot}^{\max} = 1.5$ m [19], [20]. Since the weather conditions for the example application are good, there is no need for the use of a helicopter. This resulted in a simplified model by assuming that the helicopter was never used, i.e. $nd = d_{ts} = 0$ and by removing the constraints on the accessibility.

One maintenance team consists of two maintenance technicians for safety reasons. The team can work 7 hours per day in the wind power system. It is assumed that it takes ½ hour to access a wind turbine (travel from the wind turbine to wind turbine and access to the nacelle).

$$h = 7\ \mathrm{h}, \tau_{\mathrm{w}} = 0.5\ \mathrm{h}$$

VI. Implementation

The model has been implemented with the commercial modeling language GAMS and solved with the free MIP solver CoinCbc. MATLAB has been used as an interface to collect and to analyze the results [22]. In order to capture the stochastic behavior of the forecasts and failures, 100 simulations were performed. The results converged well for the mean cost of preventive maintenance as defined below. The number of simulations was limited due to the high computational needs of the method. For larger problems, an alternative could be to use meta-heuristic methods.

VII. Results

A selected scenario and solution is presented in Fig. 3 and Fig. 4. The maintenance manager performs an optimization of the maintenance planning every day based on the present corrective maintenance tasks to be performed and available power forecasts. The result is a set of preventive and corrective maintenance tasks that are advised to be performed during the present day and maintenance planning forecasts for the following days. Fig. 4 shows the daily advised schedule. The advised tasks are assumed to be performed during the day.

One can notice that preventive maintenance is only performed at low power production and if corrective maintenance is required. For example, in day 7 (highlighted by the left dashed line) a failure occurs in wind turbine 1 and the solution indicates to perform the preventive maintenance task 2 in the wind turbine 2 at the same time. This is due to the fact that the tasks 1 and 2 had already been performed in the wind turbine 1, and the maintenance tasks 3 and 4 are not urgent. In day 14 (highlighted by the left dashed line), no failure occurs but the wind power production is quite low. The solution advises to perform the maintenance activities 2 and 4 in wind turbine 3.

The average total maintenance cost for performing the preventive maintenance tasks was 15,172 €. It is assumed that the transportation costs should not be paid if corrective maintenance is performed at the same time. This cost can be compared with the case where all preventive maintenance tasks are performed without taking into consideration wind forecasts, e.g. during the first days of the scenario, two days per turbine. The maintenance cost without optimization is 22,342 €. It means that 7,170 € or 32% of the costs of the transportation and production losses could have been saved using the proposed approach.

This example demonstrates that it is possible to save costs by taking advantage of low power forecasts and corrective maintenance opportunities to perform the preventive maintenance tasks. The implementation of the methodology requires that the maintenance schedule is flexible. The maintenance technicians need to be prepared to perform some service maintenance activities after a failure has been corrected (i.e. material and consumables for the service should be in the wind turbine or on the boat), if the time allows it. Moreover, the maintenance manager needs to optimize the maintenance planning on a daily basis and update the list of the remaining service and corrective maintenance tasks to be performed.

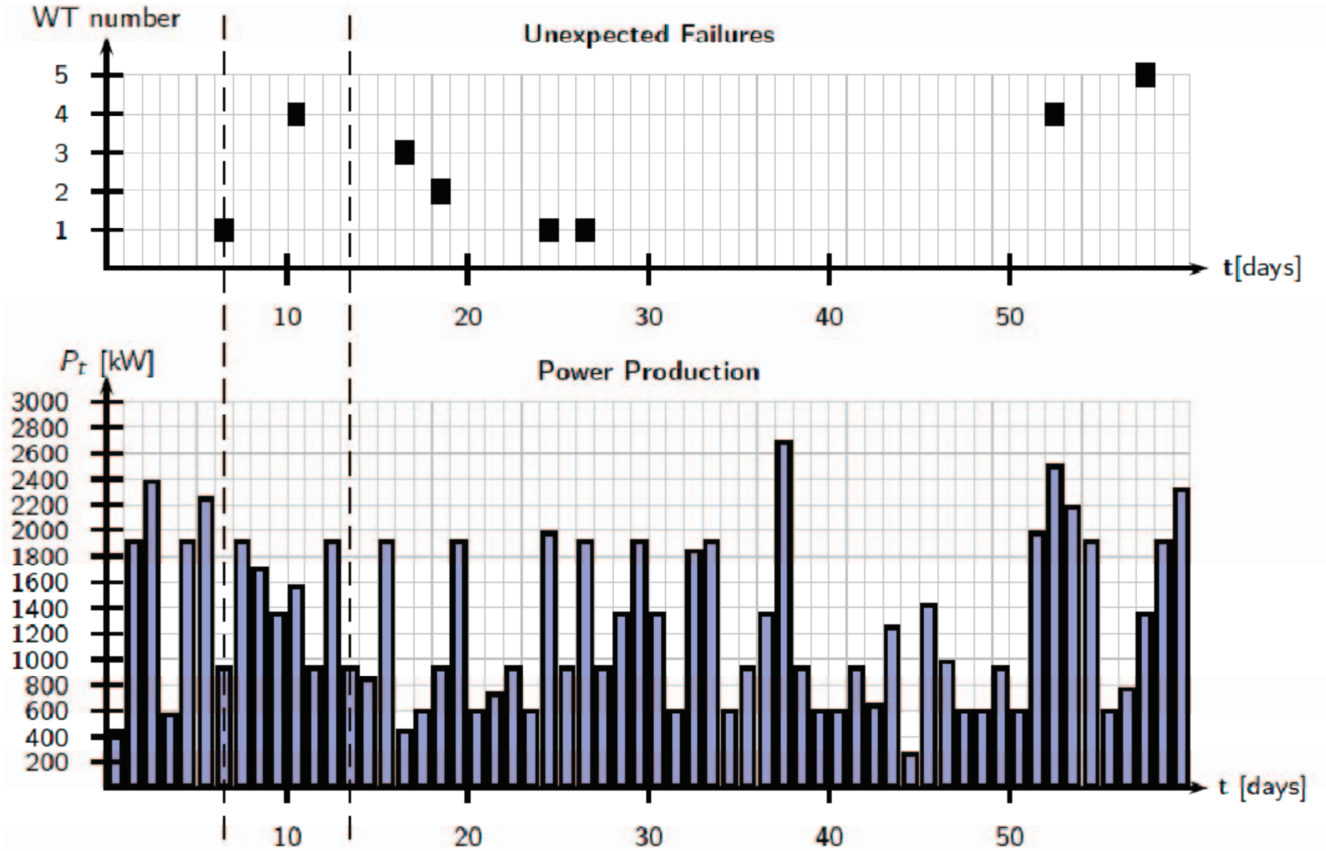

Fig. 3: Production and failure scenario.

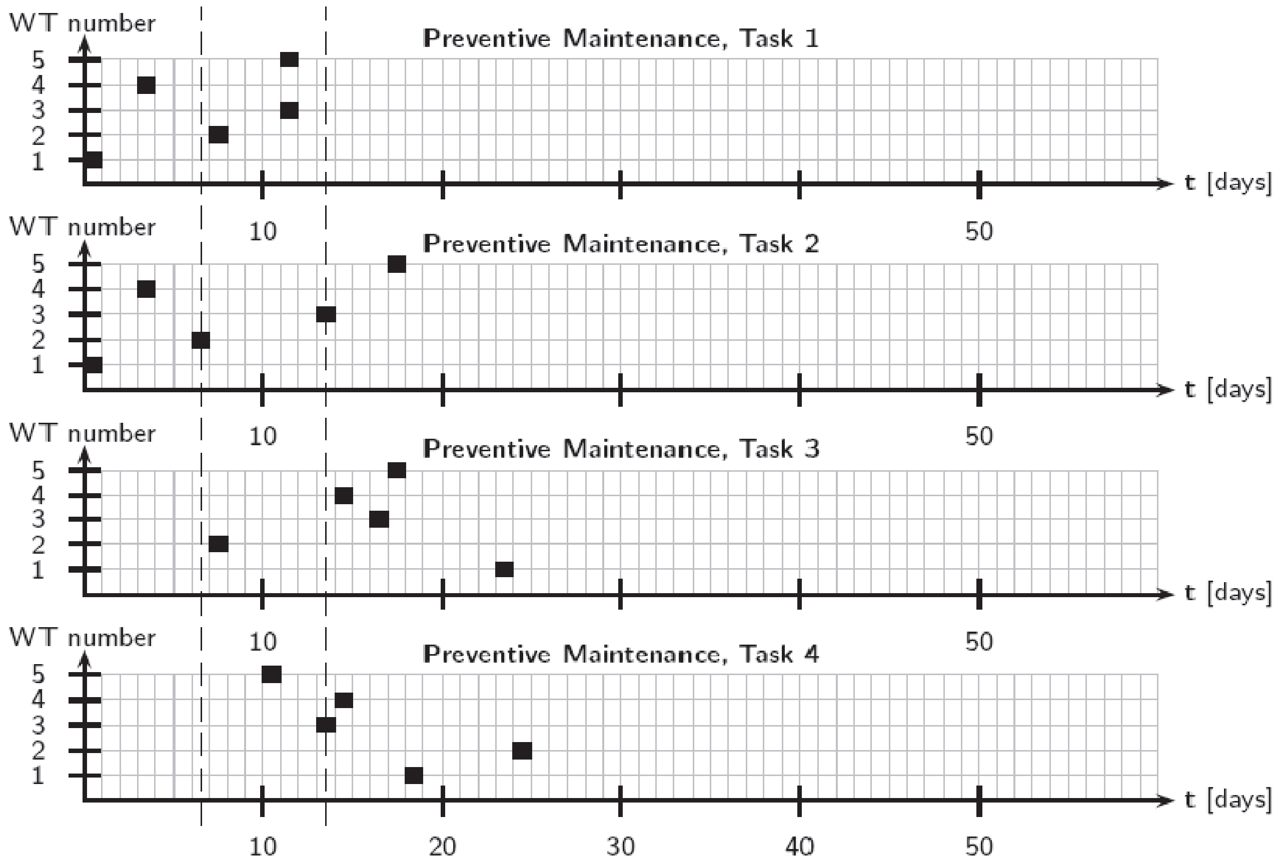

Fig. 4: Results from the planning optimization.

VIII. Conclusions and Future work

A. Conclusions

This paper presented a stochastic optimization model to take advantage of low wind power production and unexpected failures in order to perform service maintenance tasks at the lowest cost. The model was illustrated with an example using experienced wind data from an offshore wind farm. The results show that, in the presented example case, opportunistic maintenance could save 32% of the transportation and production losses compared to performing the maintenance during a fixed period.

In practice, opportunistic service maintenance requires that the maintenance planning is updated on a daily basis. Moreover, the maintenance technicians should be prepared to perform any service maintenance activity after correcting a failure if the power production is not too high and the time allows it.

B. Future work

The model could be improved by increasing the number of maintenance teams, i.e. including decisions on the size of the maintenance staff. Moreover, a prerequisite for implementation is that the maintenance technicians are prepared to perform any service maintenance activity after correcting a failure if the power production is not too high and the time allows it.

A future case study should consider far-shore large offshore wind farm where the weather conditions require the use of a helicopter.

IX. Acknowledgement

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XI. Biographies

François Besnard (S'07) was born in Rennes, France, in 1983. He received the M.Sc. degree in electrical engineering from the Royal Institute of Technology (KTH), Stockholm, Sweden and from The Ecole Supérieure d'Electricité (SUPELEC) both in 2007 and the Tech. Licentiate degree in electrical engineering from KTH in 2009.
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Katharina Fischer was born in Germany in 1979. She received the Diplom degree in electrical engineering in 2002 from Leibniz Universitaet Hannover, Germany, and finalized her Ph.D. degree in the field of thermo-mechanical failure of high-temperature fuel cells in the mechanical engineering faculty of the same university in 2008.
Since 2009, Dr. Fischer is a postdoctoral research fellow at the Division of Electric Power Engineering, Department of Energy and Environment, at Chalmers University of Technology in Gothenburg, Sweden, and part of the Wind Power Asset Management (WindAM) group. Her current research interests include reliability analysis and maintenance optimization for wind power plants.

Michael Patriksson was born in Vreta kloster, Sweden, in 1964. Since 2004, he is a professor of applied mathematics at the Dept. of Mathematical Sciences at Chalmers Univ. of Tech. and at the Dept. of Mathematical Sciences at the University of Gothenburg, in Göteborg, Sweden. He is also a guest professor of optimization at the Dept. of Mathematics at Linköping Univ., in Linköping, Sweden, since 2009. He also held the position as a scientific advisor at the Fraunhofer-Chalmers Centre (FCC) for industrial mathematics, also in Göteborg, during 2002/2008, and has had an affiliation as visiting professor with the KTH School of Electrical Engineering in Stockholm. He received his PhD degree in optimization at the Dept. of Mathematics at Linköping University in 1993, and was a visiting postdoctoral student at the Dept. of Mathematics at York Univ. at Heslington, UK, in 1993, and at the Dept. of Mathematics at the Univ. of Washington at Seattle, WA, USA, in 1994/1995. His research interests span nonlinear, integer and combinatorial optimization theory and algorithms and applications-related optimization research questions in, among other fields, maintenance planning, traffic network management, quantitative logistics, radiation therapy, and multi-objective design under uncertainty. He is a member of INFORMS, Mathematical Programming Society, and SIAM. He is an associate editor of the scientific journals Journal of Optimization Theory and Applications; Transportation Research, Part B; and Transportation Science. He is a reviewer for Mathematical Reviews and for more then 30 journals in applied mathematics.

Ann-Brith Strömberg was born in Alingsås, Sweden, in 1961. She holds a position as Associate Professor at the Department of Mathematical Sciences, Chalmers University of Technology, and the Department of Mathematical Sciences, University of Gothenburg, Göteborg, Sweden. She received her PhD in optimization in 1997 from Linköping University, Linköping, Sweden, was an Assistant Professor Non-tenure at Chalmers University of Technology, Göteborg, Sweden, 1998–2002, and held a position as researcher at Fraunhofer-Chalmers Centre for Industrial Mathematics (FCC), Göteborg, Sweden, 2002–08. Her research interests include mathematical modelling, non-differentiable optimization, multi-objective optimization under uncertainty, discrete and combinatorial optimization, and applications of optimization to maintenance planning, energy production and use, and quantitative logistics.

Adam Wojciechowski was born in Poznan, Poland, in 1982. He received his MSc. degree in Engineering Mathematics in 2007 and the LicEng. degree in Mathematics in 2010, both from Chalmers University of Technology, Göteborg, Sweden. He is currently a PhD. student at the Department of Mathematical Sciences, Chalmers University of Technology and the Department of Mathematical Sciences, University of Gothenburg, Göteborg, Sweden. His research interest are in optimization, especially integer programming applied to maintenance optimization.

Lina Bertling (S'98-M'02-SM'08) was born in Sweden, Stockholm in 1973. She holds the Chair of Professor in Sustainable Electric Power Systems and is the Head of the Division of Electric Power Engineering, at the Department of Energy and Environment, at Chalmers University of Technology, in Gothenburg, Sweden, since January 2009. She has been with Svenska Kraftnät, i.e. the Swedish Transmission Systems Operator, during 2007-2009, and as a manager of the Research and Development from 2008. She has been with the Royal Institute of Technology (KTH), School of Electrical Engineering, in Stockholm, during 1997-2009, where she became Associate Professor in 2008, and finalized her Ph.D. in 2002 on reliability-centered maintenance for electric power distribution systems. She has been visiting researcher at the University of Saskatchewan during the spring semester 2000, and a postdoctoral fellow at the University of Toronto, and associated with Kinectrics Inc. during 2002/2003. Her research interests include transformation of the electric power systems into smart grid and the application of probabilistic methods for reliability analysis and maintenance management. Dr. Bertling is the Chair of the Swedish PE/PEL Chapter, and the Vice Chair of the IEEE PES Subcommittee on Risk, Reliability and Probability Applications (RRPA). She is a member of the Editorial board of the IEEE Transactions of Smart Grid. She was General Chair of the first IEEE PES Innovative Smart Grid Technologies (ISGT) Europe Conference, in Gothenburg, 2010. She is a member of the Swedish National Committee of Ciréd and the World Energy Council, and a member of Cigré. She is a member of the Scientific Board of the Swedish Civil Contingencies Agency (MSB) and a Board member of the Swedish Wind Power Center hosted by Chalmers University of Technology**.**