Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

An Optimization Framework for Opportunistic Maintenance of Offshore Wind Power System

François Besnard *, *Graduate Student Member*, Michael Patriksson†, Ann-Brith Strömberg†, Adam Wojciechowski† and Lina Bertling‡, *Senior Member*

***Abstract*—A sound maintenance planning is of crucial importance for wind power farms, and especially for offshore locations. There is a large potential in cost savings by maintenance optimization to make the projects more cost-efficient. This paper presents an opportunistic maintenance optimization model for offshore wind power system. The model takes advantage of wind forecasts and corrective maintenance activities in order to perform preventive maintenance tasks at low costs. The approach is illustrated with an example to demonstrate the value of the optimization. In this example 43% of the cost to perform preventive maintenance could be saved using the proposed method.**

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

I. Introduction

High costs for maintenance planning and low availability are crucial problems today for the wind power operators. The installed capacity of wind power has been growing exponentionally in the world during the recent years. For example, 56GW was installed in Europe at the end of 2007. The target of the European Wind Energy Association is to reach 180GW in 2020 [3]. The target is expected to be achieved with an increased share of offshore wind power, from 1.3% today to 20% in 2020 [1]. Offshore locations have the advantage of available space and high wind resources. However the maintenance costs are much higher due to hard-to-reach locations. This results in large uncertainties about the economical returns of the projects.

Maintenance costs can be reduced by the use of reliable wind turbine concepts and optimized maintenance decisions. The reliability of wind turbines and connection system has received a great attention in the last years, see for example [14], [5]. Condition monitoring and its costs have been discussed for example in [12] and [11], but few articles discuss models and methods in order to improve maintenance strategies and decision making. An approach based on Reliability Centered Maintenance and Asset Life-Cycle Analysis is proposed in [8] in order to select a suitable maintenance strategy. Quantitative maintenance optimization is discussed in [7] and the time delay model is proposed to derive optimal time to perform inspections on wind turbines. A method, called RCAM, is proposed in [9] for assessing quantitatively the optimal balance between corrective maintenance and preventive maintenance for distribution power system. Corrective maintenance is performed at failure i.e. stochastically; preventive maintenance includes every maintenance tasks performed in order to reduce the failure probability before a failure occurs [2]. RCAM could be applied to determine the right maintenance balance in wind power systems.

Maintenance activities at wind power systems consists of corrective maintenance, scheduled preventive maintenance and often condition based maintenance (based on e.g. vibration monitoring) for the large components (e.g. gearbox, bearings, generator and blades). The focus in the following is on preventive maintenance and how to reduce their costs. Preventive maintenance tasks are performed at fixed time intervals of 6 months, one year or 5 years. They includes e.g. visual inspections, changes of consumables (greasing, lubrification, oil filters), oil sampling and retightening of the bolts. The tasks and intervals are often based on manufacturer recommendations. Indirect costs for performing preventive maintenance tasks include production losses and transportation. Transportation costs are high for offshore environment since special vessels or helicopters are required to access the wind turbines. In general the preventive maintenance in a wind turbine is performed at a fixed day without taking into consideration wind forecasts or corrective maintenance. The preventive maintenance costs could be reduced if the tasks were performed when low power production is expected or when corrective maintenance is required in a wind turbine.

This article presents a linear integer optimization model to take advantage of such opportunistic occasions. The output of the model is an optimal planning of corrective and preventive maintenance tasks for the day in regard to production forecasts and required corrective maintenance. The optimization should be performed every working day by the maintenance manager. The model is somewhat

This work was supported by Vindforsk, the Swedish Centre of Excellence in Electric Power System (EKC2) at KTH and Chalmers Technical University.

*School of Electrical Engineering, Royal Institute of Technology, KTH, Stockholm. (e-mail: fbesnard@kth.se)
‡Chalmers Technical University and Department of Energy and Environment, and Division of Electric Power Engineering. (e-mail: lina.bertling@chalmers.se)
†Department of Mathematical Sciences, Chalmers University of Technology and Department of Mathematical Sciences, University of Gothenburg. (e-mail: mipat@chalmers.se, anstr@chalmers.se)

inspired by an opportunistic maintenance optimization model that was proposed for the aircraft industry [4]. The paper begins with a description of the system and underlying assumptions of the model. The mathematical model is then described. The model is further illustrated through an example to demonstrate the value of the optimization.

II. Model Description

A. Time framework

Wind power forecasting received a great focus during the last years for wind turbine control and operation scheduling. See [13] for an introduction to the subject and state-of-the-art. Forecasting models have been developed to predict wind power production up till 10 days. 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 alternative is to use seasonal forecasts based on wind power historical data for the horizon above the first 10 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. Wind power point forecasts are assumed available for the short horizon interval (SH) and seasonal forecasts for the long horizon interval (LH).

- The short horizon interval is discretized into $N_{T_{short}}$ time steps, each consisting of one day. The set of time steps in this interval is defined as $T_{short} = \{1, ..., N_{T_{short}}\}$. Ex: $N_{T_{short}} = 10$.
- The average hourly power production during one time step t is $P_t, t \in T_{short}$
- The long horizon interval is discretized into $N_{T_{long}}$ time steps, each consisting of one week. The set of time steps in this interval is defined as $T_{long} = \{N_{T_{short}} + 1, ..., N_{T_{short}} + N_{T_{long}}\}$. Ex: $N_{T_{short}} = 8$.
- The expected power production during maintenance hours is estimated by a discretized distribution. L levels of production are defined. For each level $k \in \{1, ..., L\}$ a power production is associated, denoted P_k^{LH}, as well as a number of available working hours for each time step $t \in T_{long}$, denoted h_{kt}^{max}. An example is shown in Fig. 1.

B. System description

The system consists of a set WT of N_{WT} wind turbines. Ex: $N_{WT} = 5$.

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.

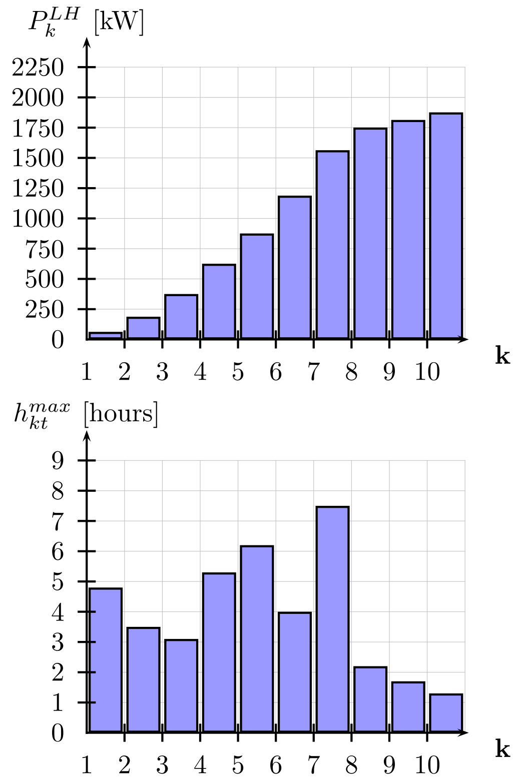

Fig. 1. For a given power loss level $k \in \{1, ..., L\}$ and time step $t \in T_{long}$ corresponds a number of available maintenance hours h_{kt}^{max} at power loss P_k^{LH}.

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 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 is P_t^{CM}. 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 electricity output, i.e P_t (in kWh) for the short horizon interval and P_k (in kWh) for the long horizon interval. The price for performing a corrective maintenance task at day $t \in T_{short}$ is the product of the induced losses P_t^{CM} with the electricity price. The transportation costs consist of fixed cost C_{tr} each day when transportation is required, they 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. Ex: $h = 7$. 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_{kt}^{max} and no supplementary hours are considered. (See Fig. 1 for an example)

For the long horizon period it is assumed that on average two preventive maintenance activities are done each time the wind turbine is accessed. Moreover it is assumed that the maintenance team works for $h - 2 \cdot \tau_w$ hours each time the wind park is visited.

III. Mathematical Model

A. Notation

Sets and indexes

$T = T_{short} \cup T_{long}$ Set of time steps
$t \in T$ Index of time steps
$i \in WT$ Index of the wind turbines
$CM \subset WT$ Set of wind turbines requiring corrective maintenance
PM Set of preventive maintenance tasks
$j \in PM$ Preventive maintenance tasks index
$k \in \{1, ..., L\}$ Index of power loss levels for LH

Costs and production parameters

C_{pen} Penalty for supplementary maintenance hours [€/h]
C_{el} Electricity cost [€/kWh]
C_{tr} Site transportation cost [€]
P_t Expected power loss for SH if maintenance is performed [kW], $t \in T_{short}$
P_k^{LH} Power loss levels for LH, $k \in \{1, ..., L\}$
P_t^{CM} Power loss if a corrective maintenance task is done at step t, $t \in T_{short}$

Time parameters

w_{ij0} Number of time steps before preventive maintenance task j in wind turbine i should be performed , $t \in T, i \in WT, j \in PM$
τ_i^{CM} Time to do corrective maintenance in WT i, $i \in CM$
τ_j^{PM} Time to do preventive maintenance task j, $j \in PM$
τ_w Time to access the nacelle of a wind turbine
h Available maintenance hours during the short horizon
h_{kt}^{max} Available working hours at step t at power loss level k ,$k \in \{1, ..., L\}, t \in T_{long}$

Decision variables

$$x_{ijt} = \begin{cases} 1 & \text{if preventive maintenance task } j \text{ in wind} \\ & \text{turbine } i \text{ is performed at step } t \\ 0 & \text{otherwise,} \end{cases}$$
$t \in T_{short}$, $j \in PM$, $i \in CM$

$$y_{it} = \begin{cases} 1 & \text{if corrective maintenance task in wind} \\ & \text{turbine } i \text{ is performed at step } t \\ 0 & \text{otherwise,} \end{cases}$$
$t \in T_{short}$, $i \in CM$

Auxiliary binary variables

$$z_t = \begin{cases} 1 & \text{if the wind park is visited at step } t \\ 0 & \text{otherwise,} \end{cases}$$
$t \in T_{short}$

$$v_{it} = \begin{cases} 1 & \text{if the WT } i \text{ is visited at step } t \\ 0 & \text{otherwise,} \end{cases}$$
$t \in T_{short}, i \in WT$

Auxiliary non-negative variables

h_{tk} Maintenance hours used at power loss level k at step t $t \in T_{long}, k \in \{1, ..., L\}$
e_t Supplementary maintenance hours, $t \in T_{short}$ $t \in T_{short}$

B. Objective function

$$\min \sum_{t \in T_{short}} \Bigg[\Big[\sum_{i \in CM} \overbrace{y_{it} \cdot P_t^{CM}}^{\text{CM costs}} + \overbrace{\sum_i \sum_j x_{ijt} \cdot \tau_j^{PM} \cdot P_t}^{\text{PM loss costs}} \Big] \cdot C_{el}$$
$$+ \overbrace{z_t \cdot C_{tr}}^{\text{Transport cost}} + \overbrace{e_t \cdot C_{pen}}^{\text{Penalty working hours}} \Bigg]$$
$$+ \overbrace{\sum_{t \in T_{long}} \Big[\sum_k h_{tk} \cdot [P_{kt} \cdot C_{el} + \frac{C_{tr}}{h - 2 \cdot \tau_w}] \Big]}^{\text{Long horizon PM loss and transport costs}}$$

C. Constraints

Maintenance is performed if any of the preventive maintenance or corrective maintenance task is performed:

$$z_t \geq v_{it}, \qquad i \in WT,\ t \in T_{short}.$$

Maintenance is performed in wind turbine i if any of the preventive maintenance or corrective maintenance activities in this wind turbine is performed:

$$\begin{aligned} v_{it} &\geq x_{ijt}, \qquad i \in WT,\ j \in PM,\ t \in T_{short}, \\ v_{it} &\geq y_{it}, \qquad i \in WT,\ t \in T_{short}. \end{aligned}$$

The next constraint force the corrective maintenance task i to be performed during the short term horizon:

$$\sum_{t \in T_{short}} y_{it} = 1, \qquad i \in CM.$$

Each preventive maintenance task is performed during the remaining time steps allowed:

$$\sum_{t=1}^{w_{ij0}} x_{ijt} = 1, \qquad i \in WT,\ j \in PM.$$

The number of maintenance working hours used is lower than the number of hours available. Otherwise a penalty is paid during the short horizon:

$$\begin{aligned} &\sum_{ij} x_{ijt} \cdot \tau_j^{PM} + y_{it} \cdot \tau_i^{CM} + v_{it} \cdot \tau_w \leq h + e_t, \quad t \in T_{short} \\ &\sum_{ij} x_{ijt} \cdot [\tau_j^{PM} + \tau_w/2] = \sum_{tk} h_{tk}, \qquad t \in T_{long} \\ &h_{tk} \leq h_{tk}^{max}, \qquad t \in T_{long}, \\ &\qquad k \in \{1, ..., L\}. \end{aligned}$$

IV. Illustrative Example

This example consists of five 3MW wind turbines with two preventive maintenance tasks to perform on each turbine. The tasks could be e.g. visual inspection of different components, oil sampling, greasing the bearings or changing the lubrication. A scenario of 60 days is used. It means that 60 optimizations are performed using the model previously described. It has been assumed that the first preventive maintenance task has to be performed within the first 20 days and the second preventive maintenance should be performed during the first 50 days:

$$\begin{aligned} &N_{WT} = 5,\ N_{T_{short}} = 10,\ N_{T_{long}} = 6, \\ &w_{i10} = 20,\ w_{i20} = 50,\ \tau_1^{PM} = 3,\ \tau_2^{PM} = 3. \end{aligned}$$

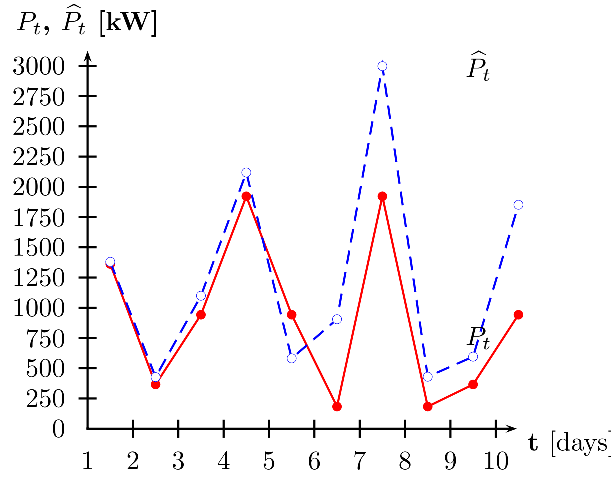

Fig. 3. Real power production P_t(full line) and forecast $\widehat{P}_t$(dashed line) during the short horizon T_{short} for one optimization step.

Failures occur in wind turbines 1, 2 and 5 during the scenario. The failure scenario can be seen in Fig. 2 together with the scenario for the power production . The times to repair are given in table I.

TABLE I
Time to Perform corrective maintenance, τ_i^{CM}, in hours.

WT1	WT2	WT 5
3	2	3

The power scenario was based on real wind data during the summer time in the south of Sweden. Only the daily average wind speed was used. A discretized power curve was used to convert the wind data into power data. The wind power forecasts P_t for the short horizon are assumed to be known with growing uncertainty. The uncertainty is assumed normally distributed with variance growing from 1% of the rated capacity of a wind turbine for the first day to 20% for the 10^{th} day. An error scenario $\widehat{P}_t$ is created at each optimization step. An example of power forecast versus real power production is shown in Fig. 3.

The corrective maintenance loss P_t^{CM} is calculated based on the wind power forecasts.

For the long horizon, $L = 10$, and the power production levels P_k^{LH} are described in Table II.

TABLE II
Power Production Levels, P_k^{LH}.

P_1	P_2	P_3	P_4	P_5
100	300	600	900	1200
P_6	P_7	P_8	P_9	P_{10}
1500	2000	2500	2800	3000

The electricity price has been assumed to be 0.05€ per kWh (average electricity plus green certificate price in Sweden in 2007). The cost for transportation is assumed to be 500€ per day and would include the fuel and possible daily crew costs. The penalty cost for supplementary maintenance hours is assumed to be 100€ per hour for a team of two maintenance technicians.

$$C_{tr} = 500€,\ C_{el} = 0.05€/\text{kWh},\ C_{pen} = 100€/\text{h}$$

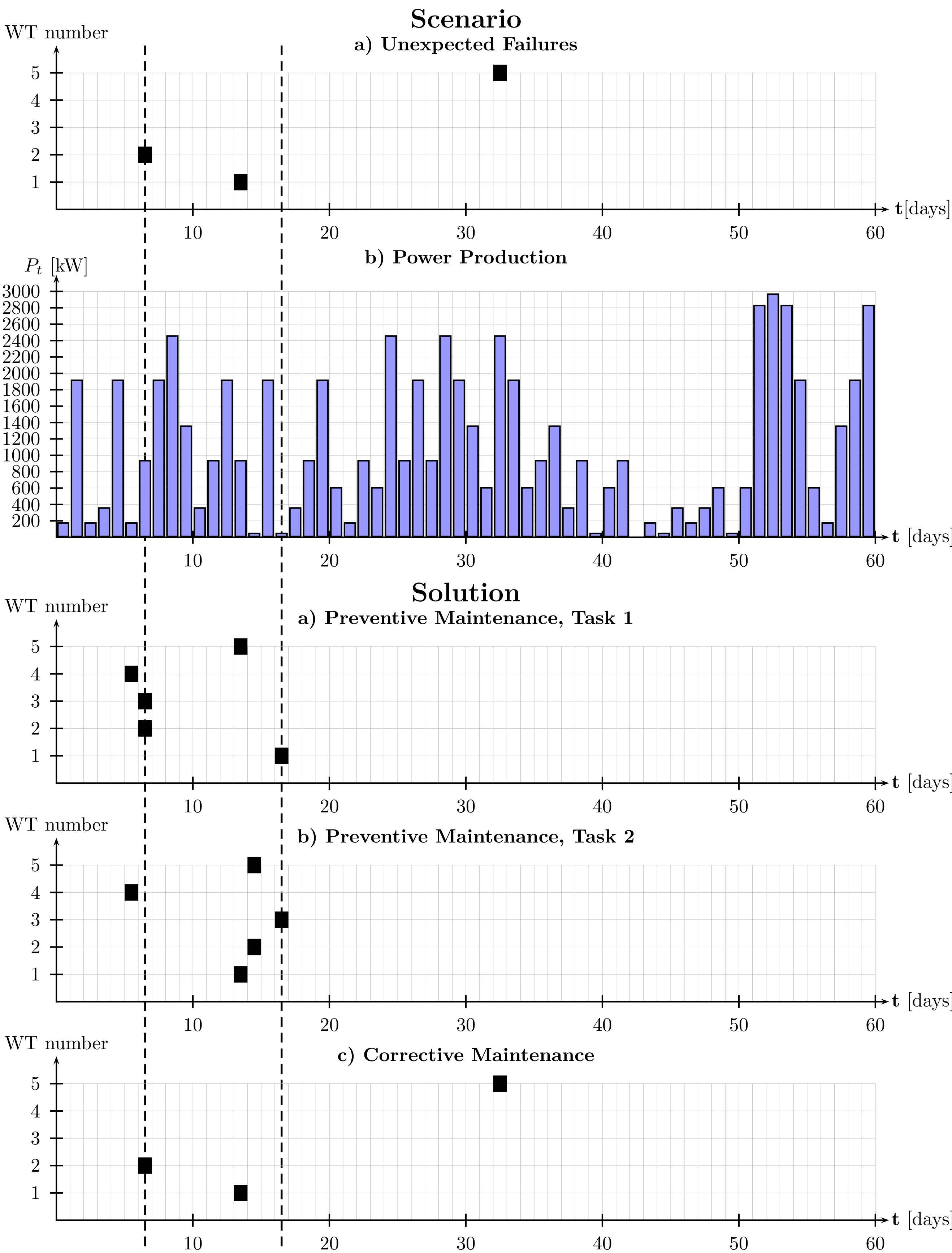

Fig. 2. Failure and power production scenarios and one optimization result for one simulation of the example. The dashed lines present the advised maintenance schedules for the day 7 and 16.

One maintenance team (two persons for safety reasons) operates on the wind power system. The team can work 7 hours per day in the wind power system. It takes 1/2 hour to access a wind turbine.

$$\tau_w = 0.5,\ h = 7$$

The long horizon forecasts for the number of available maintenance hours h_{kt}^{max} are assumed constant during the time step and based on statistics from the scenario. The corresponding histogram for h_{kt}^{max} is shown in Fig. 1.

V. Analysis

The model has been implemented with the commercial modeling language GAMS. The free MIP solver CoinGlpk was used to perform the optimization. MATLAB has been used as an interface to collect and analyse the results [6]. In order to capture the stochastic behavior of the forecasts, 50 simulations have been performed on the scenario with different stochastic forecasting errors.

VI. Results and discussion

The solution of one simulation of the example is shown in Fig. 2. The maintenance manager performs an optimization of the maintenance schedule 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. Figure 2 shows the daily advised schedule and it is assumed that the advised tasks are 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, at step 16 the wind power production is low and it is advised to perform preventive maintenance task 1 in wind turbine 1 and task 2 in wind turbine 3. At step 7, a failure occurs in wind turbine 2 and the solution indicates to perform preventive maintenance task 1 in both wind turbines 2 and 3. One can notice that the total time to perform all the maintenance activities is 8h. Also, the solution is to use one supplementary maintenance hour to avoid to have to access the same wind turbine later.

The average total maintenance cost for performing the preventive maintenance tasks was 2300€. 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, one turbine a day. The maintenance cost without optimization is 4050€. It means that 43% of the cost could have been saved using the proposed approach.

This example demonstrates that it is possible to save major maintenance 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 manager has to re-optimize the maintenance schedule in the morning of every working day and the maintenance tasks to be performed are available only after the optimization.

VII. Closure

A. Conclusion

An optimization model was presented to take advantage of low wind power production and unexpected failures in order to perform preventive maintenance tasks at low costs. The opportunistic model was illustrated with an example. The result for this example was that 43% of the preventive maintenance cost could be saved.

B. Future Work

The model will be further developed to include probabilistic forecasts of power production and to consider unaccessibility to the wind turbines in case of bad weather. A case study is planned to demonstrate the value of the model in real life.

References

[1] Delivering offshore wind power in Europe - Policy recommandations for large-scale deployment of offshore wind power in Europe by 2020. Technical report, 2007.

[2] SS-EN 13306:2001. *Maintenance Terminology*. Swedish standart, 1st edition edition, 2007.

[3] C. Kjaer A. Zervos and S. Clifford. Pure Power - Wind Energy Scenarios up to 2030. Technical report, EWEA, 2008.

[4] N. Andréasson. *Optimisation of opportunistic replacement activities in deterministic and stochastic multi-component systems*. Licentiate thesis, Department of Mathematics, Chalmers University of Technology and Göteborg University, Sweden, 2004.

[5] N. Barberis et al. Aspects of relevance in offshore wind farm reliability assessment. *IEEE Transaction on Energy Conversion*, 22(1):167–173, 2007.

[6] M.C. Ferris. MATLAB and GAMS: Interfacing Optimization and Visualization Software. Technical report, University of Wisconsin, 2005.

[7] J. Watson J. A. Andrawus and M. Kishk. Wind turbine maintenance optimisation: principles of quantitative maintenance optimisation. *Wind Engineering*, 31(2):101–110, 2007.

[8] M. Kishk J. A. Andrawus, J. Watson and A. Adam. The selection of a suitable maintenance strategy for wind turbines. *Wind Engineering*, 30(6):471–486, 2006.

[9] L. Bertling, R. Allan and R. Eriksson. A reliability centred asset maintenance method for assessing the impact of maintenance in power distribution systens. *IEEE Transaction on Power Systems*, 20(1):75–82, 2005.

[10] E.N. Lorentz. A study of the predictability of a 28-variable atmospheric model. *TELLUS*, 17:321–333, 1965.

[11] D. McMillan and G.W. Ault. Condition monitoring benefit for onshore wind turbines: sensitivity to operational parameters. *IET Renewable Power Generation*, 2(1):60–72, 2008.

[12] J. Nilsson and L. Bertling. Maintenance management of wind power systems using condition monitoring systems-life cycle cost analysis for two case studies. *IEEE Transaction on Energy Conversion*, 22(1):223–229, 2007.

[13] P. Pinson. *Estimation of the uncertainty in wind power forecasting*. Doctoral thesis, Ecole des Mines de Paris, France, 2006.

[14] J. Ribrant and L. M. Bertling. Survey of failures in wind power systems with focus on swedish wind power plants during 1997-2005. *IEEE Transaction on Energy Conversion*, 22(1):167–173, 2007.

François Besnard (S'07) was born in Rennes, France, in 1983. He received the M.Sc. degree in systems engineering from the Royal Institute of Technology (KTH), Stockholm, Sweden and from The École Supérieure d'Électricité (SUPELEC) in 2007.
He is currently a Ph.D. student at the RCAM-group at KTH School of Electrical Engineering. His research interests include maintenance optimization, reliability, wind power and power system.

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 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 an affiliation 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 non-linear, integer and combinatorial optimization theory and algorithms and application-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 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 is a researcher at the Dept. of Mathematical Sciences, Chalmers Univ. of Tech., Göteborg, Sweden. She received her PhD in optimization in 1997 from Linköping Univ., Sweden, and was research assistant at Chalmers Univ. of Tech. 1998-2002.
Her research interests are in mathematical modeling, maintenance planning optimization, applications of discrete and combinatorial optimization, and quantitative logistics.

Adam Wojciechowski was born in Poznan, Poland, in 1982. He received his M.Sc. degree in engineering mathematics in 2007 from Chalmers University of Technology, Göteborg, Sweden.
He is currently a Ph.D. student at Mathematical Sciences, Chalmers University of Technology and Mathematical Sciences, Gothenburg University, 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 Stockholm, Sweden, in 1973. She is Professor in Sustainable Electric Power Systems and Head of the Division of Electric Power Engineering, at the Department of Energy and Environment, at Chalmers University of Technology, in Gothenburg, Sweden. She has been with Svenska Kraftnät, i.e. the Swedish Transmission System Operator during 2007-2008 responsible for the R&D. She has been with KTH School of Electrical Engineering (EES), in Stockholm, during 1997-2008 were she finalized her Docent degree, Associate Professor, in 2008, and the Ph.D. in 2002 both in Electric Power Systems. She was a visiting postdoctoral student at the University of Toronto, associated with Kinectrics Inc. during 2002/2003. Her research interests are in; transmission and distribution system, and high voltage equipment planning, and methods for reliability assessment and modeling, and maintenance planning. She was the general chair of the 9th International conference on probabilistic methods applied to power systems (PMAPS) in Stockholm, in 2006. Dr. Bertling is a senior member of IEEE and a member of Cigré and Cired. She is the secretary of the IEEE PES Subcommittee on Risk, Reliability, and Probability Applications (RRPA), and is involved in several IEEE activities. She is reviewer for several journals, and is engaged as an evaluator by the EU commission. She is a member of the Royal Swedish Academy of Engineering Sciences (IVA).