DEPLOYMENT OF MULTI-AGENT-SYSTEMS FOR OPTIMIZING O&M OF WIND TURBINE

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ABSTRACT

Maintenance management for wind turbines (WT) aims on the one hand at reducing the overall maintenance cost and on the other hand at improving the availability.

Although modern onshore WT attain high technical availability of up to 98 %, the evaluation of maintenance work in previous projects shows, that high WT availability requires additional maintenance work and costs. There is a considerable scope for optimizing reliability and maintenance procedures. A possibility therefore is to systematically make use of available knowledge and past experience. At this point, information coming from databases, statistical methods as well as sound statements are essential. The consideration of several conditions e.g. weather conditions, power forecasts, stock keeping etc. are essential for optimal maintenance decisions. However, due to this enormous amount of information sophisticated tools are needed. The contribution will present the possible application of high-performance computing methodologies, which may help wind farm operators (WFO) examining optimal maintenance strategies. The so called Multi-Agent-System (MAS) which is a new discipline in the world of Artificial Intelligence (AI) and the Data Mining (DM), which is a high-performance computing methodology used to observe and deduce hidden knowledge and logical dependencies of a great amount of data using several appropriate algorithms, should be investigated and a methodology for the use of AI in WT maintenance is proposed.

NOMENCLATURE

λ	failure rate

Sub-, superscripts

t	time
t_p	Preventive replacement time
$F(t)$	Time to failure probability distribution function
$f(t)$	Time to failure probability density function
C_p	Preventive replacement unit cost
C_c	Corrective replacement cost unit
$N(t_p)$	Expected number of failures within the considered interval (0, t_p)
$TEC(t_p)$	Total expected cost per unit time

Abbreviations

MAS	Multi-Agent-System
WT	Wind Turbine
PM	Preventive Maintenance
CM	Corrective Maintenance
WFO	Wind Farm Operator
WF	Wind Farm
AI	Artificial Intelligence
DM	Data Mining

ABMS	Agent-Based-Modeling and Simulation
PR	Preventive replacement
CR	Corrective replacement
CIR	Constant Interval Replacement
ABR	Age Based Replacement
FTA	Fault Tree Analysis
ANN	Artificial Neural Networks
CBM	Condition-Based Maintenance
SCADA	Supervisory Control and Data Acquisition

INTRODUCTION

The efficiency of *WT*s has been substantially improved in the past two decades in both technical and economic view. The continuous development of wind power use permits purposeful advancements of the system technology in order to increase both efficiency and performance of the turbines. Nevertheless, earlier intensive and broad analyses in research projects [1], [2] show that the efficiency of modern *WT*s and their equipment units are not obligatory positively proportional to their reliability. However, today's organization of operating supervision and maintenance makes it still difficult to use the various experiences from the operating and historic data purposefully for future improvements of maintenance activities.

Up to now maintenance planning is usually still accomplished individually and intuitively by the *WFO*, although a multiplicity of different aspects (e.g. energy yield, availability, weather condition, personnel employment, material costs etc.) with partly complex and opposite effects on availability and costs should be taken into account (Fig. 1) [3]. At present the *WFO* can't consider these different interests of the various aspects to the necessary extent for making sound decisions. There is obviously a lack of tools that could handle and manage all those aspects simultaneously.

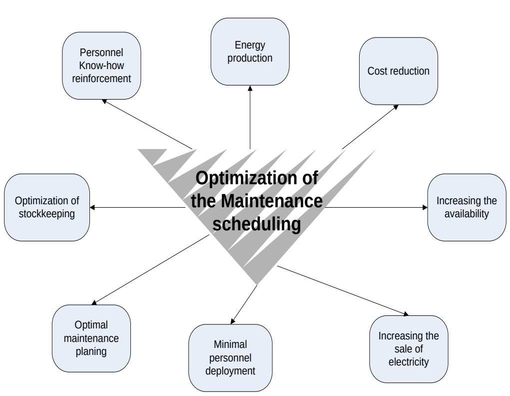

Figure 1: Competitive interests in the maintenance process

In the past, only little focus was put in the use of methods and models of *AI* within the area of maintenance planning. The so called Multi-Agent-System (*MAS*), also known as Agent-Based-Modeling and Simulation (*ABMS*) can model the competitive aspects in such a way that the (intelligent) Agents negotiate quasi among themselves, which interests to be considered in decision-making [4]. An intelligent Agent is a computer system capable of flexible action in some dynamic environment, whereby it is meant by flexible the characteristics reactive, proactive and social. Social ability in Agents is the ability to interact with other Agents (and possibly humans) via some kind of Agent-communication languages. Thereby each already mentioned competitive aspect is represented by one or several Agents. These Agents are programmed to cooperate with each other in order to determine an optimal total conception. As a result of the Agents communication either a particular or several optimal alternative solutions can be suggested resulting in a list of requirements of effective Preventive Maintenance (*PM*).

The project *MAS-ZIH* 'Use of Multi-Agent-Systems as Support for Reliability-Based Maintenance', which is it funded by the German Federal Ministry of Environment, Nature Conservation and Nuclear Safety, is going to investigate the possibility of using *AI* in *WT* maintenance. The project duration is three years, starting last October 2011. Therefore, the findings presented here, represent the first steps in the field and will give an overview about the methodology and expected results.

1. METHODOLOGY OF ARTIFICIAL INTELLIGENCE

The reliability-oriented maintenance of *WT*s relies particularly on the management and the evaluation of operating and maintenance data [2]. However, today's organization of data acquisition and data management by the *WFO* doesn't permit the easily use of experiences [8]. Additionally *WFO*s/service companies are missing tools and necessary information (e.g. failure statistics, weather forecasts, staff disposition, etc.), instructions and recommendations needed for their maintenance decisions.

1.1 ARTIFICIAL INTELLIGENCE

By estimation of failure probabilities, remaining useful life and early recognizing of possible damages and errors as well as by using wind and power forecasts, maintenance tasks and procuring of spare parts could be better planned and unexpected stops could also be avoided. For an efficient maintenance planning the economic boundary conditions e.g. spare part and personnel costs or the temporal development of the fluctuating electricity tariff at the electricity market are to be considered. For the support of a foresighted maintenance strategy a *MAS* is to be developed, which uses the reliability characteristics and the cost information from *WFO* and weighs the competitive interests of the different aspects for the studied case and then suggests favored maintenance measures for the decision-maker.

A schematic representation of the research within the work is shown in fig. 2; where different Agents manage different tasks.

Some of them have the task to analyze the failure rates, while others regard weather and power forecasting, the third category considers the question of cost of the whole maintenance process. A main goal thereby is to submit the *WFO* with an arranged list of requirements and proposals, on how the next maintenance should look like.

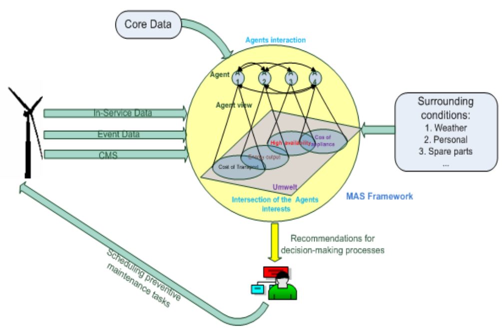

Figure 2: Use of *MAS* for improving the maintenance decisions

1.2 HYBRID APPROACH OF *MAS* AND DATA MINING

This approach consists of using the advantages of both technologies *MAS* and *DM*. Before modeling the *MAS*-Model, some knowledge will be deduced by applying the *DM* for the historic data of the *WFO*. This allows the Agents having some initial states, needed for making sound simulation.

Data Mining

To understand the dependencies of historic *PM* and repair, professional *DM* Tools are used for this task. Such dependencies could identify the components that failed mostly and simultaneously with a given analyzed subcomponent or also possible cluster populations regarding the behavior of the subassemblies concerning the factors that play a dominant role on the failure of the analyzed component e.g. failure causes or downtimes etc. Fig. 3 shows an example for an extract of the Tree view that analyzes the behavior and dependencies of the subassembly ‘electric converter’ for a *WT* type in the coast region of Germany. The figure shows that when this subassembly failed because of an ‘Unscheduled repair after malfunction’, and when the ‘electric generator’ was also affected at the same time and the whole downtime takes less than four hours, then the cause of this failure is usually ‘malfunction of control system’ otherwise it was ‘other causes’ and so on.

MAS

The approach of the dynamic modeling and simulation using *MAS* can make an important contribution in the area of maintenance of *WT*. In the past the analysis systems have integrated the reliability and maintenance aspects more and more in their evaluation. Several proven techniques already obtain considerably successes i.e. [13]. The existing methods for the modeling of availability/reliability can be divided into two groups: static and dynamic methods. [9].

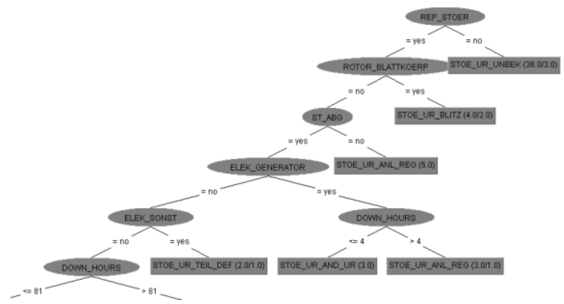

Figure 3: Extract of the Tree view ‘electric converter’

Static methods require less information about the system characteristics than dynamic methods. A logical consequence of this decreased information requirement is their application in the early phases of a project. Although this knowledge base can be quite limited, static methods achieve good estimations for expected future availability and reliability of the object regarded [9]. In addition they are generally more intuitive and simpler in their application and attain faster results than their dynamic counterparts. The main impairment is their inability to treat time-based changes. Since the temporal sequences cannot be represented with static methods, they are generally less suitable for the modeling of maintenance activities, where maintenance planning and maintenance strategies are based mainly on time management [9].

Quite contrary to the static methods the strength of the dynamic methods lies in their ability to combine the temporal effects and the system developments. This characteristic makes the representation for system aging as well as the maintenance scheduling possible. Well-known examples of these dynamic methods are Markov Chains and Dynamic Fault Tree Analysis (FTA), which were already used successfully in the past [10]. Nevertheless these two techniques have large deficits, e.g. the Markov chains suffer an inevitable „condition explosion“, if they are used at large-scale systems and with mass data [11], while FTA already reach their borders, if the system models contain complex feedback loops [12].

Many investigations have been done in the area of dynamic methods using *AI* for optimizing the maintenance. Z. Tian, Y. Ding and F. Ding [13] review the current research status of maintenance of wind turbine systems, discus the application of Artificial Neural Networks (*ANN*) based health prediction tools in that field, and develop a Condition-Based Maintenance (*CBM*) approach for wind power generation systems to address maintenance planning issues.

E. Byon [14] examines the optimal repair strategies for wind turbines operated under stochastic weather conditions and lengthy lead times with the objective to minimize the expected average cost over an infinite horizon. He formulated the problem as an observed Markov decision process for these goals.

MAS is seen as more applicable dynamic method for combining time-based changes and system developments [21]. Moreover, in order to get the Agent to do the task, one must somehow communicate the desired task to this Agent. This implies that the task to be carried out must be specified by *us* in some way. An obvious question is how to specify these tasks: how to tell the Agent what to do. One way to specify the task would be simply to write a program for the Agent to execute (an Object as usual known in the object-oriented programing). The obvious advantage of this approach is that one is left with no uncertainty about what the Agent will do. It will do exactly what one told it to, and no more; one can say that the Object does it for free and it cannot refuse a method invocation. But the very obvious disadvantage is that one has to think about exactly how the task will be carried out himself, and if unforeseen circumstances arise, the Agent executing the task will be unable to respond accordingly. More usually, one wants to tell the Agent what to do without telling it how to do it. One way of doing this is to define tasks indirectly, via some kind of performances measure. There are several ways in which such a performance measures can be defined. The first is to associate utilities with states of the environment. Whereby a utility is a numeric value representing how 'good' a state is: the higher the utility, the better. The task of the Agent is then to bring about states that maximize utility - one does not specify to the Agent how this is to be done. In this approach, a task specification would simply be a function *u* which associates a real value to runs (Simulation runs) themselves [21]:

$$u\colon\ R\ \rightarrow \mathbb{R}$$

One can say that, contrary to Objects, Agents do it because they want to; of course as soon as the service requester is authorized, the Agent has enough resources available, and the action is convenient for the Agent.

The Agents functioning could be also divided into deliberative and reactive [21]. Many researchers have argued that neither a completely deliberative (symbolic world model, long-term goals, reasoning capabilities, Planning) nor a completely reactive approach (situation-action rules, behavior-based architectures) are suitable for building Agents. Reactive Agents can also hardly communicate and collaborate (only through actions that modify the common environment. They have suggested using hybrid systems, which attempt to marry classical and alternative approaches. An obvious approach is to build an Agent out of two (or more) subsystems: a deliberative one, containing a symbolic world model, which develops plans and makes decisions in the way proposed by symbolic *AI*, and a reactive one, which is capable of reacting quickly to events without complex reasoning (see fig. 4).

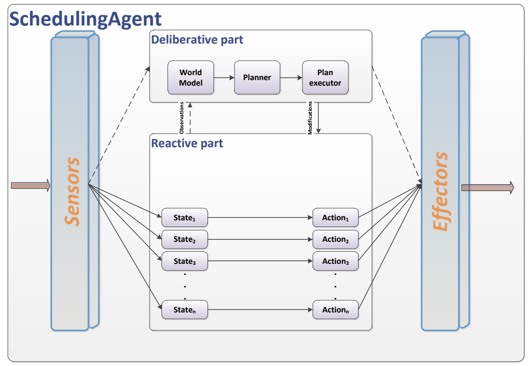

Figure 4: An effective architecture for the Agent

MAS is seen as an adequate technology for seeking out unknown and unexpected behavior of complex systems as well as for filtering the most important knowledge, those the *WFO* needs later for his maintenance planning [21]. Figure 5 illustrates a *MAS* platform with several modules. The Agents representing many objects (components, subassemblies, weather, spare parts stock keeping etc.) interact and communicate with each other, in order to find the optimal „solution" for a given problem. The communication between Agents includes coordination (e.g. divide a task between a group of Agents, distributed planning etc.), cooperation (e.g. share intermediate results, share resources, distributed problem solving etc.), negotiation (e.g. find the Agent that can provide a service with the best conditions etc.) and forming coalitions (trust other Agents, increase utilities…).

Coalition is somehow a special case of cooperation and collaboration, but stays anyway different and difficult to realize because of the fact of considering all possible aspects that could help managing and creating optimal coalitions. Agents want to know earlier how much every coalition could earn, and how this could maximize its utility. This makes the task more complex in the way that, everyone (Agent) wants also the same and has similar goals. So it becomes hard to convince an Agent with a utility u_1 to join a coalition with another one with a utility u_2; given $u_1 > u_2$. An example of these coalition issues could be the contact of availability arrangement between a *WT* (willing maximizing its operating time availability) and *WF* (willing minimizing electricity cost transport by temporary marginally lower tariff); the revenue that the *WF* earns is not obligatory credited to an individual *WT*, but the whole *WF* itself. Other examples of such situations, where strength cooperation between Agents is needed, are the optimal replacement interval for a certain component or the best scenario of the team employment for tasks shared at different wind farms. Therefore *MAS* regards several concepts in its analysis. It assigns Agents to analyze the so called Look-back database, in order to examine the past experiences; other Agents are assigned to explore the Look-Ahead database for information and forecasts (e.g. the electricity tariffs of the next hour or days or also the power and weather forecasts as well as information concerning the stock keeping or to Team disposition).

2. *MAS* MODULES

An entire model based on the idea of categorizing the maintenance activities and the failed maintenance tasks in quality levels (Perfect, Imperfect, Minimal, Worse and Worst) introduced by [15] (see also [16] and [17]) is developed, where a Perfect maintenance task is a total replacement of wear out components or subassemblies, the Imperfect maintenance tasks are e.g. greasing, oiling, adjusting etc., and the Minimal maintenance task is reuse of old existing spare parts in another *WT*. Quality levels worse and worst maintenance are related to maintenance and repair induced failures. These maintenance activity levels have an obvious impact not only on the health and useful life of the components and subassemblies but also on future maintenance strategies. The whole model is created by taking into account the several factors i.e. financial, weather conditions and staff disposition (see fig. 5). It consists of five closely interconnected modules, which are the modules for: Failure-Rates, Production, Logistic, Weather and Cost. This separation provides the option of using different simulation methods as well as an easy extension.

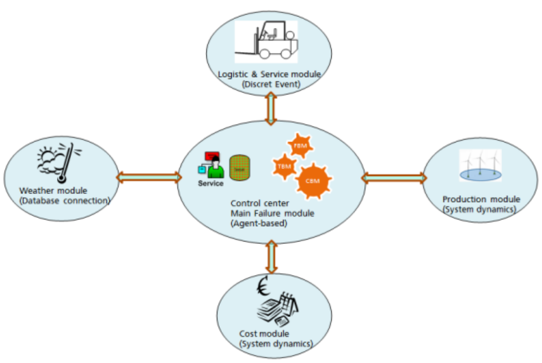

Figure 5: *MAS* Modules

The systems and their subassemblies will be represented by appropriate Agents, which have their own parameters and methods that enable them to act and react with their environment. Each one of those systems will represent an environment of its subassemblies (e.g. Generator-environment). All systems of the *WT* are in turn part of their own environment named *WT*-Types-environment. The *WT*s at last are housed in the Farm-environment (see fig. 6). This interconnected scheme makes the communication for homogeneous Agents inside an environment easier; the Agent is therefore more autonomous and self-directed, more flexible and possesses the ability to learn and to adapt its behaviors based on experience. Autonomy is a very important difference between Agents and traditional programs; Ability to pursue goals in an autonomous way, without direct continuous interaction or commands from the user e.g.; given a vague/imprecise goal, the Agent must determine the best way to attain it. Agents decide for themselves whether or not to perform an action on request from another Agent, in contrast when a method is invoked on an Object, it is always executed.

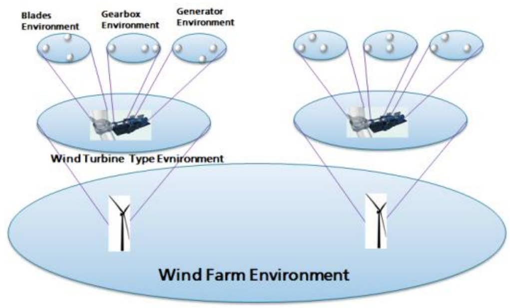

Figure 6: Interconnected Environment architecture

2.1. FAILURE-RATES MODULE

Based on the idea of characterizing the maintenance activities with quality levels, the Failure-Rate module triggers the interruptions in the Production module by message passing and calculates therefore the *PM* and repair costs for the actual activity. The failure rates are calculated and updated after each maintenance activity using a developed algorithm, thus it provides the Agents with the necessary updated input parameters over the failure behavior and failure frequency of the *WT* and their subcomponents continuously. For this first step, sources and information of the WMEP[1] failure database are explored and analyzed on their applicability for a showcase.

Generally *PM* merges all maintenance activities which are not induced by a system failure. Two major criteria impact the failure rate; the mode of maintenance task (*PM* or corrective maintenance *CM*) and its associated maintenance interval impacts but also the level of quality (the so called effectiveness of maintenance task). Therefore the state after a maintenance action was performed on a component is supposed to be one of the following five levels: perfect, imperfect, minimal, worse or worst [15] see fig. 7.
By the Perfect maintenance (*PM* or repair) the system state is restored to be ”as good as new”, and by the Imperfect maintenance (*PM* or repair) a maintenance action that restores the system to a state somewhere between ”as good as new” and ”as bad as old”. Both Perfect and Imperfect maintenance will lead to decreasing of the failure rate.

[1]WMEP, the scientific measurement and evaluation program (WMEP), was conducted by the institute ISET from 1989 to 2006. During these 17 years 193.000 monthly reports of operation and 64.000 maintenance & repair reports from 1,500 *WT*s were collected and analyzed [5]. The database of this program contains a quantity of detailed information about reliability and availability of *WT*s and subassemblies, the *PM* and repair costs, the failure causes, the failure effect and the removal of the malfunction. This provides one of the most comprehensive studies of the long-term behavior of *WT*s worldwide.

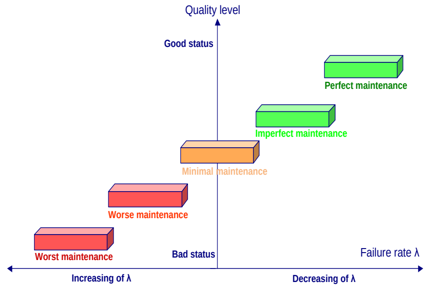

Figure 7: Maintenance Quality levels

While by the Minimal maintenance (*PM* or repair) the system state is "as bad as old" which therefore lead to no change of the failure rate. By the Worse (System is in operating state worse than just prior to the maintenance action) and Worst (System breaks down right after maintenance action) maintenance (*PM* or repair) the failure rates obviously increase after the maintenance action.

A novelty was introduced by D. Lin and M. Zuo. [22] through categorizing the failure mechanisms into two concepts; maintainable failure mechanisms and non-maintainable failure mechanisms. *PM* (including tasks like e.g. Cleaning, Adjusting, Creasing, Oiling, and Inspection…) will affect maintainable failure mechanisms exclusively, whereas non-maintainable Failure mechanisms remain unaltered. Although many works consider the dependence between maintainable and non-maintainable failure mechanisms [16], but for the simplicity of the modeling it's more realistic to assume that both are independent.

Therefore, the system failure rate $\lambda_{Failure}(t)$ of the system (subcomponent) will take the form:

$$\lambda_{Failure}(t) = \lambda_{maint}(t) + \lambda_{non\_maint}(t)$$

Furthermore, one of the important issues in optimal maintenance planning is the determination of a *PM* policy. Thus a *PM* policy specifies how *PM* activities should be scheduled. Generally *PM* policies can be divided into two main categories: periodic and sequential. Periodic *PM* ensures that a system (subcomponent) is maintained at integer multiples of some fixed time intervals and undergoes only minimal repair at failures between these *PM*s. Those minimal repairs only restore the function of the system (subcomponent) when it is failed, but do not change the general health condition of the system (subcomponent). The definition of sequential *PM* is quit the same as periodic *PM* with the only exception, that the system (subcomponent) is maintained at a sequence of time intervals which (may) have unequal lengths. Generally periodic *PM* is more convenient to schedule and easy to manage, whereas sequential *PM* is more realistic when the system (subcomponent) requires more frequent maintenance as it ages [22]. Each *PM* category has a different impact on the system (subcomponent) failure rate.

The literature research shows that there are many works dealing with the impact of *PM* on the failure rate, but three approaches of them have been studied extensively; a Hazard Failure Rate model by Lie and Chun [23] and Nakagawa [24], [25], an Age Reduction model and a Hybrid model by Lin. et. al. [22].

Hazard Rate *PM* Model

The hazard rate function after the i^{th} *PM* becomes:

$$a_i\lambda_{i-1}(t);\ for\ t\ \in (o;\ t_{i+1} - t_i)$$

when it was:

$$\lambda_{i-1}(t);\ for\ t\ \in (o;\ t_i - t_{i-1})$$

where $a_i > 1$ is the adjustment factor for the hazard rate function due to the i^{th} *PM*. In addition, Nakagawa [25] also assumes that the hazard rate function is zero for a new piece of equipment. Based on these model assumptions, one can say that the hazard rate *PM* model represents the situation wherein the equipment's hazard rate function is an increasing function of time when there are no *PM* interventions, each *PM* resets the hazard rate function value to zero, and the rate of increase of the hazard rate function gets higher after each additional *PM* [22].

Age Reduction *PM* Model

The effective age after the i^{th} *PM* reduces to b_iE_i if the equipment's effective age was E_i just prior to this *PM*, where $b_i < 1$ is the improvement factor in the effective age of the equipment due to the i^{th} *PM*; it is an indicator of the achieved quality level of *PM* activity. The effective age of equipment is the same as its actual age before the first *PM* is performed.

The equipment's health condition right after the first *PM* is represented by its hazard rate function value which is equal to the same value as that when the equipment's actual age was b_1t_1. If we use $\lambda_0(t)$ to represent the failure rate function prior to the first *PM* for $t \in (0;\ t_1)$, then

$$\lambda_1(t) = \lambda_0(b_1t_1 + t);\ for\ t\ \in\ (0;\ t_2\ -\ t_1)$$

represents the failure rate function of the equipment in the time interval of $(t_1;\ t_2)$. The hazard rate function of the equipment is then a function of its effective age and each *PM* reduces the effective age of the equipment to a certain extent and could be generally described as:

$$\lambda_i(t) = \lambda_{i-1}(b_it_i + t);\ for\ t\ \in (o;\ t_{i+1} - t_i)$$

Hybrid Model

The hybrid model proposed by Lin et al. [22] is used to model the effect of a *PM* activity on the failure rate function of maintainable failure modes. However, *PM* does not change the hazard rate function of non-maintainable failure modes. *PM* is performed at a sequence of intervals. The objective is to determine the optimal *PM* schedules to minimize the mean cost rate. This hybrid model incorporate the advantages of the age reduction and hazard rate *PM* models. Generally the hybrid model ensures that the effects of a PM task are modeled by two major aspects:

1. Long-term effect when the component is set into operation again (a_i)
2. Immediate impact after the *PM* is accomplished (b_i). The failure rate after the i^{th} preventive maintenance activity becomes:

$$\lambda_i(t_i + t) = a_i\lambda_{i-1}(b_i t_i + t);\ for\ t > 0$$

Where t_i is the time when the i^{th} *PM* is performed and $t \in (0; t_{i+1} - t_i)$. See fig. 8 for the comparison of the three *PM* models.

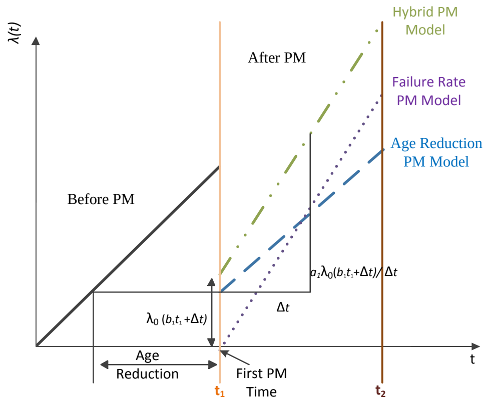

Figure 8: Comparison of the reported *PM* models

2.2. PRODUCTION MODULE

The Production module supplies the Agents with crucial information regarding the energy output and negotiates the best times of a maintenance measure based on power forecasts and SCADA data. The reliability-relevant SCADA operational data are first prepared and analyzed on their applicability in an earlier step. Subsequently, the power forecasts, already developed at Fraunhofer IWES and used by several *WFO*s and Transmission System Operators in Germany, are sighted, selected and forwarded as input parameters for the appropriate Agents. It provides the Logistic module with the needed information.

2.3. WEATHER MODULE

The development of the Weather module has the purpose to introduce weather conditions on basis of weather forecasts into maintenance planning. After identifying and evaluating existing meteorological aspects and their influence as well as relevant parameter for the maintenance, the results of the weather forecasts, bought from an accredited German institute for weather prognostics, are made available as input data for the appropriate Agents.

2.4. COST MODULE

Costs play a vital role in the maintenance organization; with the help of the Cost module it is to be demonstrated, how costs can be considered, affected and reduced during the reliability-oriented maintenance. Based on some basic maintenance Policy models dealing with cost issues e.g. ‘Total Replacement Models’, ‘Partial Replacement Models’ , ‘Replacement Models with Imperfect Maintenance’ or ‘Inspection Models’ [18], which give an estimation of the optimal interval point to make a replacement with minimal costs. This estimation takes into account the labor costs, components costs and material costs etc., all relevant cost parameters will be prepared as inputs for the appropriate Agents, who will cooperate to get the optimal policy model and therefore the best replacement time. For example by Total Replacement Models there are usually two types of replacement option:

- Preventive replacement (*PR*), which follows a predetermined preventive maintenance policy.
- Corrective replacement (*CR*); following the equipment failure.

Generally Total Replacement Models consider the following policies:

- Constant Interval Replacement (*CIR*), where the replacement is done after a certain constant time interval.
- Age Based Replacement (*ABR*), where the replacement is done when the equipment reach a certain operating predetermined time-age.

Constant Interval Replacement - *CIR*
Usually the replacement in this model is done after the failure (*CR*) or after a certain constant time interval t_p (*PR*). The aim of this model is how to determine the optimal time interval between two preventive replacements (see fig. 9) by using the optimization criteria that minimize the total expected cost per unit time.

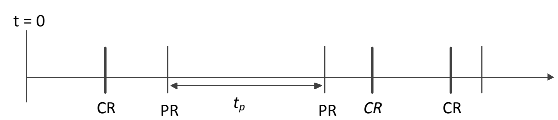

Figure 9: Component Maintenance lifetime

When a failure occurs, it will take place within the time interval $(o,\ t_p)$, therefore the total expected cost per unit time $TEC(t_p)$ for this interval t_p is defined as [18]:

Equation 1:

$$TEC(t_p) = \frac{TEC(0,\ t_p)}{Length(o,\ t_p)} = \frac{C_p + C_c\ * N(t_p)}{t_p}$$

The expected number of failures for the time interval t_p will be [26]:

$$N(t_p) = \int_0^{t_p} \lambda(t)dt \; = \int_o^{t_p} \frac{f(t)}{1-F(t)}dt$$

where $\lambda(t)$ is the failure rate.

Following this policy, the amount of failures is considerable, that means that many *PR*s could be done when the operating time of the equipment is bellow t_p, which consequently makes this policy less efficient.

Age Based Replacement - *ABR*
In this case, the *PR* is done after the component reach a certain operating time-age (t_p). In case of component failure a *CR* is done and the next *PR* is scheduled after a predefined time t_p (see fig. 10). The optimum of this policy is here again by minimizing the function $TEC(t_p)$ (equation 3).

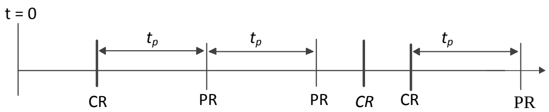

Figure 10: Age Based Replacement Maintenance policy

In case the component reaches the *PR* time t_p, this will happen with a probability of $R(t_p)$, or fail before that time with a probability equal to $F(t_p)$. The expected length of the cycle is therefore equal to t_p times the probability of the cycle $R(t_p)$, in addition t_i the expected length of the failure cycle times the probability of the failure $F(t_p)$. The length of the failure cycle can be estimated by calculating the expected value of the failure distribution $M(t_p)$ (equation 2), where $f(t)$ is the time to failure probability density function [18].

Equation 2:
$$M(t_p) = \int_{-\infty}^{t_p} \frac{t * f(t)}{F(tp)}dt$$

Equation 3:
$$TEC(t_p) = \frac{C_p R(t_p) + \; C_c \; F(t_p)}{t_p R\big(t_p\big) + M(t_p)F(t_p)}$$

The figure 11 illustrates the benefit of using *CIR* and *ABR*. While by *CIR* the replacement must already be done after a given period t_{p1} (which is the minimum of the function curve $TEC(t_p)$ for *CIR*), the *ABR* policy enlarges the replacement time until an ulterior date t_{p2}, using the life cycle of the component in a better way.

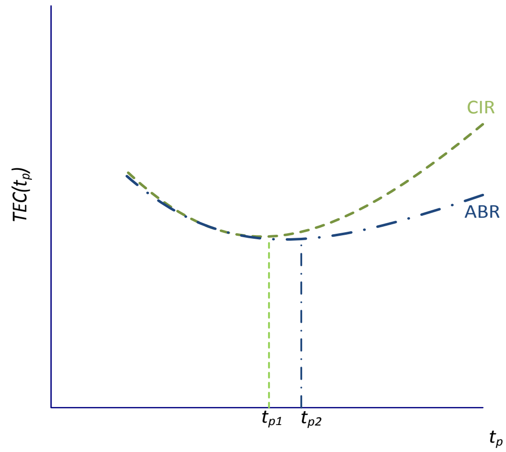

Figure 11: $TEC(t_p)$ plot for *CIR* and *ABR* policies

2.5. LOGISTIC MODULE

The consideration of logistics and resources factors is indispensable for the optimization of maintenance strategies for *WT*s/*WF*. The Logistic module will be interconnected with the Production module in order to manage the whole maintenance scheduling.
Carrying out maintenance activities requires the utilization of different types of resources; spare parts and materials, help-tools, manpower, instruments, money are examples of those resources. The management of these resources simultaneously, their planning so that the correct quantity of every resource is available in the time and form that is needed, turns most cases into an arduous task for which many *WFO* are not prepared [18]. As a consequence, some of *WFO* will incur a series of costs derived from the excessive possession of certain resources that are not necessary, whereas at the same time, the lack of other essential ones will lead to serious losses in their operations and a definitive decrease in the desired quality of service. Therefore, the activity of maintenance resources management can be seen as a critical activity for the maintenance function by the *WFO*/service companies [18].
Within this module many input data (e.g. spare parts stock keeping, components costs, transport cost etc.) and different techniques and methods, of major application, for the management of maintenance resources (Maintenance Staff Planning and Scheduling, Maintenance Materials Requirements Planning...) will be available for the appropriate Agents, helping them suggesting optimal decisions in order to decrease the logistic burden and Life Cycle Costs. Some of the problems to deal with could be classified as follow:

- How to determine the maintenance workflow. Classified by skills?
- How to determine the ideal number of maintenance teams schedules?

- What is the quantity of normal hours extra hours, and hours to be contracted with external service companies, that will be necessary?

Examples of the Agents optimal propositions, dealing with logistic module could be the decision whether to make a short, medium or long term scheduling maintenance activities for some components or *WT*s.

Next figure (see fig. 12) illustrates again the interactions of all above modules inside *MAS*. Those interactions are in the reality a kind of communication between Agents of all modules. This communication is varying between sharing information, negotiation and forming coalitions, making the decision-making more strength.

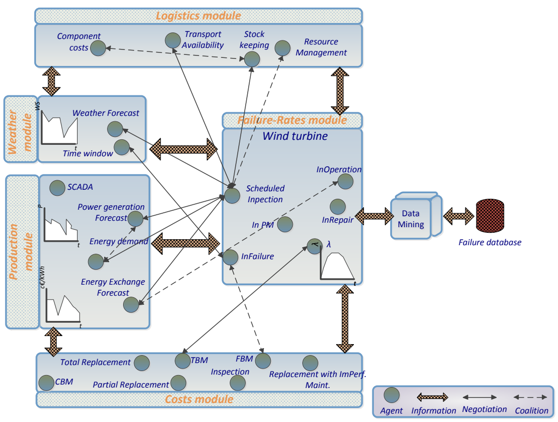

Figure 12: interactions of all modules within *MAS*

CONCLUSION

The advantages of using *AI* have been described in the contribution. Sophisticated Tools using *AI* are able to improve operating maintenance activities and help the *WFO* managing their task planning, taking into account several surrounding conditions in the analysis. For doing so a methodology has to be developed which was briefly described in this paper. The following points should be kept in mind when investigating the use of *AI* in *WT* maintenance:

- Using a common failure database enables sophisticated approaches by analyzing the history of the subassemblies in order to deduce and to forecast the failure behavior of different subassemblies e.g. by using *AI*.
- *DM* and *MAS* are promising technologies in the field of maintenance of *WT*, but using them separately has some impairments. The use of a hybrid methodology to analyze dependencies between failure rates, weather conditions, logistics etc. is proposed.
- Using several cost optimization methods/algorithms will help by making the optimal decision in both reducing costs and improving availability.
- A balance between economic, reliability, availability and organization issues needs to be achieved by the model developed.

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