Early Concepts for the Coupling of a Nuclear Plant Computer to a Computerized Maintenance Management System for Autonomous Prognostic Model Development

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ABSTRACT

Every day large amounts of process data are recorded in a variety of industries. For nuclear power plants, these data are stored within the Plant Computer (PC). As parts begin to degrade and components fail, maintenance personnel are responsible for making repairs and recording these repairs in a Computerized Maintenance Management System (CMMS). By coupling the information in the PC and CMMS, failure data can be extracted and repurposed for lifecycle prognostic models. Existing prognostic methods can be utilized to develop lifecycle models and predict the Remaining Useful Life (RUL). These efforts are currently done manually and require substantial amounts of time to develop. This results in offline predictions, which can drastically reduce response time for preventative maintenance. This paper outlines an early concept that uses data mining based on Big Data efforts in order to couple the plant computer data with the CMMS so that prognostic information can be gathered, sorted, and analyzed automatically. The extracted failure data can be used to autonomously update or build prognostic models based on component failure times, stressor information, and signal/residual values. An effective future implementation of this concept means that the results could be used as *a priori* prognostic information in lifecycle prognostic models, and the updating and/or development of such models can be automated for improved response time.

1. INTRODUCTION

Lifecycle prognostics describes a set of data based models that can potentially give an accurate determination of the health of a system or component using several different forms of data such as usage time, usage stress, and degradation indicators. As more information is collected, knowledge of the system increases allowing for increasingly advanced models and the possibility of increased prediction accuracy. These data based models are valuable for condition-based maintenance efforts including preventive maintenance. In order to effectively extract and utilize prognostic information from existing operations, it is necessary to develop a semi-autonomous extraction routine. This algorithm would be responsible for repurposing maintenance information with the intent to retrieve failure data from process files. The result of such an algorithm is a detailed network of failure information on specific parts and systems, which is the main component necessary to update and develop predictive maintenance models. It is necessary for this extraction to be carried out autonomously to increase decision time and decrease uncertainty for the operator. The extraction algorithm is the first step of the process towards improving predictive maintenance in commercial applications, and will be loosely outlined in the following sections of this report. The second step of the process is the utilization of the extracted failure data to build or update prognostic models in a quick and efficient manner. The set of tools needed to achieve this goal must meet several requirements including near-to-full autonomy and high confidence decision-making in order to have utility in pre-existing commercial applications.

To make the concepts discussed in this paper easier to follow, examples will discuss how the proposed design might affect a system that includes a 3-phase motor and pump combination. The ideas discussed should be scalable to most nuclear plant components with modifications to aspects such as choice of measurements. Specifics on the application to assets and components will not be covered for this early discussion.

2. OVERVIEW OF LIFECYCLE PROGNOSTICS

The following section will highlight the important aspects of lifecycle prognostic models, and the types of information necessary to build them.

There are several steps involved in the development of a lifecycle prognostic model. The path from data collection to risk mitigation is outlined in Figure 1.

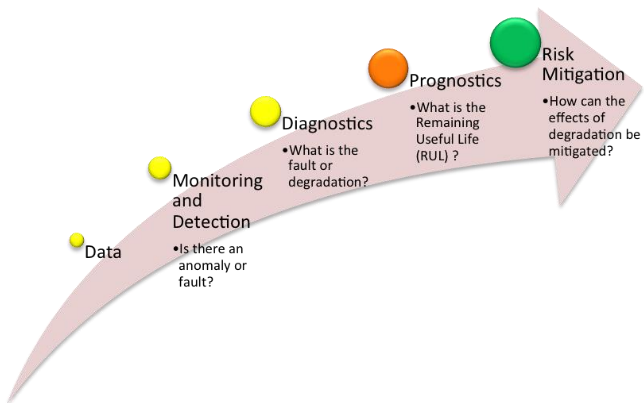

Figure 1. Path of phases from data collection to risk mitigation including detection, diagnosis, and prognosis (Hines 2008).

The first step of lifecycle prognostics is data acquisition. During the data collection process, monitoring is conducted that can detect anomalies or faults from on-line data samples. Faulted data is then compared to an analytical, empirical, or hybrid model to determine residuals that are related to degradation of the system. These residuals are combined into a system health indicator that is a measure of the total degradation in the system. Using a prognostic model, these health indicators, or prognostic parameters, are used to obtain RUL predictions. The RUL predictions are subsequently available for risk analysis and mitigation.

Prognostic models are typically divided into three different types depending on the failure data available. Type I prognostics is based on past failure time distributions and is often referred to as traditional reliability analysis. This type of prognostic model only utilizes past failure times and does not require any additional failure data. Therefore, it can be conducted before operation of additional cycles. During operation, as stressor information such as operating condition or load is obtained, the model transitions to a Type II prognostic model. In parallel to the Type II models, anomaly detection can be conducted on the failure data. When specific signals such as temperature or pressure are tracked over lifetime and show an increase in damage to the system, the Type I or II model transitions to a Type III prognostic model. Type III models use the tracked degradation across multiple signals to measure the overall system health. The transitions between prognostic model types can be seen in Figure 2.

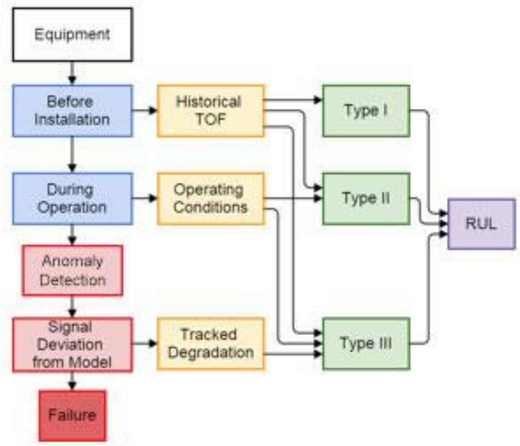

Figure 2. Transition between prognostic model types dependent on availability of failure information (Nam 2015).

Only the component run time is needed to perform Type I prognostics, which can be mined directly from the CMMS. The ability to develop Type II and Type III prognostic models is dependent on the ability to collect stressor and degradation data for the component or system in question. With respect to nuclear power plant applications, these data are stored between the PC and CMMS. Data from both of these sources are necessary to develop these lifecycle models. Effectiveness of the proposed concepts will be dependent on the ability to obtain these data for future validation and development.

3. OVERVIEW OF PUMP-MOTOR SYSTEM

To show how the proposed concepts can be applied to a real world situation, a pump-motor system is being used. A simple diagram of this system is shown in Figure 3.

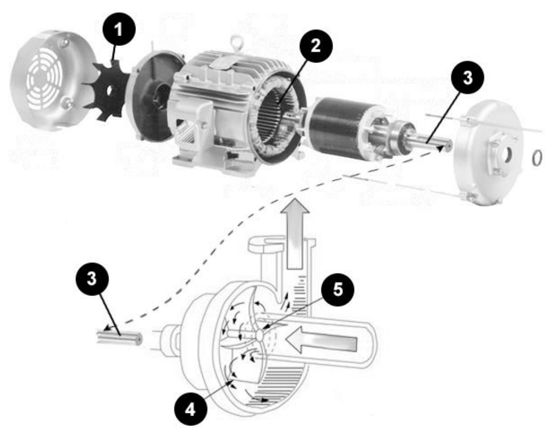

Figure 3. Diagram of simple motor-pump system. The top of the figure contains a separated 3-phase motor with labeled cooling fan (1) and coil windings (2). The output shaft of the motor (3) spins the impeller (4) by feeding into the impeller eye (5) (Hernandez 2006) (Skvarenina 2004)

Within this theoretical setup, there are several fault or failure modes to consider. For the 3-phase motor, the cooling fan (1) in Figure 3 can break a blade reducing cooling to the motor. This would be an example of a system fault. Also bearings that surround the motor shaft (3) can fail. The pump consists of one major failure mode, which occurs with degradation of the impellor fins. There are several ways that the fins can degrade, which are visually represented in Figure 4.

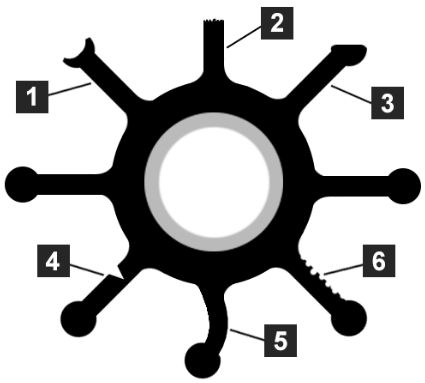

Figure 4. Representation of 6 types of impeller degradation: (1) fin-pitting, (2) vein tearing, (3) flattening, (4) vein ripping, (5) bowing, and (6) vein-pitting.

Impeller fins are used to regulate a vacuum within the pump, which creates the differential pressure needed to drive the fluid. The effect of each of the degradation forms listed in Figure 4 may have a unique effect on the pump-motor system. The distinctiveness of each degradation type is important for cataloging of CMMS entries.

Aside from degradation/failure modes, the availability of sensors in a system also affects decision-making. The assumption of what measurements are available both on-line and those taken during maintenance events has serious impact on the ability to effectively develop a data-mining algorithm. The sensor data available will change the degree to which Type II and III prognostic information can be discovered for the nuclear power plant, or more specifically, the system or component under investigation. With commercially available signals, effective lifecycle prognostics models have already been developed for pumps (Jeffries 2014), motors (Nam 2013), and other systems such as heat exchangers (Welz 2014). The practical development of these models is limited by the current availability of plant data. The coupling algorithm will be designed to increase the availability of necessary prognostic data and consequently the ability to develop these prognostic models.

The choice of a pump-motor system is very meticulous with respect to this paper's application to nuclear power plants. There are numerous pumps within the plant that are critical to plant operation. An example is the primary Reactor Coolant Pump (RCP) in a Pressurized Water Reactor (PWR). This means that accurate prediction of pump-motor failure times could have a significant impact on planned and predictive maintenance. It is important to note, however, that the specifics of this system are arbitrarily chosen to provide insight into the purpose and functionality of the autonomous prognostic program.

4. NUCLEAR PLANT CMMS FRAMEWORK CHALLENGES

To effectively mine out maintenance information from the CMMS, certain information in regards to the parts and components being serviced must be recorded (Bertolini 2013). For example, rather than a record stating that pump 6 was serviced at 12:03pm on cycle-day 4, the CMMS would require additional specific information such as pump model, reason for maintenance, activity (primary or redundant), recorded time of failure, etc. This would provide additional knowledge to increase the ability of a data mining algorithm to locate useful information.

Another aspect of the CMMS software that should be evaluated is the need for asset-specific maintenance information. Current CMMS work orders are tailored to an application, but not always a specific system. To gather useful information on a specific part or component, a pump may need a different CMMS record than a motor. Availability of additional information may directly affect the resulting models. This type of customized CMMS database may be necessary as the data mining algorithm is being developed, evaluated, and validated during future research.

As previously mentioned, specifics on the design of a CMMS standard for coupling with the nuclear plant computer will be decided based on future research needs. The CMMS design will be directly related to the specific needs of the data-mining program within the coupling algorithm with respect to the development of lifecycle prognostic models. The availability of these data, and the ability to manipulate existing CMMS frameworks are two of the major challenges in the development of a coupling algorithm.

5. PLANT COMPUTER FRAMEWORK CHALLENGES

Current nuclear plants have most of the information required to perform lifecycle prognostics on components, but access to the data is not always straightforward. Some components may need additional sensors, data collection systems, and data storage systems. Additionally, future plants could have/need data systems specifically designed to support lifecycle prognostics. These challenges will largely affect the success of a coupling algorithm. With the intent to apply concepts discussed in this paper to the nuclear fleet, any changes to the plant computer framework would likely need to be minimal. With the Nuclear Regulatory Commission (NRC) supervising critical plant design standards, substantial changes to the plant computer would be difficult to implement.

Other than challenges such as the need for additional transducers and data acquisition systems, there are a few minor changes that may need to be made depending on current plant computer operations. Similar to the CMMS, specifics on changes to the plant computer framework will be dependent on the coupling algorithm design. For example, one modification that may need to be made is the sampling frequency. There are several methods of frequency analysis that require a specific or large sample rate, therefore if the plant computer takes data from a sensor at 1 Hz, it may need to be increased to 100 Hz. Changes such as this may have minimal impact on plant computer operations, and will need to be carefully examined before implementation.

In the design of the coupling algorithm, several assumptions about the current software design of plant computers in the U.S. will have to be made. As a generic guideline for current American plant computer design, Westinghouse pressurized water reactor nuclear power plant documentation (Westinghouse 1984) will be used.

6. EARLY COUPLING ALGORITHM CONCEPT DESIGN

The coupling algorithm is tasked with collecting useable prognostic information from the CMMS and combining it with information mined from the plant computer data. Extracting data from existing systems is the first step of predictive model development. Manual extraction from human efforts is ineffective and time consuming for many applications. The idea behind the coupling algorithm is a self-sustaining procedure with its own runtime that can remove the necessity for human facilitated data extraction. An early conceptual design of the algorithm is shown in Figure 5.

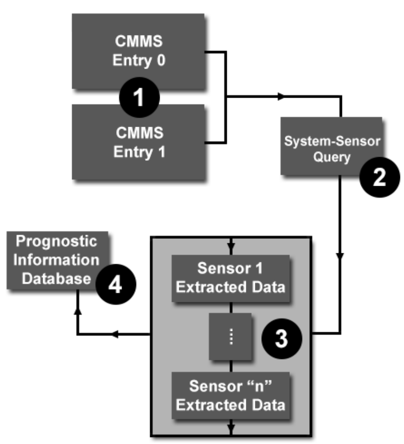

Figure 5. Flow diagram of coupling algorithm design concept.

The algorithm itself consists of many smaller algorithms to achieve such a goal. The resulting product is able to automatically detect the presence of a recently completed work order, which contains timestamps associated with the part's or asset's failure time. The coupling algorithm begins with the polling of the CMMS database. As seen in Figure 5, at step 1 the service information for a specific part is polled. This includes the current maintenance cycle and the previous cycle. With respect to the pump-motor system discussed earlier, if the pump impeller were serviced, the algorithm would poll the maintenance information for the current event (ex: impeller replaced on 1/4/15 at 02:44) and the past event of the same category (ex: impeller replacement on 10/14/14 at 16:00). In order to determine what data must be extracted from the plant computer, the CMMS polled maintenance records are passed to a sensor query (Figure 5 step 2). The sensor query looks at the system under maintenance (pump-motor system) as well as the specific part (pump impeller) in order to return the associated sensors and their location within the plant computer records. The next step extracts the information from the plant computer (Figure 5 step 3). The data for each sensor related to the system is extracted for both maintenance services between the time of startup and time of failure. After this step is completed, the resulting sensor information is processed and passed to a prognostic information database (Figure 5 step 4).

During this process, the user can either specify constraints on the data extraction, or the computer will choose constraints based on optimization efforts. The user will always be aware of the program's status through the use of alert tools (progress bars, status beacons, etc.). Extracted data will be sent to a directory, which will be displayed to the operator in the event that the worker needs to intervene or wishes to catalogue specific files for offline evaluation. Visual aids will be used to display current system information to the operator, such as most recently extracted raw failure data, cross-correlation values between signals during the latest cycle, and even proximate fault detection results. These tools are grouped in a manner that will provide near-instantaneous information to the end-user.

After extraction, the data is sorted depending on the corresponding prognostic model type, and stored for later use in lifecycle prognostic models. Historical data has a different utility than current cycle data. As the algorithm strips out a current cycle, the data can be used for monitoring. Once the information has been sent to a prognostic database, it can be used to update existing models as a separate task of continuous model improvement. Current cycle data is of key importance for critical decision-making.

7. PROGNOSTIC INFORMATION DATABASE

It is necessary to provide background into the inputs for prognostic models; the link between the coupling algorithm and the model inputs is a detailed prognostic information database. The coupling algorithm is responsible for sorting extracted data into this database, which has a structure similar to that in Figure 6.

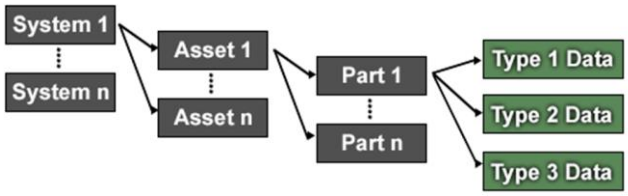

Figure 6. Prognostic information database example structure

By sorting different types of prognostic data into an isolated database, the files are immediately available for model development purposes. This database is standalone from the coupling algorithm and model development to allow for each to run simultaneously and independently from one another. The utilization of the extracted data as input to prognostic models is discussed below.

8. AUTOMATED PROGNOSTIC MODEL TOOLKIT CONCEPTS

The purpose of extracting useful prognostic data from historical process data files is to improve maintenance efforts. Two of the primary concerns in the development of predictive maintenance models are quick response time, and high prediction/model confidence. There are several stages in the development of prognostic models when utilizing data gathered from the coupling algorithm. Lifecycle prognostic models can be updated/transitioned as additional information is gathered. The first information stored in the database will be simple failure times for the different components, which is Type I prognostics. As additional failure times are measured, monitoring efforts can be updated and prognostics based on current information can be assessed. When stressor information is incorporated with the preexisting failure times, the model can be updated to Type II prognostics. As the coupling algorithm reads in more data, it will be able to extract useful signal values related to the failure times of components. For example, if the inlet water temperature sensor value for a pump increases over each failure cycle, the coupling algorithm will identify that temperature signal as useful. Once the coupling algorithm has identified several useful degradation signals, it will store them as Type III prognostic data. All three forms of prognostic data can be used to update existing monitoring and prognostic efforts.

The main focus of this prognostic model "toolkit" is the automation of model efforts. Automating the model process results in a standard for data development, which reduces variance in decision-making and increases model development time. Outside of the transition from manual to autonomous model development, current industry standard and state-of-the-art prognostic methods are still utilized for internal functionality. Additional sub-algorithms will be included to improve the automated results, but will still rely on existing state-of-the-art methods.

One example of a supplementary function is a model update tool that distinguishes between assets repaired to "as good as used (AGAU)" and "as good as new (AGAN)" conditions. Based on the degree of repair, the model is altered in different ways. In Figure 7, the failure distributions are provided for different outcomes in order to highlight the differences between a single run to failure, a run and repair to AGAU condition, and a run and replacement to AGAN condition.

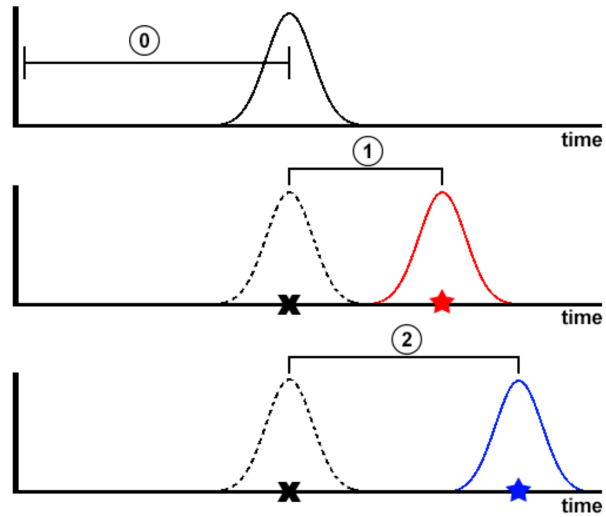

Figure 7. Representation of the differences in model updating for "as good as used" and "as good as new" maintenance levels

Referring to Figure 7 above, the top outcome describes the failure distribution for a single run. The time 0 is the Time to Failure (TTF) of the asset. This can be represented by electrical winding failure in the pump-motor system. In the middle outcome, it is assumed that the asset initially fails at the mean of the original failure distribution. The cause of the failure is then repaired and the asset is certified to AGAU condition, resulting in an addition to the lifetime of the asset labeled as 1 in the Figure. This would be a repair of the electrical windings in the failed pump-motor system. This repair shifts the failure distribution to the right (red). In the bottom outcome, the asset initially fails at the mean of the original failure distribution similar to the middle outcome. The cause of the failure in this outcome is replaced, which results in the asset being certified to AGAN condition. This would be a replacements of the electrical windings in the motor. The resulting shift in the failure distribution can be seen in blue. The necessity for discrimination between the AGAU and AGAN conditions is the difference in these shifts. The increase in TTF for the AGAN condition is larger than that of the AGAU condition. By discerning the results in the differences of these repair outcomes, model predication accuracy can be increased, and the uncertainties of these distributions can be decreased over a single repair distribution. There will be many supplementary functions such as this within the toolkit, as well as industry standard prognostic model functionality.

Due to the complex nature of prognostic model developments, the prognostic model toolkit will contain a large number of supporting functions. It is important to note that with so many automated decisions, the user/operator is still in control of the process. Each stage of the program will allow the user to override options and set a desired path. This allows for the benefits of an automated process without the disadvantages of a "black box" program. Not only is the user able to specify individual options, but also certain supplementary options can be turned off for simple and fast model development requirements.

9. NOVELTY OF METHODS AND COMPARISON TO CURRENT STATE-OF-THE-ART EFFORTS

To discuss the novelty of ideas presented in earlier sections, it is important to identify the focus of these new approaches. While significant attention is given to internal functions, the novelty of these ideas is in the process mechanism, specifically the automation of prognostic data extraction and model development. Never before has predictive maintenance been standardized with an automated model development process that begins with prognostic data extraction and ends with RUL predictions on a commercial scale. By automating these processes, predictive maintenance efforts may be improved through increased response time, reduced human interaction (decreased error), and decreased variability in prognostic model development. In many applications, predictive maintenance efforts will not be effective enough for implementation until these improvements have been satisfied. This makes the novelty of presented ideas very attractive. The utilization of the coupling algorithm and prognostics toolkit may allow for industry-wide implementation of prognostics and advanced diagnostics on a large scale. To companies, the novelty of these programs lies in their ability to reduce unexpected downtime for maintenance as well as improve scheduling of part orders. The possibility for increased safety is another appealing outcome that may be achieved through the implementation of these programs. All of these efforts will increase the availability of information to the operator/user.

The novelty of automation with application to nuclear power is rather significant. While human operators will always be present in a nuclear power plant, industry is pushing towards a higher level of plant automation. Figure 8 shows the levels of automation from manual control to full autonomy.

These levels show the change in influence a machine or human has on an activity. The current level of automation for nuclear power plants is around level 5. Coupling of the CMMS and plant computer can push reactor operations closer to full autonomy. This not only simplifies the data extraction process, but also allows for improvements to reliability, safety, and most importantly decision-making for continued operation.

	LEVEL	DESCRIPTION
Increased Autonomy	10	Computer Decides Everything, Full Autonomy
	9	Computer Excecutes and Chooses When to Inform Human
	8	Computer Excecutes and Only Informs Human if Asked
	7	Computer Excecutes Action and Informs Human of Selection
	6	Computer Excecutes Decision if Human does not Veto
Current Level	5	Computer Suggests Action, Human Approves or Rejects
Decreased Autonomy	4	Computer Suggests Single Alternative
	3	Computer Narrowed Selection
	2	Computer Offered Alternative Decisions
	1	Manual Control by Human

Figure 1. Adaptation of Sheridan's 10 levels of automation (Bradshaw 2011).

It is important to reiterate that the methods discussed in this paper are not novel because they supersede or replace the current state-of-the-art prognostic methods. The automation of data extraction is necessary to increase response time for operators, but will rely on prognostic indicators and functions that are currently used during manual extraction. The automation of model development utilizes existing methods with individual runtime envelopes to facilitate autonomous control. This allows for new automation methods to retain existing validation of prognostic functions as a baseline, and provide increased confidence to the end-user.

10. CONCLUSIONS

With the presence of large pre-existing databanks for storing nuclear power plant process data and maintenance records, the coupling of the plant computer to a computerized maintenance management system could allow for the extraction of useful diagnostic, prognostic, and reliability information. This data can be passed to modified existing state-of-the-art prognostic functions and tools in order to autonomously create and update prognostic models for individual assets and components. With additional research applied to the methods described, effective application of predictive maintenance in commercial applications may be possible. The automation of model development and predictions may lead to increased response time and decreased variability in the model development process. These potential benefits of these methods are immeasurable across the multitude of possible applications.

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