Methodologies in Prognostics



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**Table of Contents:**

* **Introduction (3 - 5)**
  + **Current Maintenance Trends**
  + **Overview of Prognostic Ideas**
* **Prognostic Approaches (5 - 9)**
  + **Data-Driven Approaches**
  + **Model-Based Approaches**
  + **Probability-Based Approaches**
  + **Hybrid Approaches**
* **Conclusion (9)**
* **References (10)**

**Introduction**

Increasing complexity is a phrase that can be synonymously used describe most systems employed in the modern industrial environment. Regardless of the field of interest, the growing body of knowledge, drive to increase efficiency, and advances in technology touch nearly every process as the pressure to stay relevant in competitive world markets push firms to adapt their equipment and infrastructure. The consequence of these new and unfamiliar systems has led to the departments within these firms tasked to maintain their operation struggling to keep up with the unique needs and resources they require. To cope with these changes, several maintenance strategies have been developed to mitigate the gaps in coverage and yield the reliability that is expected from such systems. The two dominant strategies that have emerged from these developments are policies focused on reactive and preventative methods.

Reactive methods employ a run until failure approach that simply allow equipment to run without concern until an event occurs that renders them unable to perform the task they were designed for. At this point of failure, specific action plans are developed to correct the problem within an identifiable timeframe so that quantifiable measures can be determined and factored into the expected output of the system. In this manner, the cost associated with failures can be captured an incorporated into benefit-cost analysis during the decision process of design and implementation to help leadership make better choices. Preventative methods take a different approach to maintenance activities. These methods center around recommended and estimated actions taken over the active life of the system that seek to extend its runtime and limit the impact of failures. While being applied in a somewhat blind manner, focusing on critical points of the systems operation helps reduce cost on major repair and prevents complete system failures that can extend to other parts of the process.

Though these methods as well as others have gone a long way to increase the reliability, availability, and stability of new systems, maintenance activities in industrial facilities are still the costliest component of operation. With diminishing marginal utility, comprehensive maintenance strategies only provide a limited benefit on their own and in some instances can increase the cost of maintenance work processes. Reactive and preventative methods can sometimes extend the downtime between repairs, leave vital areas of the system unaccounted for, and divert critical resources away from jobs of higher importance with the addition of unnecessary task to the maintenance work list. To experience the full benefit of maintenance strategies the knowledge of how and when to appropriate them in the proper manner must be exercised which in turn can reduce their use to only when they are needed preventing wasted time and expense. This leads to a necessity to redefine what the term maintenance stands for and expand this thought to a more procedural context representing “the need, firstly, of ‘perceiving’ phenomena, next, of ‘understanding’ them, and finally of ‘acting’” (Dragomir, et al. 2009)

Having the ability to predict the future state of any piece of equipment could potentially present the opportunity to prepare, plan, and in some instances avoid the negative result of the misappropriation of maintenance resources. This could help to avoid costly shutdowns, stock the appropriate number of spare parts, create well defined operating disciplines to better utilize redundant systems, as well as a host of other benefits. An Attempt to deliver this ability has grown into an entire field of study known as the science of prognostics which uses various modern techniques and technologies to infer the Remaining Useful Life (RUL) and End of Life (EOL) conditions of specific equipment based on its’ known current state and any past information on it. Being a subset of the increasingly popular idea of Condition-Based Maintenance (CBM), more generally known as preventative maintenance, this concept presents the opportunity for large improvement gains over traditional approaches since it “differs from preventative maintenance by basing maintenance need on the actual condition of the machine rather than some preset schedule” (Sethiya 2011). The general theory behind prognostics relies on the thought that future states of a system over its lifetime will be a product of its past environment and use.

The implementation of this concept through different strategies has been limited in scope thus far, but has proven to be superior to older methods. Primarily integrated into technical approaches involving engineering disciplines such as statistical reliability, physics of failure modeling, feature extraction, signal processing, and automated reasoning relevant strategies that make use of prognostics include Prognostic and Health Management (PHM), System Health Management (SHM), and Vehicle Health Management (VHM) which is mostly used in transportation applications. Even though these strategies have only been used in limited cases, these cases span many industries and have been shown to be extremely reliable in critical areas. The extent to which prognostics is used include sectors such as manufacturing, heavy equipment, mining, power generation, aerospace, defense, automotive, and rail. Being particularly effective in yielding accurate results in rotating equipment specific cases of its implementation include predicting EOL and RUL states for helicopter components and wind mill power generation units which have allowed for better mitigation techniques to be applied to circumvent failure mechanisms and provide for safer operation. The flexibility to apply this concept to this wide variety of industrial applications comes from different methods with which it can be applied.

**Prognostic Approaches**

Prognostics in action is seen in various forms that have been developed from the latest technology and consist of a plethora of methods and tools to predict the future state of equipment. Since “prognostic aims at anticipating the time of the failure and thus is done *a priori*” (Tobon-Mejia, et al. 2011), all of these mechanisms that utilize the concept of prognostics require significant prior information on the equipment of focus. Depending on what and how this information is employed, the many unique implementation of prognostics can be placed into one of four classifications which represent distinct methodologies. These methodologies include data-driven, model-base, probability-based, and hybrid approaches.

Data-driven prognostics represents the most accurate, but also the most expensive of these approaches. As the name implies, data-driven approaches require actively streaming information about the current condition of the equipment to be collected and stored continuously or at least in a relatively small and consistent intervals. This information is generally collected through online sensors and monitors that ‘watch’ the equipment and report what they ‘see’. Then applying the theory of pattern recognition, statistical or machine learning techniques ‘read’ the information from databases to identify trends and predict future outcomes. Statistical techniques are fairly straight forward and present the opportunity understand how conclusion are drawn from the collected data which allows for better reasoning and the identification of failures with the methods and tools by those who interpret them. This permits for better control and a high level of trust when using predictions. Typically multivariant statistical methods are used such as canonical variate, partial least squares, linear and quadratic, static and dynamic, regression, and principle component analysis. This method differs greatly from the machine learning techniques that are incorporated into data-driven approaches. These black-box methods offer the ability to more accurately identify nuances that might not be obvious through standard statistical approaches but present a severe problem when it comes to the interpretation of results. Incorporating machine learning methods such as artificial neural networks, Bayesian networks, hidden Markov models, and fuzzy logic, this set of methods involve complex decision trees base on multiple layers of logic built into the algorithms structure that is formed from a unique process of sifting through the data and using those conclusions to compute coefficients and build binary search trees. The intricate and massive set of calculations used to yield results leads to the inability to understand how the decision was made within any amount of reasonable time. This usually results in a difficult decision when selecting which methods to use in these prognostic techniques though sometimes the breadth or shape of the incoming data can lead to an obvious choice.

Usually focusing on the original structure of the system to determine the future effects on equipment, model-based prognostics approach the problem of predicting future states of equipment in a different manner. Also known as physics-based prognostics this framework of implementation is somewhat limited as to the scope of its use. Being based on mathematical models of the equipment and the system it is located it, the models must be relatively accurate and be representative of the first principles of the system’s and equipment’s failure modes. Systems where physical models can’t fully describe its functionality due to extreme levels of complexity and variation prevent the implementation of such approaches. However, model-based prognostics can be useful in certain situations and allow for an easy and less expensive way to incorporate prognostic ideas into the maintenance process. These models rely on the ability to describe a system or piece of equipment based on measured data which is used to calculate parameters and predict future behavior. They can be quantitative in nature and allow for direct measurements of future conditions or qualitative in nature and be used to identify the likelihood of an equipment’s future condition in comparison to a specified function. By using this approach the cost from sensors, monitors, and all the associated hardware with them that directly measure the current state of the equipment can be avoided while still providing some of the benefit of prognostics.

Probability-based prognostics, also called experienced-based prognostics, represents the oldest, easiest, and least expensive of the these approaches to implementing prognostics ideas. The way in which this approach is done relies on possessing prior knowledge of the system in an active state. Organizing this knowledge into a database and then performing analysis on it is then done to predict how the system will perform over future time intervals. By examining past failures and the events that led to them probability distribution such as normal, exponential, and Weibull distributions can be fit to the data to describe the probability of an event occurring over a specific period of the equipment’s or system’s run time. This can allow for predictions to made with a certain sense of certainty though this is not as reliable as some of the previous methods mentioned. However, despite not yielding the same level of certainty that some of the other approaches offer this method can still be useful in many application where certain factors limit the ability of other methods to be used. Since this approach simply needs historic data to be implemented it can be easily done in almost any environment and doesn’t typically lead to unintentional miscalculations since only some interval of certainty will be known. With these characteristics this approach is popular in many fields and has been proven to better at anticipating the onset of failure modes for equipment in systems. Advances in technology only aid in the spread of this technique as better methods of data collection create more detailed descriptions of a systems historical behavior and create clearer pictures of what to expect in the future.

Hybrid prognostic approaches seek to incorporate multiple aspects of each of the approaches above to determine the future health of a system and therefore predict future metrics such as RUL and EOL. This approach mixes different methods in a way that allows them to aid each other in calculating the final predictions. By doing this it moderates the weight that each method has on the final decisions and allows each to account for deficiencies in the other. In addition it also prevents the overall cost of implementation from getting to high by leaving out components that might otherwise be critical in a single method approach and compensating for them with pieces from other methods. Considered as a kind of ensemble approach, this prognostic methodology could prove to be the most universal moving forward as this concept is applied to more systems and the benefits of such ideas are realized.

**Conclusion**

The field of technical prognosis is relatively new discipline in engineering that is a constant topic of research and is continuously being developed. Even though the material benefits of such approaches are somewhat difficult to quantify due to the small number of real world applications the future looks promising and with the pace industrial growth and a desire to limit cost in the maintenance process the implementation of such ideas only appears to be on the rise. With the only obstacles to wide spread use being cost and ease of integration the lower cost of necessary components and advance technology only seem to aid in the propagation of this idea.

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