Abstract: Condition based maintenance has been coming to the fore especially in recent decades and it is at the expense of conventional maintenance strategies. The main driving factors for this change are significant savings in operating costs, the effort to increase the reliability of complex systems and progress in embedded systems technologies. Predictive maintenance is based on continuous device monitoring, evaluating its condition and uses knowledge of technical diagnostics and prognostics. Technical prognosis comparing to technical diagnosis is still not well mapped and explored and is quite new area of interest as could be seen from conference papers and journals dealing with this problem. There is still a lack of real deployment and applications and even the taxonomy of methods is not well established. This paper aims to familiarize the reader with problems the technical prognosis is facing to, with the main goal of technical prognosis (Remaining Useful Life Estimation), with related methods including areas of application. This paper is more review of methods than description of specific implementation.

Keywords: TECHNICAL PROGNOSIS, TECHNICAL DIAGNOSIS, CONDITION-BASED MAINTENANCE, PREDICTIVE MAINTENANCE, MODEL-BASED PROGNOSIS, DATA-DRIVEN-PROGNOSIS, PROBABILISTIC PROGNOSIS, NEURAL-NETWORK, PARTICLE FILTERS, FUZZY SYSTEM, CLASSIFIER

1. Introduction

Conventional maintenance strategies (like corrective and predetermined) do not cover needs for modern complex and expensive systems. Keeping minimal maintenance expenses and prolonging the systems operability is one of the key element helping to survive in really competitive segment such an automotive or an aerospace industry. Condition based maintenance (CBM) approach seems to be suitable alternative to the conventional methods [11] and is considered as sub-group of the preventive maintenance [5] and [15]. Sometimes there is a term Predictive Maintenance used as a equivalent to CBM. Technically it is sub-group of CBM as defined in [5]. CBM deploys embedded diagnosis and prognosis to determine functional state of the equipment. Equipment degradation and prognosis of the potential failure is derived from the current and previously monitored state and is based on an evaluation of the operational conditions. Moreover this approach provides feedback and could help to prolong the uptime and system durability. Health and Usage Monitoring System (HUMS) could be mentioned as a typical example of the CBM system. HUMS could be used for monitoring the vibration/hum vibrations respectively rotor blades vibration. Analysis of those vibrations and proposed corrective actions leads to minimizing the vibration levels for specific flight modes and helps to prolong life-cycle of the helicopter fuselage, because vibration causes mechanical stress potentially leading to material cracks.

Even the start-up costs are quite high the long-term financial profit will be reached as is proven by several studies like an application of CBM strategy/system for wind power plants located in coastal waters [2]. Cracks and breaks often occur in the rotor blades material (usually fiberglass) due to weather conditions (hail, lightning) or due to possible collisions with birds. Cracks, unless are not fixed by special techniques (fill in with an adhesive material patch), gradually expand over time and sooner or later the entire blade has to be replaced. Such replacement is relatively expensive and, moreover, can take up to 20 days, after which the plant produces electricity, and thus leads to further financial losses. However, in case a permanent monitoring system is deployed, in this case, infrared thermography and ultrasound diagnostics, then any new crack could be detected with a reasonable time manner and crack growth could be monitored, its size could be predicted and optimal maintenance could be scheduled. A potential crack could be consequently fixed before irreversible damage occurs to the blade, and therefore causes the necessary replacement of high costs. This type of monitoring is part of the whole field of interest called – Structure Health Monitoring/Management - SHM. Typical areas of SHM application are airframe monitoring for cracks, hull of ships monitoring for cracks caused by corrosion etc.

CBM methodology is under extreme focus last decades. Older conventional maintenance methods are getting on background or are combined. Optimal maintenance of a multi unit system combines different maintenance strategies from cost point of view [22]. Reliability Centered Maintenance (RCM) is another approach combining all maintenance strategies to guarantee maximal reliability [15], [22].

There is a long history of the technical diagnosis/diagnostics comparing to technical prognosis/prognostics, which is quite new field of research interest. Prognosis and diagnosis are the key players in service planning, maintenance and in minimizing the down state of the equipment (aerospace is one of the critical area). Continuous increase of embedded system computation performance enables deployment of complex diagnostic algorithms in places, where it was not realistic several years ago. A huge number of data analysis are moved from specialized computation center directly into a monitoring systems and enable us to evaluate conditions in real-time [25]. Diagnosis focuses on detection, isolation and identifies failure when they occur comparing to prognosis, which focuses to predict failure before they occurs. It means that technical prognosis could be understood as an extending/complementary element of technical diagnosis. We are able to determine not only the current state but we are able to predict future state with some relevance level and probability based on the element and component degradation by using diagnosis and prognosis. The main goal of the technical prognosis is to make end of life (EOL) and remaining useful life (RUL) predictions that enable timely maintenance decision to be made [4]. Prognostics should be performed at the component of sub-component level and should involve predicting the time progression of a specific failure mode from its incipience to the time of components failure.

![Figure 1-1 Relation between Diagnosis and Prognosis per [23]](image-url)
RUL is estimated in discrete time manner and is usually computed with some period adequate to system dynamic and normal component/sub-component life time. We get sequence of time series of RULs, which should track ground truth within predefined limit. Trajectory of estimation is quite useful metric and could indicate the estimation accuracy or could be at least approximated. See next Figure 1-2 describing graphically the most important attributes associated with RUL like Estimation trajectory, estimation tolerance, RUL mean, RUL confidence interval etc.

Figure 1-2 Remaining useful life and associated attributes

2. State of the Art – Current Research Topics

A wide range of metal powders (from light alloys through steels to Technical prognosis, which is being considered as a specific usage, is Prognostic Health Management (PHM) quite new field of seems quite like still considered as the weakest point in CBM processing chain. There a lot of applications of prognostics method but the results and accuracy varies and are not always sufficient even researches claims so. Although a lot of patents have been registered and a lot of journal/conference papers have been published the area of technical prognosis is still quite new and not well researched, especially robust real system applications are still missing. Here are the main items of current research topics in area of technical prognosis:

Metrics for RUL Estimation – defining correct metrics, which enable us to compare different type of algorithms, methods and will help us in evaluating probability of prediction. Definitions for prediction horizon, prediction confidence interval, algorithm performance accuracy, algorithm performance robustness, algorithm precision, algorithm performance trajectory, have been proposed in [16], [17], [18], [23].

Prognostics Methods Classification – there is a lot of different prognostics methods which are suitable for a specific usage, depending on historical data availability, first principle model availability etc. Researchers/Engineers who are not deeply familiar with could be lost in the number of different models and approaches [19], [21].

Prediction Frameworks – there have been several prediction frameworks defining all steps needed for proper RUL prediction proposed during past years. All those frameworks are usually quite deployment area specific and are more use case studies than real long term applications. [1], [13].

New real application – use cases. Prognostics frameworks have been applied mainly to resolve following problems: Machinery/Materials (prognostics of flight actuators [3], crack growth monitoring in gearboxes of a helicopter [7]), Automotive where it is essential part of the OBD diagnostics. Electronics (electrical components failure, battery life prognosis [25]), Limited Sensing applications [4] applicable to all previous areas.

In next sections we will just briefly describe current applied methods of technical prognostics.

3. Prognostics Method

There is a significant number of prognostic approaches but the taxonomy is not clearly defined and consensually agreed yet. Most common classification splits prognostics approaches to free main groups: model-based prognosis, data-driven prognosis and experience-based prognosis [7], [19]. We can see prognostic taxonomy proposed in [11], [23].

![Figure 3-1 Taxonomy of prognosis in maintenance proposed in [11], [23]](image)

Each of the approaches has its own pros and cons and sometimes the hybrid methodology is used or methods are mixed within specific prognostic frameworks

Data Driven Prognosis

A data-driven approach use the ordinarily observed operating data (currents, voltages, calorimetric data power, vibration and acoustic signals, temperature, pressure, oil debris,) to track, approximate and forecast the system degradation behaviour [19]. Measured input/output data is the major source for getting a better understanding of the system degradation behaviour.

The data-driven (DD) approaches rely on assumption that the statistical data are relatively unchanged unless a failure occurs in the system. The common cause variations are entirely due to uncertainties and random noise and special cause variations (e.g. due to degradations) account for not attributed to common cause [11]. The data driven prognosis is based on statistical and learning techniques from the theory of pattern recognition. These range from multivariable statistical methods (static and dynamic principle component, linear and quadratic discriminant, partial least squares and canonical variate analysis) to black-box methods based on artificial neural networks (probabilistic neural networks, multi-layer perceptrons, radial basis functions), graphical models (Bayesian networks, hidden Markov model), self-organizing feature maps, signal analysis (filters, auto-regressive models, FFT etc.), decisions trees and fuzzy rule based systems [11], [12], [19]. Most of the work in data-driven prognostics has been applied in areas of structural health management. Many of those systems use vibration sensors to monitor the health of rotating machinery such as helicopter gearboxes. Some systems monitor the exhaust gases or the oil stream from the engine for contamination that could indicate a fault and it evaluation [19].

As a particular example we can mention applying the dynamic neural networks (DNN) on relatively accurate jet engine life prediction. New NNRAX (Neural Network Auto Regressive Model) has been developed, that enables authors to compute the stresses and temperatures at critical locations of gas turbine, in orders of less computation time than required by more detailed thermal and stress non-linear models. Real engine flight data are used as an input data set for the neural network training needs. Authors demonstrated model reduction technique for computing critical component parameters for RUL. Dynamic neural network model reduces the original thermal model of a turbomachinery component and the temperatures could be computed on the fly if needed. The results show that such data driven prognostic techniques can be applied with minimal error in RUL estimation while taking into account the actual operating conditions [14].
Dynamic Wavelet Neural Network (DWNN) utilization and RUL estimation of bearings could be mentioned as another example of the current research in this area. Neural network was trained by using vibrations signals from the damaged bearings with different level and signs of wear. This approach seems to be accurate enough for the diagnostic and prognostic purposes [24].

The ability to transform and to reduce large amount of noisy data into smaller amount of valid and meaningful data set is the big advantage of the data driven approaches. The big disadvantage is the dependency on quality and quantity of operating data, which is driving key element of the prognostic accuracy and reliability. Sometimes there is a problem especially in aerospace area that we are missing faulty data and we are not able to properly adjust/teach neural networks.

![Figure 3-2: The overall architecture of the WNN prognostic system introduced in [24]](image1)

In summary, the data driven approaches are preferred in case large amount of run-to failure data set is available in required operational range and in case system models are not available (eg. model is not known, too complex or not shared because of intellectual property).

**Model Based Prognosis**

Model-based approaches or so called physics-based are applicable, when relatively accurate mathematical model could be developed from first principle of system’s failure modes [10]. Models could be classified as a qualitative or quantitative. The quantitative model represents mathematical and functional relationship between the inputs and outputs of a system, while the qualitative models represents these relationships in terms of qualitative functions centered on different units in the system [23]. Model based approaches are based on analytical redundancy. A process contains analytical redundancy if an input or output can be calculated by using only other inputs or outputs. In the simplest case, the analytical redundancy is utilized by comparing the outputs from the real process and outputs from a process model, which is fed by the same inputs as the real process. Inconsistencies between the model and the real process are represented as a residuals. In case of no fault the residual should be close to zero (considering the model accuracy, signal noise etc.) and in the case of a fault the residual should be significantly non zero if it is sensitive to that particular fault. A number of residuals are used and they are made sensitive to different faults to achieve the fault isolation [13].

There is limited number of real application in this area and it could be considered as a most complex and accurate approach. Use cases defining model based approach has been created for suspension system in [13], where simple state-space model was defined and degradation measurement was involved as a slowly changing feature. Degradation measurements was connected to potential crack in suspension system and based on the system load (Palmer-Miner Law). Simulations proving this approach were performed.

Another use case was demonstrated on battery health prognosis, where Li-Ion battery degradation model was developed and based on changes in internal resistances (features), received from electro-impedance spectroscopy (EIS) the degradation in battery capacity e.g. RUL was estimated with acceptable accuracy (5-10%). Most of the technique for estimation was based on Bayesian network and particularly on particle filter approach [16].

Per [3] Impact Technologies has developed a diagnostic and prognostic framework for flight actuators. This model-based approach to prognostics and health management (PHM) deploys physical modeling and advanced parametric identification techniques, along with fault detection and failure prediction algorithms, in order to predict the time-to-failure for each of the critical, competitive failure modes within the system. This approach for condition-based maintenance seems to overcome ‘black-box’ based health-monitoring.

The big advantage of model-based approach is the possibility to take into account the physical knowledge of the system into the monitoring process, in other wording it means that we can reduce the amount of sensed parameters or we could determine some parameters directly from a model. Model adaptation to a system degradation is another advantage of these methods, because it helps to keep the prognostics accuracy at demanded level.

**Experience/Probability Based Methods**

These methods have the longest history, comparing to other previous approaches does not require too much detailed data and utilize different kinds of probability distribution functions - PDFs, which were parameterized for individual systems / subsystems / components based on production parameters, operational data, statistical data from history. The most commonly used distribution functions are normal, Weibull and exponential distribution. A typical distribution describing the failure rate versus time is called a "bathtub curve", which was first time published in 1965 and still has its merit. This prognostics methods also provides confidence level in which we operate and we can rely on. This is important for determining the probability and accuracy of our estimate. PDF is used in reliability analysis. This approach is still most common and is very often applied in the electrical industry.

![Figure 3-3: Graphical Comparison of prognostic methods [23]](image2)

**4. Conclusion**

Technical prognosis is a relatively new and still evolving engineering field that is struggling with limited number of real deployments. Recent developments, however, shows that the new methods, namely neural networks and fuzzy decision trees are applicable, provide satisfactory results and with further optimization it will be ready for real deployment even in embedded. Also, we can expect significant development and new use-cases of model-based prognosis, which will particularly benefit from the popular model-based development (MBD), which relies on precise and accurate first principle models. MBD will provide better access to more complex physical models. We can expect with more application of the CBM system as those systems are crucial in savings of operation costs and thus provide great value-added to big companies.
5. References


