Towards a Methodology for Design of Prognostic Systems

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ABSTRACT

An effective implementation of prognostic technology can reduce costs and increase availability of assets. As a result of the rapidly growing interest in prognostics, researchers have independently developed a number of applications for asset-specific modeling and prediction. Consequently, there is some inconsistency in the understanding of key concepts for designing prognostic systems. This further complicates the already-challenging design of new prognostic systems. In order to progress from application-specific solutions towards structured and efficient prognostic implementations, the development of a comprehensive and pragmatic methodology is essential. Prognostic algorithm selection is a key activity to achieve consistency throughout the design process. In this paper we present a design decision framework which guides the designer towards a prognostic algorithm through a cause-effect flowchart. Failure modes, application characteristics, and qualitative and quantitative metrics are used to determine an appropriate approach for the stated problem. The application of the methodology can reduce the time and effort required to develop a prognostic system, ensure that all the possible design options have been considered, and provide a means to compare different prognostic algorithms consistently. The framework has been applied to different prognostic problems within the power industry to illuminate its effectiveness. Case studies are presented to show how the framework guides designers through the choice of prognostic algorithm according to system requirements. The results demonstrate the applicability of the methodology to the design of prognostic systems which consistently meet the established requirements.

1. INTRODUCTION

Successful implementations of prognostic techniques provide benefits for maintenance planning which result in cost-effective operation of assets (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2007). Traditional approaches to design of prognostic systems have been focused on applying prognostic techniques on a case-by-case basis to create a fit-for-purpose solution for each application. These solutions are not easily transferable to other domains, and therefore impede the adoption of prognostics applications in industrial fields.

In order to generalize the adoption of prognostics techniques a clear and consistent justification of the use of prognostic algorithms is needed. This justification should provide mechanisms for prognostics model selection so as to integrate this criteria into the design flow. Accordingly, in this paper we present a generally applicable methodology to design prognostics applications systematically. The main goal of the methodology is to choose a priori an adequate prognostics algorithm that meets the system requirements. This requires shifting from taxonomy and classification of prognostics approaches towards a design framework for the systematic selection and design of prognostic applications based on strategic decision points.

The main contribution of this paper is the development of a design decision framework which integrates the knowledge needed to design prognostics applications. As a proof-of-concept, we have analyzed its usability in different applications within the power industry. The successful implementation of this framework can (1) reduce the time and effort required to develop a prognostic system; (2) ensure that all the possible design options have been considered; and (3) provide a means to compare different prognostic algorithms consistently.

The remainder of the paper is organized as follows: Section 2 presents the state of the art analyzing existing prognostics methodologies and classifications. Section 3 defines the overall methodology and the activities undertaken within the methodology. Section 4 specifies the design decision framework as a crucial activity within the design methodology. Section 5 presents the applicability of the design decision framework through the analysis of different case studies within the power industry. Finally, Section 6 draws conclusions and presents the future work of this research.

2. STATE OF THE ART

Due to the fast growth of prognostics applications, there are divergences in the literature with respect to the definition of prognostics (e.g., see (Sikorska, Hodkiewicz, & Ma, 2011) for different definitions). Literally, the word prognosis is a combination of two Greek words: *prog* - before; and *gnosis* - knowledge. Accordingly, a widely accepted prognosis definition is: *the ability to acquire knowledge about events before they actually occur* (Vachtsevanos et al., 2007). While in the medical field it has been used to predict the probable course of a disease, in the industrial field it is aimed at foretelling the Remaining Useful Life (RUL) of a component after a fault (or a specific failure mode) is diagnosed, i.e., prognosis specifies the fault-to-failure progression of an asset.

Accordingly, in this work we consider prognosis as the process of assessing the RUL of a component based on run-to-failure data, degradation-specific equations, or their combinations. These predictions must include mechanisms to represent the inherent uncertainty of a prognosis, and predict within reasonable bounds (Sankararaman, 2015).

Prognostics techniques focus on predicting fault progression and providing an early indicator of the RUL in order to implement asset-specific maintenance strategies, and thereby reduce costs and increase availability. In recent years a plethora of new techniques have been proposed for prognosis of engineering assets. Our goal is to design a prognostics methodology for the systematic design of prognostic applications including systematic prognostics algorithm selection. Accordingly, we review the scientific literature addressing the proposed prognostics algorithm classifications (cf. Subsection 2.1) and prognostics methodologies (cf. Subsection 2.2).

2.1. Classification of Prognostics Techniques

Two groups, data-driven and model-based prognostics techniques, have been identified by many authors as prognostics approaches derived from historical data and expert knowledge respectively (e.g., see (An, Kim, & Choi, 2015)). However, not all the proposed classifications in the prognostics arena have been limited to these groups. This situation emphasizes the general lack of agreement on fundamental design activities. There is no unique solution for the classification criteria, and depending on the viewpoint, the same approach can be classified in a different way. However, a generally accepted classification framework is needed for the systematic design of prognostic systems.

(Sikorska et al., 2011) define four groups for RUL prediction influenced by the ISO 13881-1 (ISO, 2004): knowledge-based, life expectancy, Artificial Neural Networks (ANNs), and physical models. Prognostics techniques are grouped accordingly, and their advantages and disadvantages are discussed. Despite ANNs having been widely used for many prognostics applications (Haykin, 1998), attributing a group level entity to a specific technique may not be accurate. Besides, due to the ambiguity of some groups, some techniques can fit in more than one group. For instance, Particle Filtering (PF) (Daigle, Saha, & Goebel, 2012) is grouped within life expectancy models. However, according to the engineering requirements, PF needs a degradation equation and observation data for RUL estimation. Therefore, it could fit within physical models as well. They define advantages and disadvantages and tips for using or avoiding each approach. This classification is useful for case-by-case comparison between alternative approaches, but it is necessary to link these approaches through a design process to integrate them seamlessly (e.g., design decision points to choose a model according to design requirements).

The classification proposed in ISO 13881-1 focuses on 12 different groups (ISO, 2004) (see Table 1). This results in a flat classification tree without hierarchies. It is possible to further refine this classification by gathering the proposed groups to create structured and non-overlapping boundaries and choose a model according to design requirements.

(Si, Wang, Hu, & Zhou, 2011) further develop data-driven statistical approaches based on the direct or indirect nature of the condition monitoring data. For direct condition monitoring data the following groups are addressed: regression based, Wiener, Gamma, and Markov processes; while for indirect condition monitoring data: stochastic filtering approaches, covariate hazard approaches, and Hidden Markov Model based approaches are covered.

(Lee et al., 2014) provide an overview of alternative approaches with their respective advantages and disadvantages. Unfortunately, they are considered separately and there is no link between them. The authors suggest a ranking method based on concepts of quality function deployment and house of quality (Govers, 1996) to rank the suitability of prognostics algorithms with respect to the specific problem. A combination of engineering attributes and customer needs is used to rank prognostics algorithms. The idea of ranking prognostics algorithms is interesting, but still the designer needs to assess the adequacy of the algorithm on a case-by-case basis.

(An et al., 2015) group approaches into model-based and data-driven techniques. The authors present practical options to select a prognostic algorithm identifying possible issues for data-driven (Neural Networks, Gaussian Process Regression) and model-based (Particle Filtering) techniques and comparing their results through a case study. Aligned with our design decision framework, the authors present a model selection tree with 3 decision points (1) existence of information: physical model, loading or no information; (2) damage growth: simple or complex; and (3) noise level: small or large. From these decision points four prognostic techniques are suggested. In our design framework we address a complete set of prognostic approaches including combinations of model-based and data-driven approaches. To this end, it is necessary to consider more design decision points, highlighting the cause/consequences of alternative paths in the tree.

(Liao & Kottig, 2014) classify prognostics approaches into Experience-Based (EB), Data-Driven (DD), and Physics-Based (PB) models. From the combination of these approaches, they provide a comprehensive overview of hybrid approaches identifying the following groups: (1) EB with DD; (2) EB with PB; (3) DD with DD; (4) DD with PB; and (5) a combination of EB, DD, and PB. The proposed flowchart for hybrid approaches is influenced by this work (cf. Subsection 4.3). We complement this work by including (1) high-level drivers to select a hybrid prognostic configuration; and (2) different connections between DD and MB approaches.

Table 1 displays the approaches gathered in this subsection considering relevant grouping aspects and analyses if the approach addresses model selection aspects.

Table 1. Summary of prognostics classification approaches

Reference	Prognostic groups	MS
(Sikorska et al., 2011)	Knowledge-based, life expectancy, ANNs, & physical models	x
(ISO, 2004)	Behavioral models, statistical, probabilistic, ANNs, life expectancy, reliability based, deterioration based, knowledge based, rule based, causal tree, & case-based reasoning	x
(Si et al., 2011)	Data-driven	x
(Lee et al., 2014)	No grouping	✓
(An et al., 2015)	Model-based & data driven	✓
(Liao & Kottig, 2014)	Experience based, data-driven, physics based, & hybrid	x

Legend: MS: Model Selection; ANNs: Artificial Neural Networks

There are some papers in the literature that deal with model selection related issues (Lee et al., 2014; An et al., 2015). However, the addressed techniques are only a subset of the existing approaches for prognostics applications. As for the classification criteria, the common factors for all the reviewed approaches are the data-driven (including Neural Networks, reliability, and life-expectancy groups) and model-based (including behavioral and physical groups) techniques. Besides, it is possible to consider experience (knowledge) based techniques as another group, but there are not many techniques which can be grouped here other than Fuzzy logic. Therefore, for the sake of simplicity, we will not consider it as a separate group (see Section 4 for more details).

The classification of prognostic approaches is not of practical use without a clear connection with the system design process. It helps the designer to choose a group of approaches, but within the same group further design choices need to be adopted to select a suitable prognostics algorithm according to system requirements. This requires introducing engineering criteria into the classification trees in order to adopt prognostics design decisions systematically. To this end, we propose the transformation from classification-like approaches towards design decision-like flowcharts based on trade-off analyses and design decision metrics.

2.2. Prognostics Design Methodologies

The need to develop a generally applicable methodology has been recognized in the literature (Uckun, Goebel, & Lucas, 2008). However, some of the proposed approaches have used a particular solution technique (e.g., see (Peysson et al., 2009)), and others need to be developed further in order to be generally applicable. This subsection analyses some of the prognostics methodologies presented in the literature, to explain the direction of this work.

(Kumar, Torres, Chan, & Pecht, 2008) proposed a methodology for electronic products. To this end, they (1) identify the critical failures, (2) establish a healthy baseline based on monitoring data, (3) incorporate a physics-of-failure model into the prognostics model, and (4) evaluate the RUL based on the Mahalanobis distance from baseline. Although the hybrid approach reduces uncertainty, the method is not generally applicable because it may not be feasible for specific requirements (e.g., lack of run-to-failure data). For the sake of generality, prognostics model selection criteria is necessary instead of focusing on a specific prognostics algorithm.

(Uckun et al., 2008) identified the need of a universal methodology to design prognostics and health management systems and gather some of the key activities of the methodology (see Table 2). Some of these activities have been formalized: transformation from high-level requirements to business case (Saxena et al., 2012); (2) metric selection (Saxena et al., 2008); and (3) validation and verification tests (L. Tang, Orchard, Goebel, & Vachtsevanos, 2011). A key activity that the methodology must integrate is the definition and integration of metrics as a means to introduce consistency for alternative techniques. This standardization provides mechanisms to compare prognostics approaches consistently.

(Peysson et al., 2009) introduced a methodology to perform prognostics of complex systems using damage trajectory models. The methodology introduces a generic modeling formalism for system specification linking environment, mission and process (or resources) variables. The environmental model is specified using Fuzzy logic and the damage models used are abaci. The generalization comes from the formal system specification in order to perform prognostics of complex multi-component systems. However, the methodology lacks a generalized prognostic model selection process.

(Lee, Liao, Lapira, Ni, & Li, 2009) presented a methodology for the design of e-manufacturing systems comprised of the following steps: (1) streamline: identify critical components and sort/filter/prioritize data to ensure quality; (2) smart processing: evaluate degradation, predict performance, and diagnose the failure; (3) synchronize: use of advanced technologies (e.g., agents) to introduce transparency; (4) standardize: systematic prognostics selection, platform integration, and maintenance information standardization; (5) sustain: closed-loop life cycle design (real-time feedback); embedded self-learning; and user-friendly development. The methodology integrates the Watchdog Agent (Djurdjanovic, Lee, & Ni, 2003) for automated tool selection. It ranks prognostics algorithms based on process properties (stationarity, expert knowledge, cost, computation, data dimension, or prediction span) and implements the highest ranked technique. However, the prognostics techniques considered in this toolbox are a subset of data-driven techniques, and they do not include model-based and hybrid prognostics techniques.

Table 2 shows the approaches gathered in this subsection considering relevant design activities and analyses if the approach addresses model selection aspects.

Table 2. Summary of prognostics methodology approaches

Reference	Methodology steps	MS
(Kumar et al., 2008)	FMEA; health monitoring; baseline definition; anomaly detection; param. isolation; & PoF-load matching	x
(Uckun et al., 2008)	Requirements transformation; metric, fault, sensor and model selection; validation & verification	x
(Peysson et al., 2009)	System modeling; & prognostics analysis (damage evaluation)	x
(Lee et al., 2009)	Streamline; smart processing; synchronize; standardize; & sustain	✓

Legend: MS: Model Selection; PoF: Physics of Failure

In summary, there is no generally applicable methodology which suggests a prognostic technique according to the user requirements. To aid in this process we introduce a formal procedure for the design of prognostic systems in order to approach the task systematically. This should simplify prognostic system design, and avoid repetition of redundant process steps for every application.

3. METHODOLOGY OVERVIEW

The proposed methodology framework assumes four design stages: (1) fault coverage, (2) model selection, (3) requirements transformation, and (4) validation and verification. Prognostic system developers must consider each in turn. Figure 1 depicts the generic prognostics methodology structuring these activities to meet the design requirements.

From the literature analysis some of these steps have been identified (cf. Subsection 2.2). The four stages integrated in the methodology are:

- Fault coverage or Failure Mode (FM) choice through formal criticality assessment techniques (e.g., FMECA (US Department of Defense, 1980), importance measurements (Borgonovo & Apostolakis, 2001)). Applications may prioritize a single fault type, aging behavior, or a number of important failure modes.
- Systematic prognostics model selection: a prognostic system must contain a model of degradation. This model can be simple (e.g. linear decrease of a single parameter) or more complex. It could be derived from data, or based on engineering understanding (e.g. a physics-of-failure model). According to available engineering resources, the failure mode of interest, and application specific requirements, this activity determines which is the best prognostics model.
- Transformation from high-level requirements into application specific metrics (e.g., see (Saxena et al., 2012)). This step introduces consistency by defining a transformation step to evaluate different prognostics models under the same criteria, i.e., prognostics metrics.
- Validation and verification: validate the proposed model according to the prognostics metrics (e.g., see (L. Tang et al., 2011)).

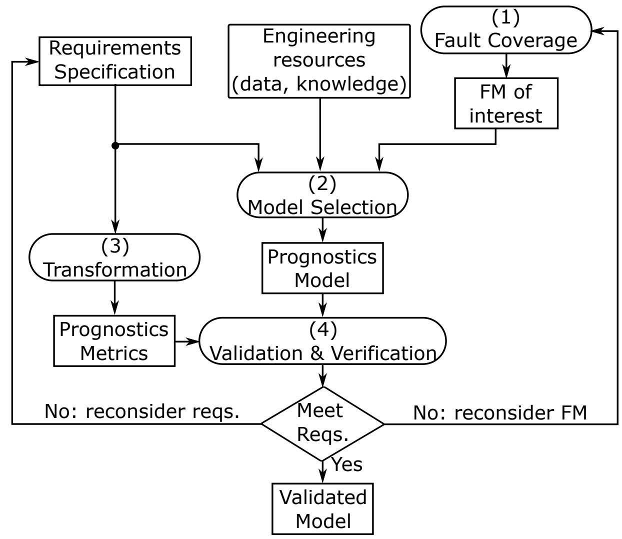

Figure 1. Generic methodology for prognostics

The choices made throughout the methodology impact the immediately connected steps, and may lead to iteration of previous steps. For instance, if system requirements are not met, the designer should reconsider the initial system requirements or the adopted failure mode.

While all the outlined activities are important for the design of prognostic applications, the main focus of this paper is on prognostics model selection. We plan to address the remainder of the design activities in forthcoming publications (see Section 6).

4. DESIGN DECISION FRAMEWORK FOR MODEL SELECTION

To present a comprehensive model selection decision framework, the applicability of different algorithms must be well understood. To synthesize this knowledge, we define a design framework based on strategic decision points, developed by analyzing case study prognostic systems. Enough cases have to be considered that general guidance can be usefully extracted, and also that a broad set of differing requirements are represented. The framework guides the designer through the prognostics algorithm selection process illuminating the trade-offs and cause-effect influences of alternative design decision points.

The approaches presented in the scientific literature focus on comparing alternative algorithms by implementing quantitative metrics (e.g., error, cost) after the development of the algorithm as post-implementation indicators. This approach results in a case-specific analysis that increases the design cost due to the need of implementing alternative algorithms for the same application. Interestingly, there is room to guide the designer in the pre-implementation phase towards an adequate prognostic algorithm by examining relevant design options, e.g., data properties; computational complexity; degradation patterns; failure thresholds; or uncertainty management.

Existing prognostic approaches are classified into three high-level groups: data-driven, model-based, and hybrid prognostic techniques. *Data-driven* techniques use monitoring data to fit a model of system behavior to the historical run-to-failure data (see Subsection 4.1). *Model-based* techniques require system knowledge in the form of the system's degradation equations (see Subsection 4.2). *Hybrid* approaches emerge in different configurations arising from the (intra or inter) combinations of data-driven and model-based techniques. Input requirements for the *hybrid* approaches depend on the hybrid configuration itself (see Subsection 4.3).

The selection of the high-level prognostics algorithm group is driven by the available engineering resources. That is, when run-to-failure data or knowledge of system's degradation equation is available, data-driven or model-based approaches are selected respectively. However, when both engineering resources are available, the selection of the high-level group incurs a trade-off decision between the availability of statistically significant run-to-failure data and complexity of the degradation equation. It may be the case that the degradation equation is too complex to model the system behavior accurately. Accordingly, data-driven techniques can be selected, provided that statistically significant run-to-failure data is available. Otherwise, hybrid prognostics techniques can be selected if the complexity is manageable and there is enough run-to-failure data.

Once the high-level prognostics group is chosen, other design criteria are used to trace a path through the group-specific flowchart, i.e., requirements and failure mode of interest.

4.1. Data-Driven Approaches

Data-driven prognostics algorithms rely on the available data to fit a model of the system behavior. The data must include run-to-failure conditions of the component under study in order to predict the RUL. Generally data-driven approaches are based on statistical pattern recognition and machine learning techniques. The main *assumptions* of data-driven approaches are that (i) the statistical features remain unchanged until a failure occurs or they change in a predictive way as the fault progresses; and (ii) availability of run-to-failure data. Thereby, the quality of the dataset determines the performance of the data-driven prognostic application. In some fields it is difficult to obtain the run-to-failure data (e.g., safety-critical or new systems).

Assuming that data-driven approaches have been selected as appropriate solutions for the application under study, the design decision process starts by examining uncertainty requirements for RUL estimation. Adequate management and representation of the uncertainty is necessary to predict the RUL with confidence, especially for safety-critical systems (Sankararaman, 2015). The deterministic estimate of the RUL may not be an adequate indicator because of its lack of judgment about the inherent uncertainty of the system. While the confidence intervals over the RUL provide a means to bound the estimation, the Probability Density Function (PDF) of the RUL estimation not only determines RUL bounds, but can also be propagated for system level uncertainty assessment. Consequently, the most accurate and potentially useful prognostics estimation will include the PDF of the RUL estimation.

Therefore, the first decision point evaluates if it is necessary to include the PDF of the RUL or not (see Figure 2). Accordingly, different prognostics algorithms can be selected.

If there is no need to extract the PDF of the RUL according to design requirements, there are alternative solutions depending on the complexity of the data, prediction span (short-term or long-term prediction), system specifications, available dataset, and knowledge of reliability distributions. Monotonicity (*m*) is used as a measure of the data complexity calculated as follows (Coble, 2010):

$$m = mean(|\frac{\#positive\frac{d}{dt}}{n} - \frac{\#negative\frac{d}{dt}}{n}|) \qquad (1)$$

where n is the number of data windows in the dataset and t is the time scale. Monotonicity is a relevant degradation parameter under the assumption that an asset will not go through repair until reaching the system failure.

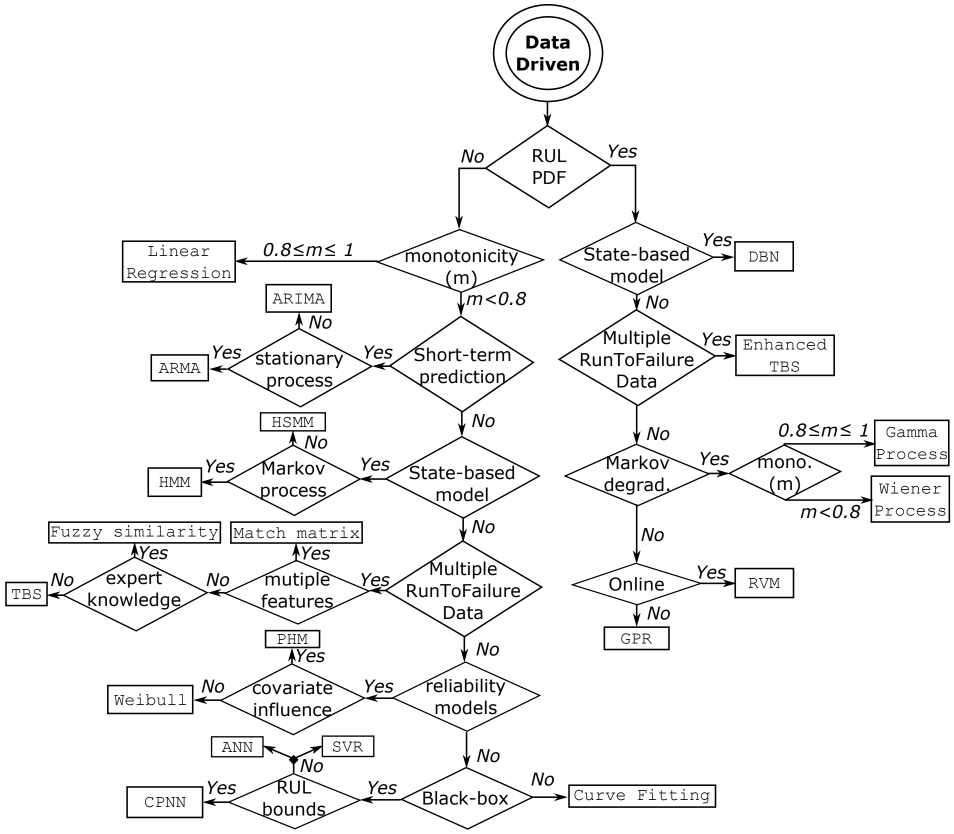

Figure 2. Flowchart for data-driven algorithm selection

If the data reflects a simple linear monotonic degradation ($0.8 \leq m \leq 1$) `Linear Regression` is an appropriate solution for RUL estimation (e.g. see (Rudd, Catterson, McArthur, & Johnstone, 2011)). However, if the data is not clearly monotonic ($m < 0.8$), more sophisticated techniques are needed. If the goal is to perform a short-term prediction (e.g., 1 step ahead prediction), linear time-series models provide an easy to implement and accurate prognostics implementation (Ling, 2013): `ARMA` models are better suited for weakly stationary processes, while `ARIMA` is a generalization of the ARMA model able to deal with non-stationary processes. A weakly stationary process must satisfy two conditions: mean and variance must be constant; and the autocovariance between X_t and $X_{t+\tau}$ must only depend on the lag τ. (Ling, 2013) introduced a Bayesian updating method for ARIMA models for uncertainty management.

For long-term prediction models, the next decision point is if the designer has knowledge of the system's state-space specification. State-based models define the system behavior through a multi-state specification transiting from a healthy state towards a failed state through multiple degradation states. In `Hidden Markov Models (HMMs)` (Tobon-Mejia, Medjaher, Zerhouni, & Tripot, 2011) the state is not directly observable, but it is deduced from observations. HMMs hold the Markovian assumption (future states are independent of all past states but the current one — independent degradation) which may be too restrictive for some systems. To overcome this assumption `Hidden semi-Markov Models (HSMM)` were proposed assuming a general distribution between states (Tobon-Mejia et al., 2011). With HMM and HSMM it is possible to calculate confidence values with the deterministic RUL estimation.

However, if it is not possible to specify the system behavior through state-based approaches, the system's behavioral pattern may be inferred from past historical experience. If multiple run-to-failure datasets of the same component are available, case-based reasoning approaches may be implemented. These techniques analyze data, define the health index (or baseline) based on data features, and accordingly evaluate if the new test data is healthy or not and predict the RUL. These approaches assume that components used for testing and training go through the same degradation process and require multiple run-to-failure histories to reuse knowledge and create predictions. If the available dataset has multiple different features `Match Matrix` is an appropriate solution (J. Liu, Djurdjanovic, Ni, Casoetto, & Lee, 2007). Match matrix improves ARMA models for long-term multivariate predictions, but it suffers from computational efficiency. Otherwise, if the dataset has a single feature, distance based approaches are more efficient for online applications. If there is expert knowledge to define the similarity or difference among alternative runs, `Fuzzy-Based Similarity` (Zio & Maio, 2010) evaluates the distance between alternative run-to-failure data based on Fuzzy membership functions instead of crisp distance evaluations. For online univariate implementations without expert knowledge, `Trajectory Based Similarity (TBS)` (Tianyi, 2010) approaches could be implemented.

If there is little run-to-failure data and the designer has knowledge of reliability models, the next decision point evaluates if it is necessary to take into account covariate influences (i.e., external factors). If so, the `Proportional Hazard Model (PHM)` (and its variants) can estimate the RUL considering external environmental influences on the component's lifetime (Gorjian, Ma, Mittinty, Yarlagadda, & Sun, 2010). For univariate reliability models, `Weibull` regression approaches (Trappey, Trappey, Ma, & Tsao, 2014) are well suited for non-monotonic data. Weibull based regression approaches require fitting the data according to the Weibull distribution parameters. Note that the Weibull distribution can be adapted to a variety of reliability distributions by fitting the parameters (e.g. exponential, Rayleigh) to provide the corresponding failure time distribution.

If the designer does not have practical knowledge of reliability distributions, it is still feasible to implement a `Curve Fitting` approach in order to fit the data with, for example, a polynomial function. Otherwise, black-box prognostic approaches estimate the RUL without interpreting the transformation process from the input data towards the output data, i.e., RUL estimation. These approaches may be useful for complex applications in which it is difficult to come up with a relationship between the input and output data.

Both `Artificial Neural Networks (ANN)` (Haykin, 1998) and `Support Vector Regression (SVR)` (Smola & Schlkopf, 2004) are semi-parametric black-box approaches suitable for prognostics analyses. ANN is a widely adopted black-box prognostic technique which provides a deterministic estimate of the RUL prediction. SVR estimates the functional relation between input and output random variables under the assumption that the joint distribution is completely unknown. The model created by SVR depends only on a subset of the training data.

For the SVR the kernel function parameters have to be estimated from the data, while for ANNs the architecture needs to be determined. The estimation of these parameters constrain the accuracy of both techniques. Another difference is that ANN suffers from the local minimum problem, while SVR gives globally optimal solutions. Probably, the wider acceptance of ANN is because there are many software implementations for ANNs, while fewer easy-to-use implementations are available for SVR. To provide RUL confidence intervals, ANNs have been extended towards `Confidence Prediction Neural Networks (CPNN)` (Khawaja, Vachtsevanos, & Wu, 2005).

As for the approaches which estimate the PDF of the RUL, the first decision point analyses if the system's state-based specification is available or not. If it is available, `Dynamic Bayesian Networks (DBN)` are a feasible option (Iamsumang, Mosleh, & Modarres, 2014). DBN models can be specified using graphical models making them an appropriate framework for the prognostic assessment of complex systems. If the state-based specification is not available, but there are multiple run-to-failure data histories, an `Enhanced TBS` approach can be implemented (Lam, Sankararaman, & Stewart, 2014).

Otherwise, if the degradation process can be represented with the Markovian memoryless property, there are different options depending on the monotonicity of the dataset: if the dataset represents a monotonic degradation pattern ($0.8 \leq m \leq 1$) `Gamma process` based prognostic implementations are feasible (Son, Fouladirad, & Barros, 2012); otherwise, `Wiener process` is more appropriate for non-monotonic degradation patterns (S. Tang, Yu, Wang, Guo, & Si, 2014). Both approaches require fitting the data to the process-specific parameters.

Finally, if the degradation process does not adhere to the Markovian process, data/function-dependent techniques are considered. These techniques require choosing correct parameters and functions to fit the actual data. Namely, `Relevance Vector Machines (RVM)` (Tipping, 2001) and `Gaussian Process Regression (GPR)` (Rasmussen & Williams, 2006) approaches require choosing an appropriate Kernel and covariance functions respectively. The final performance of RVM and GPR depends on the chosen data and function (Goebel, Saha, & Saxena, 2008). GPR is a Kernel method with Bayesian treatment for regression. It integrates multiple variables by fitting a normal distribution and then applies Bayes' rule to predict the future based on the past. However, it has relatively expensive memory and CPU requirements, and therefore may not be suitable for online operation. One solution to this problem is to distribute the implementation as in (Saha, Saha, Saxena, & Goebel, 2010). RVM is a Bayesian-inference inspired implementation of Support Vector Machines. See (Yan, Liu, Han, & Qiu, 2013) for a RVM application and see (Goebel et al., 2008) for a comparison between RVM and GPR (and ANN).

The flowchart for data-driven algorithm selection has been designed symmetrically with respect to the uncertainty requirements for the RUL specification. The majority of approaches which estimate the probability density function of the RUL, extend their non-PDF counterpart techniques including mechanisms for uncertainty analysis and representation, i.e., DBN generalizes HMM; enhanced TBS generalizes TBS; and RVM generalizes SVR.

The order of the model-selection decision points defines priorities for the prognostics algorithm selection process. The ordering is dependent on the *preference* of the system designer. The flowchart in Figure 2 prioritizes system knowledge (e.g., state-based specification) with the idea that system knowledge provides added value compared with generic prognostics approaches (e.g., curve fitting, black-box techniques). In other words, situation-specific prognostics algorithms are prioritized with respect to generally applicable techniques. Note that other orderings are also possible according to the designer's preference (e.g., complexity of the prognostic technique implementation). An interesting extension would be to parametrize decision points according to different properties (e.g., system knowledge, complexity) resulting in different algorithm selection flowcharts. This way, the decision points can be rearranged dynamically according to user-defined preferences (see Section 6).

4.2. Model-Based Approaches

For some safety-critical systems, and when the new system has not been produced yet, data-driven approaches are not viable because there will not be enough run-to-failure data to apply data-driven techniques — although there are exceptions such as the use of high fidelity simulators which can produce the necessary run-to-failure data (e.g., see (McGhee, Galloway, Catterson, Brown, & Harrison, 2014)). In these cases model-based prognostic approaches can be considered. The selection of model-based prognostic techniques is motivated by the availability of knowledge of the physical degradation phenomenon, or both knowledge of the degradation equation and actual observations (see Figure 3).

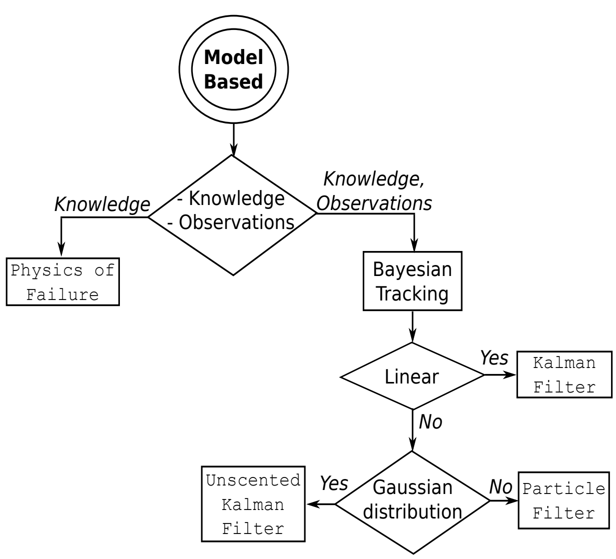

Figure 3. Flowchart for model-based algorithm selection

If there are no observations and only engineering knowledge is available, a `Physics of Failure (PoF)` model should be created defining the system degradation behavior through physics of failure equations. PoF approaches use the system's degradation properties (e.g., material, loading conditions, geometry) to identify degradation trends (typically due to over-stress or wear-out) and estimate the RUL (Vachtsevanos et al., 2007).

If observations are available in conjunction with the engineering knowledge, the RUL prediction can be solved via Bayesian tracking (or filtering) approaches. These approaches use two dependent equations to predict the future degradation of the system: the measurement equation which estimates the current state of the system (posterior PDF); and the process model which predicts the future state of the system using the current state of the system. The main *assumptions* to apply Bayesian tracking methods are: (i) the states follow a Markov process (the current state depends only on the previous state and actual conditions); and (ii) the observations are independent of the given states.

Among Bayesian tracking methods, the `Kalman Filter` focuses on the analysis of linear degradation trends. The following conditions must be satisfied to consider a function $f(x)$ as linear: (1) $f(x_1 + x_2) = f(x_1) + f(x_2), \forall x_1, x_2$; and (2) $f(\alpha x) = \alpha f(x), \forall x$.

However, if these conditions are not satisfied, there are other alternatives for non-linear degradation trend analysis. `Extended Kalman Filter (EKF)` and `Unscented Kalman Filter (UKF)` both are non-linear filters which assume Gaussian distribution for the states and noise (Daigle et al., 2012). Since the UKF provides better accuracy for highly non-linear degradation trends compared with the EKF (Daigle et al., 2012), in Figure 3 we have not added the EKF approach. For non-linear systems without the Gaussian distribution assumption, `Particle Filtering` approaches have been widely implemented with accurate results. (Daigle et al., 2012) showed in their case study that the accuracy and computational cost of UKF outperforms Particle Filtering.

Generally, model-based prognostics techniques are more specific (and complex) than data-driven techniques (e.g., PoF models). For simplicity, we have not further developed the flowchart in Figure 3 and we have included a discussion for asset-specific model-based approaches in Section 5.

4.3. Hybrid Approaches

Hybrid prognostics approaches combine different techniques to determine the RUL of the system under study. To this end, model-based and data-driven prognostic techniques are integrated through (i) the fusion of their respective results or (ii) using as input the results of complementary prognostic techniques. In this subsection we analyze the systematic design of combinations of model-based and data-driven techniques.

Influenced by the classification of hybrid approaches presented in (Liao & Kottig, 2014), the flowchart for hybrid prognostic approaches focuses on the design decision points which produce automatic combinations of model-based and data-driven approaches. From this analysis, alternative hybrid configurations arise based on the stated requirements.

Hybrid approaches combine Data-Driven (DD) and Model-Based (MB) techniques in series and parallel configurations (Penha & Hines, 2002). Series combinations (denoted with the symbol '+') use the outcome of one approach to feed another approach. Possible series combinations include intra-combinations (DD + DD) and inter-combinations (DD + MB, MB + DD) of prognosis approaches. The first approach on the series operation complements the second approach, which performs the prognostics evaluation. Parallel intra- and inter-combinations (denoted with the symbol '||') fuse the outcomes of DD and MB approaches through fusion techniques such as (Goebel & Eklund, 2007): bagging and boosting, fuzzy fusion, or statistics based fusion. As opposed to the series configuration, the parallel operation is interchangeable without influencing the result, i.e., MB || DD $\equiv$ DD || MB.

These configurations determine the goal of the combination of data-driven and model-based approaches: while series applications focus on parameter estimation (e.g., initial parameter estimation or measurement equation estimation); parallel applications are aimed at improving the accuracy of the prognostics application.

When designing hybrid prognostics applications it is possible to create them by (i) combining previously implemented data-driven or model-based approaches with other approaches; or (ii) implementing hybrid approaches upfront. If the results from the already implemented data-driven (or model-based) algorithm (selected according to the flowchart in Figure 2 or 3) are unsatisfactory, it is possible to combine it with other data-driven or model-based approaches. As Figure 4 depicts, this is the first decision point for hybrid prognostics approaches.

If the designer implements a data-driven approach, gets unsatisfactory results, and if they do not have PoF knowledge, it is possible to create *data-driven combinations* to improve the accuracy of the results. If the designer has datasets with different features or datasets of different scenarios of the same system, then parallel fusion combinations (i.e., $\mathtt{DD_1(x)}$ || $\mathtt{DD_1(y)}$, where `x` and `y` indicate different input datasets) may improve the system's prediction accuracy (e.g., see (J. Liu, Vitelli, Seraoui, & Zio, 2014) for an ensemble of SVR models).

Otherwise, if there is some form of expert knowledge it is possible to integrate it with the DD approach to improve the accuracy of the results, (e.g., see (Soualhi, Razik, Clerc, & Doan, 2014) for a combination of HMM with Adaptive Neuro Fuzzy Inference System (ANFIS)). Note that the expert knowledge considered for prognostics applications is implemented in the form of Fuzzy logic and not as rule-based or case-based systems used for diagnostics.

If there is no expert knowledge, it is feasible to use one DD approach as a parameter estimation technique in order to implement another DD approach with more accuracy, i.e., $\mathtt{DD_1(x) + DD_2(y)}$ (e.g., see (Z. Liu, Li, & Mu, 2012) for a complementary series combination of SVR and HMM).

Finally, if none of the above conditions are satisfactory, it is possible to fuse alternative DD approaches with the same dataset (i.e., $\mathtt{DD_1(x)}$ || $\mathtt{DD_2(x)}$, where x is the available dataset) to improve the accuracy of the RUL estimation (e.g., see (Hu, Youn, Wang, & Yoon, 2012) for an ensemble of multiple algorithms combined with a weighted-sum formulation).

Data-driven and model-based combinations complement each other providing mechanisms to strengthen possible deficiencies. If there exists expert knowledge, it is possible to combine data-driven, model-based, and expert knowledge in a single prognostic approach (e.g., use fuzzy logic to improve data-driven parameter estimation and accordingly, use the `Fuzzy + DD` configuration to estimate input parameters of a model-based algorithm). Surprisingly, we have not come up with any example that uses this configuration.

If there is no expert knowledge, the typical goal for hybrid prognostics approaches is the parameter estimation through complementary approaches. That is, a data-driven approach estimates input or initial parameters of a model-based approach (`DD + MB`) and accordingly, improves the accuracy of the final RUL estimation of the PoF model (e.g., see (Baraldi, Compare, Sauco, & Zio, 2013)).

Parallel combinations of MB and DD techniques (`MB` || `DD`) focus on improving the accuracy of the RUL estimation through fusion techniques (e.g., see (Baraldi, Mangili, Gola, Nystad, & Zio, 2014) for an ensemble of Kernel Regression models fused with PoF models). To the best of our knowledge, all the fusion configurations between MB and DD approaches are done with different input information due to the dissimilar nature of model-based and data-driven techniques.

As for the configurations comprised of *model-based combinations*, datasets with different features or scenarios of the same system could be combined to improve the final estimation (i.e., $\mathtt{MB_1(x)}$ || $\mathtt{MB_1(y)}$, where `x` and `y` indicate different input datasets). For instance, (Baraldi, Mangili, & Zio, 2012) implement an ensemble of Kalman Filter models. The other possible configuration for model-based intra-combinations is to add expert knowledge to model-based prognostics predictions in order to manage uncertainties (e.g.,

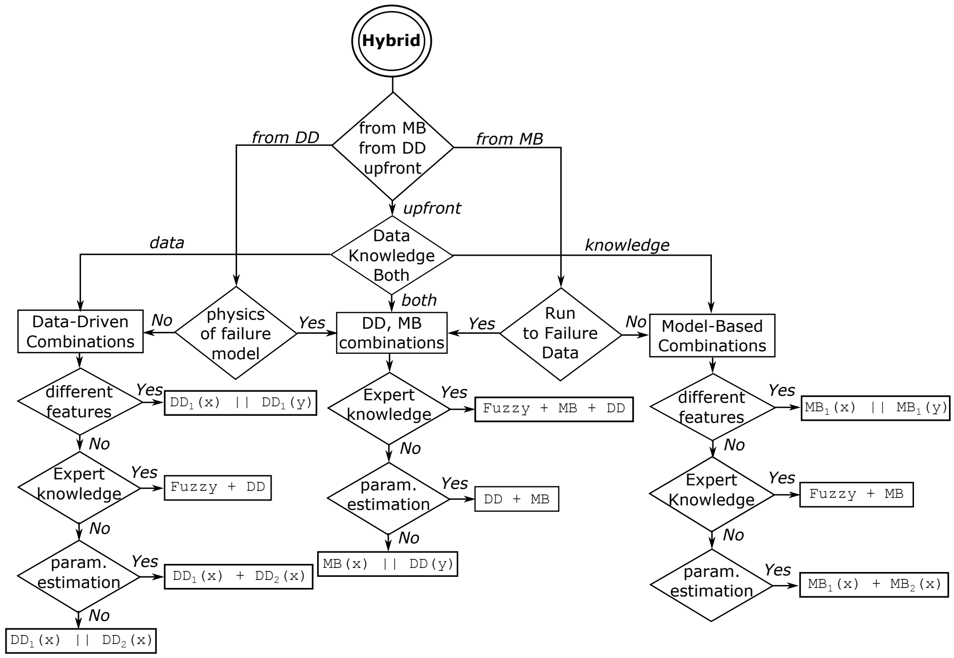

Figure 4. Flowchart for hybrid algorithm selection

see (Rodger, 2012) for Fuzzy multi-sensor data fusion with Kalman filtering).

Series and parallel combinations of model-based approaches with the same input dataset are scarce due to the lack of complementary properties between PoF techniques when combining or fusing two different degradation equations of the same system. An example of series combination with the same dataset configuration (i.e., $\mathtt{MB}_1\mathtt{(x)} + \mathtt{MB}_2\mathtt{(x)}$) is presented in (Yoon & He, 2015) using UKF to estimate the state of the degrading system, and Particle Filtering to estimate the RUL.

The flowchart for hybrid approaches provides a high-level prognostic algorithm combination guide (cf. Figure 4). This is done deliberately because low-level decisions should be adopted according to technique-specific details.

5. APPLICATION OF THE METHODOLOGY

In this section we will evaluate the design of three prognostics applications in the field of power systems in order to show the applicability of the design decision framework. Namely, the following assets will be examined: cables, transformers, and circuit breakers. Finally, we will assess the applicability of the proposed model selection framework through the analysis of different design requirements.

5.1. Cable Prognostics

There are different parameters which can indicate the fault-to-failure progression of cables such as impedance changes, physical damage, or partial discharge. Particularly, partial discharge accelerates electrical tree growth in the insulation material, and electrical treeing is one of the main causes of electrical breakdown in high voltage cables.

To the best of our knowledge, few attempts have been made to characterize a prognostics model for cables using physics-of-failure equations. In one example, (Dodd, 2003) defined a deterministic model for the growth of electrical tree structures and (Nyanteh, Graber, Edrington, Srivastava, & Cartes, 2011) classified different simulation models for partial discharge and electrical treeing including physics-based and stochastic models.

(Aziz, Catterson, Judd, Rowland, & Bahadoorsingh, 2014) pursued the modeling of the electrical tree growth using a `Curve Fitting` approach. Analyzing the design requirements for this application, we end up with the following set of decisions according to the data-driven flowchart in Figure 2:

(1) According to the design requirements, there is no need to extract the PDF of the RUL estimation. However, confidence bounds are necessary.
(2) The dataset is not monotonic: $m = 0.71$.
(3) The aim is to predict the RUL at least 1 hour in advance, i.e., long-term prediction.
(4) There is no information about the states of the system transiting through the electrical tree growth process before reaching the electrical breakdown.
(5) In total there are 25 run-to-failure data histories including multiple variables.

(6) There is no knowledge of reliability models.

(7) No black-box approach: explicitly model the transformation from input variables into RUL.

Therefore, the data-driven flowchart suggests to implement a `Curve Fitting` approach as was taken in (Aziz et al., 2014). However, if the designer decides to implement a black-box approach, the only feasible technique would be `CPNN` for uncertainty management.

If the run-to-failure histories in the dataset were enough to consider case-based reasoning techniques, the data-driven flowchart suggests `Match matrix` as an appropriate solution for prognosis of long-term multivariate systems.

5.2. Transformer Prognostics

(Abu-Elanien & Salama, 2010) presented a taxonomy for transformer physical aging mechanisms divided into two groups: (i) *transitive aging* reflects the rapid aging of the transformer due to abnormal conditions. Its possible *causes* are: highly distorted loads with harmonics, high ambient temperature, and overloading. It can be *assessed* through the measurement of the hot spot temperature. (ii) *Intransitive aging* assumes that the insulating material can withstand the designed stress. The only possible failure *cause* is the insulation deterioration. *Assessment* techniques include: degree of polymerization, dissolved gas analysis, detection of furanic compounds, recovery voltage measurement, and measurement of retaining tensile strength.

Different data-driven prognostics techniques have been presented to estimate the remaining life of transformers, e.g., (Zarei, Shasadeghi, & Ramezani, 2014) implemented an ANFIS model to estimate the end of life of a transformer based on dissolved gas analysis data samples; (Trappey et al., 2014) used linear regression and Weibull distribution to estimate the remaining life of the transformer based on furfural concentration and combustible gases.

To the best of our knowledge, only (Catterson, 2014) implemented a model-based prognostics application for transformers using a `Particle Filtering` approach based on the transformer's paper aging model. A model for paper aging is given in IEEE standard C57.91 (IEEE Power and Energy Society, 2011). The standard defines an aging acceleration factor based on the hot spot temperature. Accordingly, the implemented method estimates the RUL of the transformer through the degree of polymerization of the paper at its most aged point. According to the model-based flowchart in Figure 3, the design requirements proceed as follows:

(1) The degradation equation is available, and the hot spot temperature can be calculated from available observations. Besides, the process is Markovian and therefore, Bayesian tracking solutions are considered.

(2) The degradation of the transformer aging is not linear.

(3) There is no need to assume a Gaussian distribution for the state and noise.

In (Catterson, 2014) a Gaussian distribution was assumed to deal with the lack knowledge of the real behavior. However, as more information is available, the Gaussian assumption is no longer needed. According to the approach adopted in (Catterson, 2014) the model-based flowchart suggests the implementation of a `Particle Filtering` model.

5.3. Circuit Breaker Prognostics

Circuit breakers do not have a clearly defined physics-of-failure equation model. As pointed out recently in (Westerlund, Hilber, Lindquist, & Kraftnat, 2014) the ability to predict the aging of circuit breakers is not fully developed. Accordingly, data-driven techniques have been considered for circuit breaker prognostics.

There are failure precursor variables which indicate the degradation of circuit breakers such as SF_6 density, I^2T, or arc timing. (Rudd et al., 2011) implemented `Linear Regression` in order to extract a prognostics model based on SF_6 density data samples. These are the considered steps according to the data-driven flowchart in Figure 2:

(1) There is no need to extract the PDF of the RUL estimation. However, RUL confidence bounds are necessary.

(2) The dataset is monotonic: $m = 0.81$.

Therefore, we see that the flowchart effectively indicates the same approach as adopted in (Rudd et al., 2011). However, if we assume a more strict limit for the monotonic data assessment, e.g., $m > 0.9$, the designer will evaluate different design decisions (cf. Figure 2):

(1) There is no need to extract the PDF of the RUL.

(2) We have assumed that the data is non-monotonic.

(3) The aim is to predict the RUL some days ahead (long-term prediction) for repair purposes.

(4) There is no information about the possible states of the system transiting before the failure.

(5) There are not enough run-to-failure data histories.

Under the non-monotonic assumption, depending on the final design decisions it would be feasible to implement the following prognostics models: (i) `Weibull` based prediction (no covariance influence); (ii) `Curve Fitting`; or (iii) `CPNN`.

5.4. Analysis of Changing Requirements

To demonstrate the applicability of the model selection framework, in this subsection we will change the design requirements of the analyzed applications and examine the techniques suggested by the different flowcharts accordingly.

Uncertainty: assume that the PDF of the RUL estimation is needed for all the analyzed assets. The transformer application in (Catterson, 2014) already meets the stated requirement. The cable application in (Aziz et al., 2014) and the circuit breaker application in (Rudd et al., 2011) are redesigned according to the data-driven flowchart in Figure 2.

In both cases, the degradation pattern does not follow the Markovian process and system's state-based specification is unknown. For the cable application there may be enough run-to-failure data to implement an `Enhanced TBS`. For the circuit breaker model, there is only one run-to-failure history and therefore, `RVM` or `GPR` implementations are more appropriate for online or offline implementations respectively.

Accuracy: assume that (i) none of the analyzed applications meet the accuracy criteria; and (ii) there is no other engineering resource after the development of the applications. It is possible to combine the implemented approaches with other techniques according to the hybrid flowchart in Figure 4:

- For the transformer application the only feasible suggestion is to improve the parameter estimation (e.g., initial state, process error) of the model-based `Particle Filtering` technique through a data-driven approach, i.e., `DD + MB`, or using another model-based technique, i.e., $\mathtt{MB_1(x)\ +\ MB_2(x)}$.
- For the prognostic models developed for circuit breaker and cable assets, series or parallel implementations of different data-driven techniques can be considered in order to improve the accuracy of these applications, i.e., $\mathtt{DD_1(x)} \mid\mid \mathtt{DD_2(x)}$ or $\mathtt{DD_1(x)\ +\ DD_2(x)}$

6. CONCLUSIONS & FUTURE WORK

In this paper, a methodology to design prognostics applications is presented focusing on the model-selection problem. The main goal of the presented design-decision framework is to construct prognostic models systematically to reduce the effort required to develop a prognostic system and ensure the consideration of all the possible design options. Through different applications in the power industry the applicability of the proposed framework have been demonstrated.

In order to refine the framework and further demonstrate the applicability of the design framework, different prognostics applications will be implemented to reduce the possible subjective (qualitative) criteria. Besides, we plan to complete the methodology by integrating: (i) (automated) fault coverage analysis; (ii) transformation from requirements into prognostic metrics to compare different prognostic algorithms consistently; and (iii) validation and verification steps.

As a long-term goal we plan to develop a decision support tool, which builds semi-automatically prognostics models according to input requirements, engineering resources, and failure modes of interest. The design decision flowchart will benefit from meta-modeling techniques to reuse complex knowledge through automated design decision tools.

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