A Possibilistic Approach for Measurement Uncertainty Propagation in Prognostics and Health Management

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***Abstract*— In this paper, a similarity-based data-driven prognostic algorithm for the estimation of the Remaining Useful Life of a product is proposed. It is based on the exploitation of run-to-failure data of products, which are supposed to be characterized by similar operational conditions. The core of the contribution is the application of a possibilistic framework, namely a Random-Fuzzy Variable approach, for the representation and propagation of the measurement uncertainty, which is a crucial source of uncertainty in Prognostics and Health Management. The results obtained for a real application case as Medium and High Voltage Circuit Breakers, have shown a high prognostic power of the algorithm, which therefore represents a potential tool for an effective Predictive Maintenance strategy.**

Keywords*— *Data-driven, Measurement Uncertainty, Prognostics, Random Fuzzy Variable, Remaining Useful Life, Similarity

I. INTRODUCTION

The Remaining Useful Life (RUL) of a system is defined as the remaining time interval in which it is expected to meet its operating requirements. RUL estimation represents the core of the Prognostics and Health Management (PHM) programs which aim to a reduction of maintenance and life-cycle management costs, an increase of the systems availability and the adoption of predictive maintenance strategies [1,2]. Since prognostics deals with predicting the future behavior of engineering systems and it is almost practically impossible to precisely predict future events, it is necessary to account for the different sources of uncertainty that affect prognostics, and develop a framework for uncertainty quantification and management in this context [3].

In this paper, a novel prognostic model capable to deal with different sources of uncertainty is proposed. In particular, it represents an improvement of a similarity-based prognostic model already present in the literature. The main difference and enhancement is due to the application of a different mathematical framework for the representation and propagation of measurement uncertainty, which represents one of the crucial sources of uncertainty in PHM.

II. SOURCES OF UNCERTAINTY IN PHM

Prognostic predictions must deal with multiple sources of error like modeling inconsistencies, system noise and degraded sensor fidelity. The most prominent sources of uncertainty in PHM are [3-6]:

1) Measurement uncertainty: data collected through sensors are affected by a measurement uncertainty due to sensors inaccuracy. In particular, two kinds of uncertainty sources can be considered, typically referred to as systematic and random.
2) Present uncertainty: very often, a preliminary step in PHM is the current state estimation of the system for which RUL prediction is required. The state estimation is typically performed applying filtering approaches (Kalman filtering, particle filtering, etc.) to the data collected through sensors. The measurement uncertainty of the data and the stochastic nature of the filtering approaches are unavoidably reflected in uncertainty in the definition of the system state, which describes the lack of knowledge regarding the "true" state of the system.
3) Future uncertainty is probably the most influential source of uncertainty in PHM as future operational conditions (loading, environmental, usage conditions) cannot be precisely known in advance, but only assumptions about them can be made.
4) Model uncertainty: it is practically impossible develop models that predict the underlying reality accurately. Model uncertainty includes model parameters stochasticity, process noise, as well as a contribution due to under-modeling issues, determined by different factors such as the ignorance of certain failure modes in the analysis or, in case of application of data-driven approaches, the lack of data describing possible failure scenarios.
5) Prediction method uncertainty: once quantified, the above sources of uncertainty have to be accurately propagated on the final RUL forecast. Especially when dealing with different probability distribution families and/or non-parametric distributions, uncertainty propagation methods introduce some approximations, which lead to additional uncertainty. A typical example is represented by sampling-based approaches, such as Monte Carlo (MC) simulations, which are widely used for RUL prediction; in this case, the use of limited number of samples introduces uncertainty about the probability distribution of the RUL.

III. SIMILARITY-BASED PROGNOSTIC MODELS

Many methods for uncertainty processing in PHM are present in the literature. A widely spread alternative present in the literature is represented by similarity-based prognostic models. The hypothesis for the application of such models is that a set of run-to-failure degradation patterns are collected in a reference library. An evaluation of similarity between the test degradation pattern (monitored degradation pattern for the item for which the RUL has to be predicted) and the reference trajectory patterns in the database is then performed in order to estimate the RUL of the test item. An example can be found in [7] where the similarity is assessed based on the computation of a distance value (1):

$$d_i = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(y_k - y_{ik}\right)^2} \tag{1}$$

which corresponds to the Root Mean Square Error (RMSE) between the test product (in the followings, also referred to as target product) and i-th library specimen patterns. In particular, y_k (y_{ik}) corresponds to the observed degradation for the test product (library specimen i) at cycle (or generally time stamp) k and K is the total number of observed cycles for the test pattern. A small d_i means that the two profiles are similar or, equivalently, similar degradation processes characterize the two products, whereas large distance values are related to products that are subject to different degradation mechanisms and that should be excluded in the estimation of the RUL of the target product since are representative of different working conditions. This has allowed, in [7], to select a subset of reference items (in the following referred to as sub-fleet), showing the lowest values of distances (computed as in (1)). The knowledge of the run-to-failure degradation patterns of such items is then extracted in terms of statistical distribution of degradation rate (i.e. degradation increment between two consecutive cycles) and processed through MC simulations in order to forecast the future degradation pattern of the test product and obtain the related RUL estimation [7,8].

A similar approach is used in [9] where the sub-fleet is extracted applying a Kolmogorov-Smirnov test for the detection of the subset of reference products showing higher statistical similarity in terms of statistical distribution of degradation rate.

Finally, another common approach is to compute the target product RUL as function of the RUL of the reference items and their degree of similarity with respect to the test product. In [10], for instance, the relationship between the RUL of the test product and fleet products is determined through the application of an Artificial Neural Network.

A very simple and effective methodology is based on the computation of the test RUL as weighted sum of the fleet products RUL:

$$RUL = \frac{\sum_{i=1}^{N} w_i RUL_i}{\sum_{i=1}^{N} w_i} \tag{2}$$

where index i refers to the i-th reference product and N is the number of products composing the library. It is trivial to understand that computing the target RUL as weighted sum of the RUL of a set of products which are supposed to be characterized by similar operational conditions allows one to implicitly introduce some knowledge about the future loading and operational conditions that the test product will face in the rest of its life. In particular, weight w_i assigned to the i-th training reference pattern is computed in such a way to take into account how much similarity its degradation pattern has exhibited with respect to that of the target product during the observation window (i.e. the time interval for which the target product degradation pattern has been monitored).

Typically [11,12], the weighting coefficients w_i are computed though a bell shaped function:

$$w_i = \exp\left(-\frac{sc_i}{\beta}\right) \tag{3}$$

where the similarity coefficient sc_i, similarly to the distance d_i computed in (1), is function of the sum square error between the degradation patterns of test product and library specimen i. As for parameter β, it is an arbitrary parameter that can be set by the analyst in order to introduce the desired degree of selectivity (i.e. if β is small, few specimens are influential).

A. Proposed Model

In this paper, a novel similarity-based prognostic approach is proposed. In particular, the test product RUL is computed through (2), where the weighting coefficients are obtained mapping the distance value d_i (which gives information about patterns similarity) into weighting coefficients through a function $g(\cdot)$:

$$w_i = g\left(d_i\right) = \frac{1}{\sqrt{2\pi\sigma_g^2}}\exp\left(-\frac{\left(d_i - d_{\min}\right)^2}{2\sigma_g^2}\right) \tag{4}$$

Function $g(\cdot)$ represents a Gaussian probability density function (PDF), characterized by mean value equal to $d_{\min}$ (the minimum value among all d_i values, $i = 1, \ldots, N$) and standard deviation σ_g, such that higher weights are assigned to reference products at lower distance d_i. It is assumed, indeed, that the future operational conditions of the test product will be more similar to those of the products exhibiting higher similarity in correspondence of the observation window. This assumption allows managing and mitigating the influence of uncertainty about the future loading, operating, environmental, and usage conditions.

A further step introduced in this paper is also to consider the measurement uncertainty affecting the observed degradation patterns. In particular, the measurement uncertainty will be handled in a possibilistic framework, namely through a Random-Fuzzy Variable (RFV) approach, which has been shown to be an effective methodology to take into account, within the same mathematical framework, both the random and systematic contributions to measurement uncertainty, as will be shown in the next Section IV.

A key factor in the application of the algorithm is the value assigned to σ_g, that, similarly to parameter β in (3), introduces

the desired degree of selectivity. In Section VI, a strategy for a suitable choice of this parameter will be shown.

IV. Measurement Uncertainty: the RFV Approach

The RFV approach has been defined in the last years, as an alternative, more general solution than the probabilistic one, for the representation of the measurement results [13]. Without entering the mathematical details, this approach is based on the mathematical Theory of Evidence, which, defined by Shafer in the seventies, represents a quite new and promising mathematical theory.

When this approach is used to handle measurement uncertainty, the measurement results are expressed in terms of some particular variables, the Random-Fuzzy Variables [13,15]. As shown in Fig. 1, an RFV is composed by two functions, called possibility distribution functions: $r_{int}(x)$ and $r_{ext}(x)$. The presence of two PDs allow to consider separately, but in a unique mathematical object, the effects of all possible contributions to uncertainty on the measured value. In particular: PD $r_{ext}(x)$, called *external PD*, represents the effects of all contributions to uncertainty on the considered measured value. Hence, this PD provides the global effect on the final measurement result of all contributions to uncertainty affecting the measurement procedure. On the other hand, PD $r_{int}(x)$, called *internal PD*, represents the effects, on the considered measured value, of all systematic contributions to uncertainty.

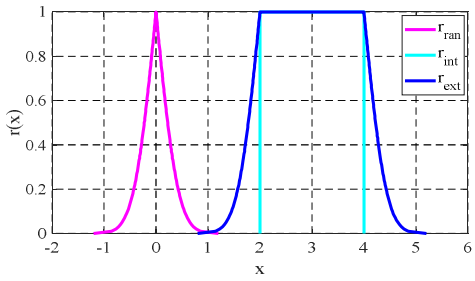

Fig. 1 Example of RFV

If an RFV is given, by decomposing its PDs $r_{int}(x)$ and $r_{ext}(x)$, it is possible to obtain also the *random PD* $r_{ran}(x)$, so that it is possible to know which are the effects, on the final measured value, of the different contributions to uncertainty: the random ones, given by $r_{ran}(x)$, and the systematic ones, given by $r_{int}(x)$.

An important advantage of these variables is that each RFV provides all confidence intervals at all levels of confidence of the measurement result. In particular, because of the possibilistic normalization condition, the PDs (internal, random and external PDs) of an RFV are always defined in interval [0, 1]. If a cut of the RFV is taken at level $\alpha \in [0, 1]$, then a closed interval is obtained, called α-cut, and this α-cut is the coverage interval, associated to the measured value, corresponding to the coverage probability 1-α [16,17]. Another great advantage of these variables is that, when two RFVs must be combined through a measurement model, appropriate operators, called *t*-norms, can be applied to combine PDs $r_{ran}(x)$ with each other and PDs $r_{int}(x)$ with each other, in closed form formula [16-19]. This allows one to obtain in a quite straightforward way how the contributions combine through the measurement procedure.

However, as in depth discussed in [16,17], the specific *t*-norm to be applied for the PD combination is not univocally defined, since, in any application, there is the possibility to choice the more suitable operator, according to all the available metrological information, which is related to both the nature of the uncertainty contributions and the way they affect the measurement procedure. In the next section, it is shown how the RFV approach can be applied to the application considered in this paper and how the metrological information is exploited.

V. Application of the RFV Approach to the Proposed Prognostic Model

For each measured value y_k, random and systematic contributions to uncertainty are considered. In particular, it is supposed that the random contributions affecting each measured value distribute according to a Gaussian PDF, having a standard deviation σ. On the other hand, it is supposed that the systematic contributions affecting each measured value distribute over an interval, and no PDF is known in this case. The interval is centered on the measured value y_k and its width is not constant but it is related to the measured value itself. In particular, if a relative error e is considered, the interval will have a semi-width $y_k \cdot e$. In our examples, σ=0.1 and e = 0.1 are assumed, being typical values for the considered application case.

Under the above assumptions, it is possible to build, for each measured value, an RFV, which shows all contributions to uncertainty and all coverage intervals in a unique variable. In particular, according to the available information:

- the random PD $r_{ran}(x)$ represents the random contributions to uncertainty and therefore is built from the given Gaussian PDF, by applying a suitable transformation, called probability-possibility transformation [17,20]. This transformation allows to transform a PDF into an equivalent PD which preserve all the coverage intervals and corresponding coverage probabilities, thus maintaining all the relevant metrological information included by the initial PDF;
- the internal PD $r_{int}(x)$ represents the systematic contributions to uncertainty and therefore is built according to the given interval. In particular, in Shafer's theory of evidence, the situation when an interval of variation is given and no PDF is known is called *total ignorance*, and is represented by a rectangular PD over the given interval. Without entering the details here, let us only say that the meaning of a rectangular PD is very different from the meaning of a rectangular PDF [17].

It follows that the RFV shape of the RFV associated to each measured value is like the one shown in Fig. 1 in cyan and blue lines. Of course, the mean value and width of the RFV change with the measured value.

The evaluation of (1) in terms of RFV brings to an RFV of the distance for each considered *i*-th curve, at each measurement instant $k = 1,\ldots, K$. However, this procedure, which is correct from the mathematical point of view, does not consider all available metrological information. If all available metrological information is employed, it is possible to find, for

each *i*-th curve, the RFV of the distance in a more immediate and accurate way, as shown in the following.

First of all, let us consider that (1) represents a mean square error. When the random contributions to uncertainty are considered, since, by assumption, the standard deviation of the given PDF is the same for each measured value, it is known that the standard deviation σ_{d_i} of the mean square error is:

$$\sigma_{d_i} = \frac{\sigma}{\sqrt{K}} \tag{5}$$

Therefore this result allows us to directly build the random PD r_{ran} to be associated to the RFV of the distance d_i from the *i*-th curve, by simply applying the probability-possibility transformation to a Gaussian PDF having standard deviation equal to σ_{d_i}. This solution is indeed straightforward and avoids to combine all different random PDs associated to the *K* measured values.

Similar considerations can be done when the systematic contributions to uncertainty are taken into account, thus also avoiding to combine all different internal PDs associated to the *K* measured values. In fact, it is also possible to directly associate a systematic contribution to uncertainty to the distance d_i, by considering that, given a generic function $z = f(a_1, a_2,\ldots, a_n)$, the relative error associated to d_i is a linear combination of the relative errors associated to $a_1, a_2,\ldots, a_n$:

$$e_z = \frac{\partial f}{\partial a_1} e_{a_1} + \frac{\partial f}{\partial a_2} e_{a_2} + \ldots + \frac{\partial f}{\partial a_n} e_{a_n} \tag{6}$$

Hence, by considering, as function *f*, the distance d_i given by (1), and considering that $e_{y_k} = e$ for every value *k* and:

$$\frac{\partial f}{\partial y_k} = \frac{y_k - y_{ik}}{d_i \cdot K} \tag{7}$$

it follows that the relative error e_{d_i} associated to distance d_i, due to the systematic contributions to uncertainty, is given by:

$$e_{d_i} = \frac{e}{d_i \cdot K} \cdot \left| \sum_{k=1}^{K} y_k - \sum_{k=1}^{K} y_{ik} \right| \tag{8}$$

Therefore, the internal PD associated to the RFV of the distance from the *i*-th curve is directly built, by considering a rectangular PD around d_i, with semi-width equal to $e_{d_i} \cdot d_i$.

Hence, by simply combining the obtained internal and random PDs [16, 17], the distance d_i is evaluated in terms of RFV (denoted D_i). Once RFVs D_i are built for all curves $i = 1,\ldots, N$, it is possible to evaluate the weights w_i in terms of RFVs as well (denoted W_i). This is possible by converting, first of all, the mapping PDF $g(\cdot)$ into an equivalent mapping PD $G(\cdot)$, as shown, as an example, by the red PD in Fig. 2 below. Then, by considering the intersection of D_i with the mapping PD, RFV W_i is readily obtained. As an example, in Fig. 2, a generic α-cut D_i^{α} of RFV D_i is considered (green line), along with the corresponding obtained interval (magenta line). This interval represents the α-cut W_i^{α}, at the same level α, of RFV W_i. Hence, by considering all α-cuts of D_i, RFV W_i is built.

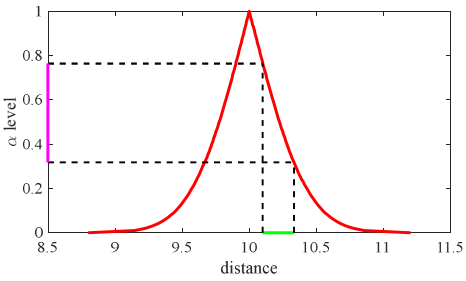

Fig. 2 Mapping PD and construction of the weight W_i

Finally, from the weights W_i, it is possible to evaluate the RUL at time instant *k*, according to (2), in terms of RFV. In particular, according to the available metrological information about the nature of the contribution and the measurement procedure, it is necessary to choose the more suitable *t*-norms to be applied. It is possible to state that the weights W_i are all uncorrelated with each other, because they are related to the *i*-th curve and all *N* curves are independent from each other. Furthermore, as far as the systematic contributions to uncertainty affecting the weights W_i are concerned, there is no reason to suppose a probabilistic compensation between each other in Eq. (2) and hence we can assume that they combine in a non-random way. Therefore, the *min* *t*-norm is chosen and a zero correlation factor applied when combining PDs r_{int}, while the *Frank* *t*-norm with the parametric value $\gamma = 0.1$ is chosen and a zero correlation factor applied when combining PDs r_{ran} [16-19]. The obtained results are shown in the following Section VI.

VI. Algorithm Validation

The application case for the presented approach are Medium Voltage (MV) and High Voltage (HV) Circuit Breakers (CBs). Since the data used in the contribution are confidential information (ABB property), the exact numerical values are not reported.

In particular, a fleet of 90 products coming from different customers, operating regions and applications is considered. The degradation pattern *y* for such products is shown in Fig. 3.

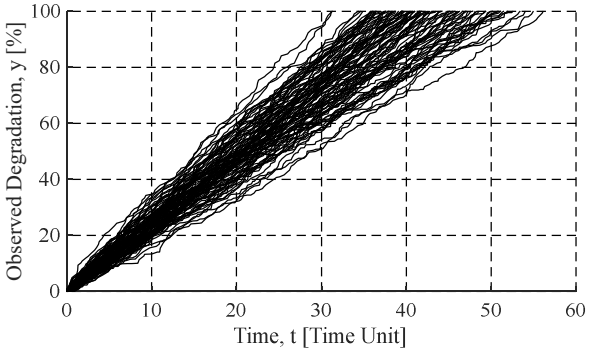

Fig. 3 Degradation pattern for a fleet of products

A degradation level $y = 0\%$ refers to a product in a perfect healthy state, whereas $y = 100\%$ means that it has reached its End of Life (EoL), that is the time instant at which the product

is not anymore able to perform its intended function and a maintenance activity, refurbishment, replacement or the disposal of the product is required. The degradation indicator can be obtained directly or indirectly from the measurement of one or more signals of interest that may provide information about the health state of the system under analysis. For the case of MV and HV circuit breakers, examples of such signals can be the measurement of the contact ablation, SF_6 gas density for gas insulated circuit breakers, and temperature of the interrupting chamber.

A. *Validation Procedure*

In order to evaluate the average prognostic performance of the algorithm in correspondence of a given level δ of degradation, the applied methodology has been run:

1) Select a test product among the fleet and use the remaining 89 items as reference library, according to the leave-one-out cross validation technique.
2) Determine an optimal value for the standard deviation σ_g for the mapping function $g(\cdot)$ (as described in the next Subsection B).
3) Run the algorithm described in Section V. From the obtained RFV, select a α-cut and obtain a confidence interval (CI) for the RUL, whose lower and upper bounds are denoted by $RUL_{\min}$ and $RUL_{\max}$ (Fig. 4).

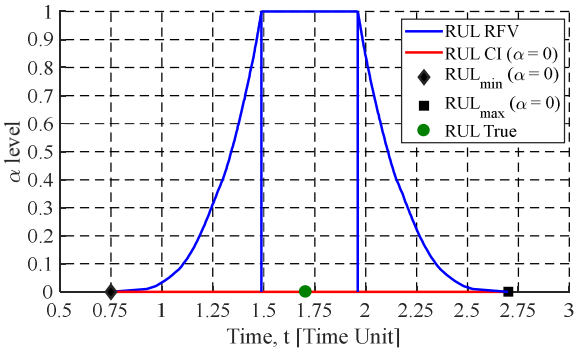

Fig. 4 RFV RUL (in black) for a given product and corresponding RUL CI (in cyan) obtained choosing α =0. Note that the actual RUL value (in red) is included in the CI provided by the algorithm.

4) Compute an indicator γ for the correctness of the prediction as in (9):

$$\gamma = \begin{cases} 1 & \text{if } \mathrm{RUL}_{act} \in [RUL_{\min}, RUL_{\max}] \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where RUL_{act} corresponds to the actual RUL value. In other words, γ is equal to 1 when the RUL prediction is correct, 0 otherwise.

5) Repeat steps 2-4 setting cyclically as test product a different product of the reference fleet.
6) Finally, the average algorithm performance in predicting the RUL of a product at the given level δ of degradation is obtained as:

$$Perf(\delta) = \frac{100}{N}\sum_{i=1}^{N}\gamma_i \quad (10)$$

so that $Perf(\delta)$ is equal to 1 (or 0) if all the RUL forecasts for the degradation level δ are correct (or wrong).

B. *Tuning the σ_g parameter*

The parameter σ_g is optimized determining for which value the algorithm provides the best prognostic performances. In particular, given a reference library for a test product the following steps are performed.

First, the M products at lower distance d_i (Equation (1)) with respect to the target product are identified.

Then, the prognostic algorithm is run for different values of σ_g, setting cyclically, for the same value of σ_g, one of the M reference products as test sample (its degradation pattern is considered known up to the value δ) and the remaining of the reference library as new training patterns (i.e. the remaining 88 products).

Finally, the optimal value of σ_g is determined among the subset of values for which performances (computed similarly to (10) averaging over the M products) are higher than a given threshold P^*, selecting the value providing the lowest mean confidence interval width.

In case for any value of σ_g performances higher than P^* are achieved, the value of σ_g providing the highest performance is selected.

The reason for which such strategy has been implemented as optimization procedure is to guarantee at the same time high prognostic accuracy and narrow confidence intervals, in order to provide valuable results from the predictive maintenance point of view.

In the following subsection the results obtained with the optimization parameter M = 18 (20% of the fleet population), P^* = 95% are shown.

C. *Results*

Fig. 5 reports the RUL prediction results obtained for one of the CBs under test. In particular, the CI for the RUL have been obtained considering the α-cut at level α = 0 of the RFV RUL.

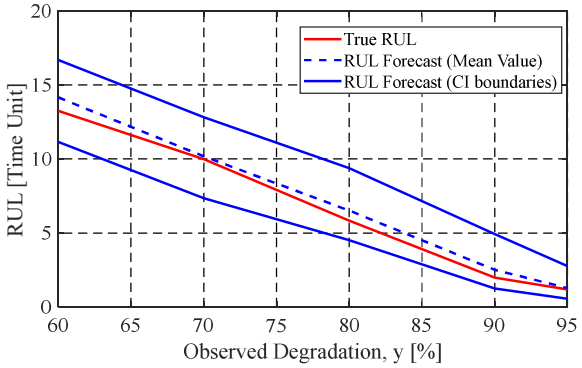

Fig. 5 RUL forecasts for a specific product. The CI have been obtained extracting α-cut at level α=0 from the RFVs provided by the algorithm.

The choice of the α-cut represents a trade-off between the width of the provided CI (amount of uncertainty about the RUL forecast) and accuracy of the prognostic result (the provided CI includes the actual RUL value). Higher levels of α-cut correspond to narrower CIs but also higher risk of incorrect forecast. In this example, the level α = 0 has been

chosen, which corresponds to a pessimistic approach. It is interesting to observe how the CIs provided by the algorithm at different levels of degradation include the actual RUL value. Furthermore, the width of such CIs decreases as the observed degradation increases, so that the prognostic information becomes more valuable from the maintenance operations optimization point of view.

An overall scenario of the prognostic efficiency of the proposed algorithm is given by Fig. 6 where the average performance at different levels of degradation are illustrated.

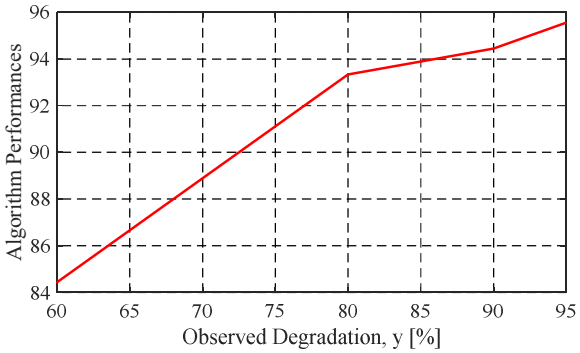

Fig. 6 Average algorithm prognostic performances at different values of observed degradation

Also in this case the results refer to CIs obtained considering the level $\alpha = 0$ of the RFV RUL. The percentage of correct RUL forecasts increases with the observed degradation, reaching a performance of almost 96% when the degradation is equal to 95%. This result demonstrates a high efficiency of the proposed model and in particular, the high prognostic power achieved at high levels of degradation (i.e. in proximity of failure) is of fundamental importance for an effective scheduling of the maintenance interventions.

VII. Conclusions

In this paper, a similarity-based data-driven prognostic algorithm for the estimation of the RUL of a product is proposed. It is based on the exploitation of run-to-failure data of products, which are supposed to be characterized by similar operational conditions, referred to as reference library. This allows one to implicitly introduce some knowledge about the future loading and operational conditions that the test product will face in the rest of its life, mitigating the effect of the future uncertainty on the final prediction.

The core of the contribution is the application of a possibilistic framework, namely the RFV approach, for the representation and propagation of the measurement uncertainty, which is a crucial source of uncertainty in PHM. Applying the mathematics of RFV, it is possible to evaluate the product RUL in terms of RFV and extract the desired confidence interval. The results obtained for the application case of MV and HV CBs have shown high prognostic performances of the proposed algorithm. In particular, a fundamental result is the high level of performances achieved in proximity of failure (almost 96% of correct predictions when the degradation is equal to 95%), highlighting the ability of the algorithm to provide valuable results from the predictive maintenance point of view.

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