Integration of Hierarchical Classification to Improve the Prognostic Results of Fuzzy Similarity

Jie Liu[1] and Enrico Zio[2]

[1] *Chair on System Science and the Energetic Challenge, EDF Foundation, CentraleSupélec, 92295, Châtenay-Malabry, France*

Jie.liu@centralesupelec.fr

[2] *Chair on System Science and the Energetic Challenge, EDF Foundation, CentraleSupélec, 92295, Paris, Châtenay-Malabry;*

Enrico.zio@centralesupelec.fr

[2] *Energy Departement, Politecnico di Milano, Milano, Italy*

Enrico.zio@polimi.it

ABSTRACT

Fuzzy similarity has been widely used for prognostics. Normally, a library of failure scenarios is available and a number of them most similar to the observed scenario are selected to generate the Remaining Useful Life (RUL) of the observed scenario, using a distance weighted-sum approach. By clustering the library of failure scenarios, those most similar to the observed scenario can be selected considering the strength of membership to the different clusters. To this aim, in this paper, hierarchical classification is integrated into the fuzzy similarity approach. First, hierarchical classification is built by Support Vector Machine (SVM), considering different failure modes. Then, for the observed scenario, fuzzy similarity is applied to select the most similar failure scenarios from different classes, considering the membership of the observed scenario to the different clusters. The selected scenarios are aggregated to generate the RUL along the observed scenario. A real case study of a system composed of a pneumatic valve and a centrifugal pump in a nuclear power plant is considered to verify the RUL prediction power of the proposed framework.

1. INTRODUCTION

Fuzzy similarity for failure prognostics relies on a library of reference failure scenarios (recorded run-to-failure data) from similar equipment. When predicting the Remaining Useful Life (RUL) of an observed scenario which is degrading, the similarities between the observed scenario and the reference scenarios are calculated. A number of reference scenarios most similar to the observed scenario are selected and the distance-weighted sum of their RULs gives the RUL of the observed scenario. Fuzzy similarity has been widely used, solely or in combination with other methods, for prognostics in different practical problems, e.g. epileptic seizures (Li and Yao, 2005), text classification (Widyantoro and Yen, 2000), financial activity (Li and Ho, 2009), Virkler crack growth (Guepie and Lecoeuche, 2015), weather (Riordan and Hansen, 2002), nuclear systems (Zio and Di Maio, 2010), power systems (Senjyu et al., 1998). Satisfactory results are reported in these works.

In practical problems, there are cases when the reference scenarios may belong to different failure modes and can be clustered into different classes considering the operation conditions, the functioning environment and other factors. In such cases, simply selecting a number of reference scenarios most similar to the observed scenario from the library may not be effective. Using the classical fuzzy similarity-based prognostic method, the selected reference scenarios may be all from the most probable class, thus neglecting other less, but still, probable classes: the diversity of the selected reference scenarios is reduced, and if the continuation of the observed scenario in the future drifts to one of the less probable classes, the prediction accuracy of the prognostics is endangered.

The prediction accuracy using fuzzy similarity is highly dependent on the richness of the library, which is more critical for a stochastic degradation process. The diversity and representativeness of the selected reference scenarios are very important for the prediction accuracy. Another challenge in using fuzzy similarity for prognostics is, then, the optimal number of the selected reference scenarios. Fuzzy similarity with a small number of reference scenarios considered is not stable, when many reference scenarios have similar high values of similarity. For example, the beginning of the degradation of similar equipment may not significantly differ from one to another, and many of them may have close similarity to the observed scenario. If only a small number of them are selected to generate the RUL of the observed scenario, the results can be non-stable, depending on the representativeness of the selected reference scenarios. On the contrary, fuzzy similarity with a large number may give non-accurate results, when only few reference scenarios are highly similar to the observed scenario and the others somewhat introduce "noise". For example, when the degradation of the observed scenario approaches the end of its life, the similarities between the reference scenarios and the observed scenario may be very different from one to another, and only few are highly similar to the observed scenario. If a relatively large number of the reference scenarios are selected, the results may not be precise. If the membership of the observed scenario to different clusters can be calculated, the selected reference scenarios from different clusters should be proportional to the memberships.

In this paper, a framework, combining hierarchical classification by Support Vector Classification (SVC) (Gunn, 1998) and fuzzy similarity (Zio and Di Maio, 2010) is proposed for prognostics of stochastic degradation processes. By analyzing statistically and/or physically the reference scenarios, (hierarchical) multiple classes can be identified, and the different classes can be modeled by SVC models. As one SVC model can only differentiate two classes, multiple SVC models are trained for different classes of the reference scenarios. The trained SVC models can judge the class that one failure scenario belongs to. For a given observed scenario, SVC, in combination with Monte Carlo simulation can estimate the likelihood that the observed scenario falls into each class. Then, reference scenarios are selected from a class proportional to the likelihood to belong to that class. And the RUL of the observed scenario is calculated as the distance-weighted sum of the RULs of all the so-selected reference scenarios.

By integrating hierarchical classification into the fuzzy similarity-based prognostic method, the diversity and the representativeness of the selected reference scenarios are strengthened.

In the case that the number of the reference scenarios to be selected in one class exceeds the number of the class samples, the total number of the selected scenarios is modified to guarantee the proportion of selected reference scenarios from each class.

The case study in this paper concerns the prognostics of the failure time of a sub-system of a nuclear power plant. The system is composed of a pneumatic valve and a centrifugal pump. The pump follows a stochastic multi-state degradation process and the valve degrades continuously (Lin et al., 2015). The results are compared with the classical fuzzy similarity, which selects directly from the library a number of reference scenarios to calculate the RUL for the observed scenario. A specific accuracy measure is used considering the stochastic degradation process.

The remainder of the paper is structured as follows. Section 2 presents SVC and fuzzy similarity. The proposed framework is also detailed in this Section. Section 3 reports the results of the case study. Some conclusions are drawn in Section 4.

2. SUPPORT VECTOR CLASSIFICATION AND FUZZY SIMILARITY

In this section, SVC and fuzzy similarity are briefly reviewed at the beginning. The proposed method is then detailed.

2.1. Support Vector Classification

Support Vector Machine (SVM) (Cortes and Vapnik, 1995) for classification is named SVC. The traditional SVC model can solve a two-class problem.

Given a training dataset of instance-label pairs $(\boldsymbol{x}_i, y_i), i = 1, \dots, N$, with $\boldsymbol{x}_i \in R^n$ and $y_i \in \{-1,1\}$, SVC formulates the estimation function as $f(\boldsymbol{x}) = \boldsymbol{w} \cdot \boldsymbol{x} + b$, and the unknowns, $\boldsymbol{w}$ and b are estimated by solving the following optimization problem:

$$\begin{aligned} &min_{\boldsymbol{w},b,\boldsymbol{\varepsilon}} \quad \frac{1}{2}\boldsymbol{w}^t\boldsymbol{w} + C\sum_{i=1}^{N}\varepsilon_i \\ &subject\ to \quad y_i(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1 - \varepsilon_i \\ &\qquad\qquad\qquad \varepsilon_i \geq 0 \end{aligned} \tag{1}$$

with C is a penalty factor that balances the flatness and the accuracy of the estimation function.

The solution of the optimization function in Eq. (1) is built as $\boldsymbol{w} = \sum_{i=1}^{N} k(\boldsymbol{x}, \boldsymbol{x}_i)$, with $k(\boldsymbol{x}, \boldsymbol{x}_i)$ being a kernel function that calculates the similarity between the two vectors $\boldsymbol{x}$ and $\boldsymbol{x}_i$ in a high dimensional space (the so-called Reproduced Kernel Hilbert Space (RKHS)). Linear kernel function, polynomial kernel function, Radial Basis Function (RBF), sigmoid kernel function are some of the most popular kernel functions used in SVM and SVC.

Details about SVC can be found in the related references.

In case of a multi-class problem, a number of SVC models can be trained to estimate corporately the class which the new instance belongs to as shown in Table 1 (Rocco and Moreno, 2002; Rocco and Zio, 2007). The SVCs are trained with the one-vs-others idea, i.e. each SVC is trained to distinguish one class and all other classes; and then, the joint outputs of all the SVC models can give the class of a new instance.

2.2. Fuzzy Similarity

Consider the monitored data $\boldsymbol{v}$ of the observed scenario and a time-dependent one $\boldsymbol{w}(t)$ in a reference scenario; for each discrete time t, $\boldsymbol{w}(t)$ has the same data structure as $\boldsymbol{v}$. For the calculation of the fuzzy similarity between the observed scenario $\boldsymbol{v}$ and the reference scenario $\boldsymbol{w}(t)$, one needs to find t_0 such that the distance score $d(t_0)$ between $\boldsymbol{w}(t_0)$ and $\boldsymbol{v}$ is minimized. In the present paper, three steps are proposed for this (Zio and Di Maio, 2010).

The first step consists in calculating the Euclidean distance between $\boldsymbol{w}(t)$ and $\boldsymbol{v}$ for all times t:

$$\delta(t) = |\boldsymbol{v} - \boldsymbol{w}(t)|^2 \tag{2}$$

The second step is the computation of the pointwise trajectory similarity and the corresponding distance score. The pointwise difference between the trajectories $\boldsymbol{w}(t)$ and $\boldsymbol{v}$ expressed by Eq. (2) is evaluated with reference to an "approximately zero" Fuzzy Set (FS) specified by a function which maps the elements of the Euclidean distance $\delta(t)$ into the corresponding similarity value $\mu(t)$. Common functions can be used for the definition of the FS, e.g. triangular, trapezoidal, and bell-shaped. In the application illustrated in this work, the following bell-shaped function is used:

$$\mu(t) = \exp(-(-\ln(\alpha)/\beta^2)\delta(t)^2) \tag{3}$$

The arbitrary parameters α and β can be set by the analyst to shape the desired interpretation of similarity into the fuzzy set: the larger the value of the ratio $-\ln(\alpha) / \beta^2$, the narrower the fuzzy set and the stronger the definition of similarity (Zio & Di Maio, 2010). Then, the distance score $d(t) = 1 - \mu(t)$ between $\boldsymbol{w}(t)$ and $\boldsymbol{v}$ is computed.

The third step is to find t_0 which minimizes $d(t)$ and to compute the corresponding distance score $d(t_0)$.

The fuzzy similarity between the observed scenario and all the reference scenarios are calculated following the previous steps. Traditionally, a number of most similar reference scenarios are selected to generate the estimated RUL of the observed scenario as weighted sum of their RULs. In the case that multiple classes exist among the reference scenarios, this traditional way may neglect some classes in the library. To avoid this, a new framework is proposed in this paper.

2.3. The Proposed Framework for Prognostics

In this paper, a new framework for prognostics is proposed, which combines (hierarchical) multiple clustering and fuzzy similarity. The proposed framework is shown in Figure 1.

The reference scenarios are firstly clustered into k classes by unsupervised classification approaches. The features that can help easily identify the different clusters are extracted and different SVC models are trained (with the extracted features as inputs) to distinguish among the different classes. The change of the extracted features with time is also modeled. For the observed scenario, Monte Carlo simulation estimates the possible future values of the extracted features of the observed scenario. The likelihood p_i that the future degradation of the observed scenario belongs to the class i is estimated, with $i = 1, \ldots, k$. Then, the fuzzy similarity between the observed scenario and each reference scenario is calculated. Supposing that a total of M reference scenarios most similar to the observed scenario are selected to generate the estimated RUL for the observed scenario, $M_i = M * p_i$ of them are taken from the most similar reference scenarios in class i.

In the case that the size of class i is less than M_i, the total number of selected reference scenarios is modified as $M = C_i/p_i$, with C_i the size of cluster i.

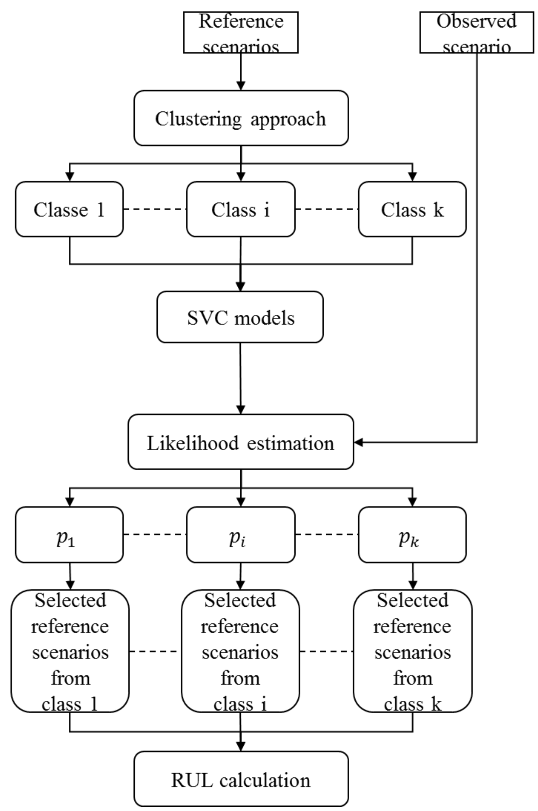

Figure 1. The procedure of the proposed framework.

3. CASE STUDY

In this section, results on a real case study are presented. The case study concerns a sub-system composed of a pneumatic valve and a centrifugal pump of a nuclear power plant. The characteristics of the system are (Yanhui et al., 2015):

- The centrifugal pump follows a stochastic multi-state degradation process, i.e. degradation states are {3 2 1 0} with state 0 the failure state. The transition rate between each pair of consequent states are known, i.e. $\lambda = 5 * 10^{-3}/(unit\ time)$. The degradation process is modeled by a continuous time homogeneous Markov chain. The degradation process of a centrifugal pump can be characterized by the holding time on each functioning state, i.e. {3 2 1}.

- The pneumatic valve is a normally-closed and gas-actuated valve with a linear cylinder actuator. It follows a continuous degradation process, whose degradation rate is dependent on the degradation states of the centrifugal pump and the pneumatic valve. The physics-based model for the pneumatic valve is given and is very complicated and time-consuming for calculation. The threshold of failure is $3.2*10^{-6}$.

- The failure of one component (pump or valve) causes the failure of the system.

Physical details on the system can be found in Lin *et al.* (2015). In Lin et al. (2015), Piecewise Deterministic Markov Process (PDMP) simulation is proposed to estimate the reliability and RUL of the system with the physical model. But it takes two much time for the computation.

Given a number (1000) of failure scenarios for this system, the framework proposed in Section 2.3 can be applied for RUL estimation.

3.1. Hierarchical Classification

The system failure can be generally divided into pump failure (noted as failure type 1) and valve failure. Figure 2 shows the holding time of the pump in different states, with respect to the previous two types of system failures. From the Figure, it appears that the two different system failures can be distinguished by the holding time of the pump in states 3, 2 and 1.

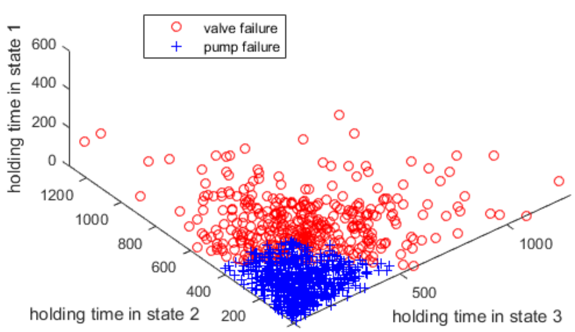

Figure 2. The holding time of the pump in states 3, 2 and 1, with respect to pump failure and valve failure.

Furthermore, Figure 3 shows the time to failures of the reference scenarios with valve failure. Statistically, the system RULs can be clustered into four categories, around the values 470, 500, 530 and 560 (in arbitrary units of time), which are noted separately as failure type 2, failure type 3, failure type 4 and failure type 5.

Among all the reference scenarios, 592, 23, 111, 185 and 89 reference scenarios are separately clustered into the classes of failure type 1, 2, 3, 4 and 5.

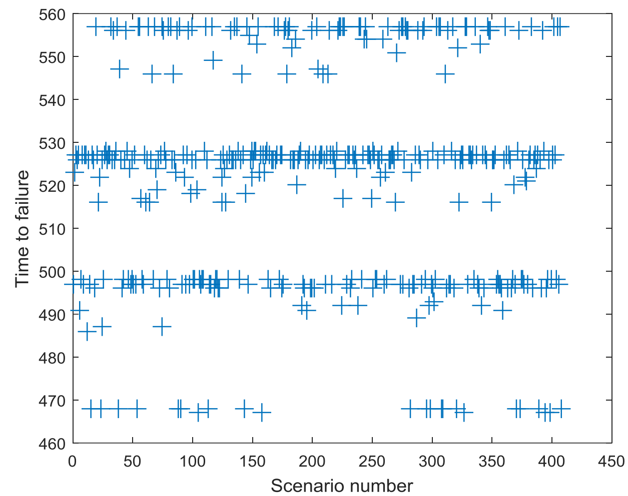

Figure 3. Time to failures of the reference scenarios with valve failure.

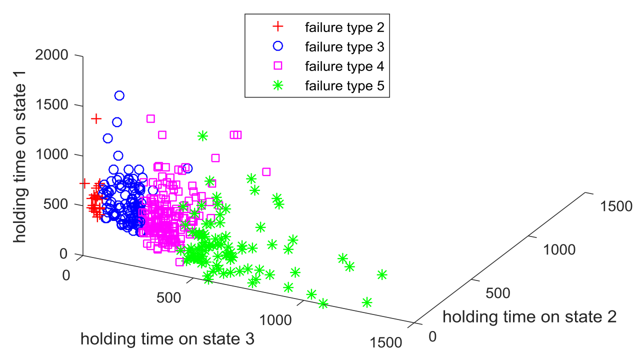

Figure 4. The holding time of the pump in states 3, 2 and 1 of reference scenarios with failure types 2, 3, 4 and 5.

Figure 4 shows the holding time of the pump in states 3, 2 and 1 of the reference scenarios with the four types of valve failures. One can observe that these four types of system failures can also be well classified with respect to the holding time of the pump in states 3, 2 and 1.

Thus, the holding time of the pump is selected as input for classification. Three SVC models are trained, noted separately SVC 1, SVC 2 and SVC 3. SVC 1 distinguishes the valve failure (classified as -1) and pump failure (classified as +1), as shown in Figure 2. SVC 2 is trained to classify the failure type 2 (classified as +1), failure type 3 (classified as +1) and failure type 4 (classified as -1), failure type 5 (classified as -1). SVC 3 distinguishes the failure type 2 (classified as +1), failure type 4 (classified as +1) and failure type 3 (classified as -1), failure type 5 (classified as -1). The classification of one failure scenario based on the results of the three SVC models is shown in Table 1.

Table 1. Classifications of different failure types with three SVC models.

Failure type	SVC 1	SVC 2	SVC 3
1	+1	-	-
2	-1	+1	+1
3	-1	+1	-1
4	-1	-1	+1
5	-1	-1	-1

Because of the stochastic degradation process of the pump, Monte Carlo simulation is combined with the SVC models to estimate the probabilities that the observed scenario falls into each failure type. Precisely, with the given historical state of the pump, one Monte Carlo simulation estimates one possible holding time of the pump in states 3, 2 and 1 during the observed scenario. Then, the trained SVC models can estimate the failure type of the pump degradation generated by each Monte Carlo simulation. A number (1000, in this paper) of Monte Carlo simulations are carried out and the number of times that the generated degradation falls into each failure type is recorded, and the membership likelihood of the observed scenario in each class is then calculated as the percentage of the simulations that falls into the corresponding class.

3.2. Prognostic Results

The proposed method is tested on several ongoing failure scenarios. Given the degradation time series data of the observed system until time t, the proposed method (noted as fuzzy-cluster in Tables 2 and 3) and traditional fuzzy similarity-based prognostics (noted as fuzzy similarity in Tables 2 and 3) are used to estimate the system RUL. Totally, the first 40 reference scenarios most similar to the observed scenario are selected. The system RUL estimated by the two methods are compared with the average RUL generated by the physical model, i.e. PDMP. Because of the stochastic nature of the degradation process, such a comparison can be more informative than the comparison between the predicted RUL and the RUL of a specific observed scenario.

Eleven observed scenarios, which belong to different failure types (as shown in column 1 of Tables 2 and 3), are considered in the experiments.

Figure 5 shows the change in the likelihoods of the fourth observed scenario belonging to the different classes of failure types, as estimated by the proposed method. The true failure type of the fourth observed scenario is type 3 and the transition time of the pump from state 3 to state 2 and from state 2 to state 1 occur at 45 and 250, respectively. The failure time is 500.

From the Figure, one can observe that the likelihoods change abruptly at the transition time from one pump state to another. Once the holding time of the pump in one state is known, the variability of the observed scenario decreases, and, thus, the probabilities estimated by the SVC models and Monte-Carlo simulations change. As more and more data on the degradation of the fourth observed scenario are available, the likelihood that this scenario falls into the 3rd scenario increases, providing more confidence.

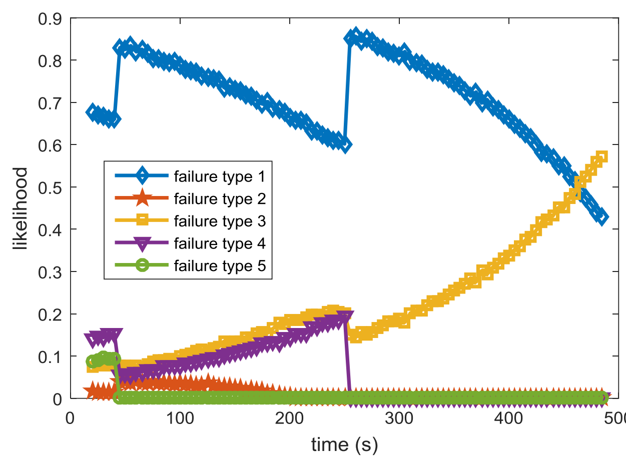

Figure 5. Likelihoods that the fourth observed scenario falls into the different classes with degradation data becoming available at different times t, as estimated by the proposed method.

Figure 6 shows the Probability Density Function (PDF) of the RUL for the fourth observed scenario, predicted using the proposed method. In comparison with that given by PDMP, the proposed method gives good results and the uncertainty bounds of the PDF decreases approaching the failure of the observed scenario, coherently with the increase of available data.

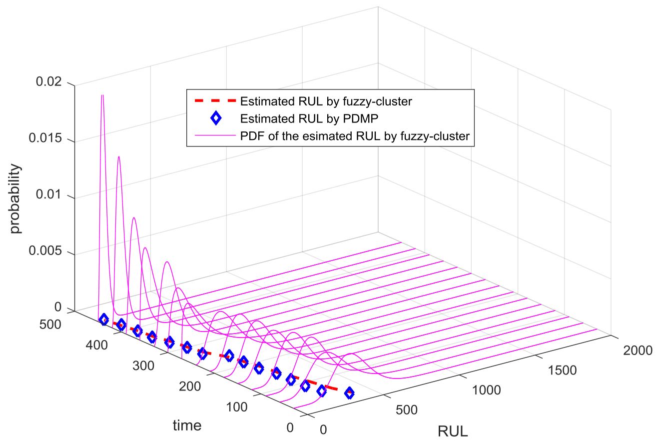

Figure 6. PDF of the system RUL estimated by the proposed method.

Figure 7 shows the likelihoods that the selected reference scenarios fall into different classes using the traditional fuzzy similarity-based prognostic method. The likelihood of the failure type 4 is nearly zero at all times. But the strength of the membership for failure type 4 of the observed scenario is very high at the beginning before time 300, as shown in Figure 5, which is given by the component degradation model. Thus, the selected reference scenarios loose the representativeness.

After the time 450, nearly all scenarios are selected from the class of failure type 3. On the contrary, because of the stochastic degradation process, the possibility of the other failure types is not zero. The diversity of the reference scenarios selected by the traditional method is low.

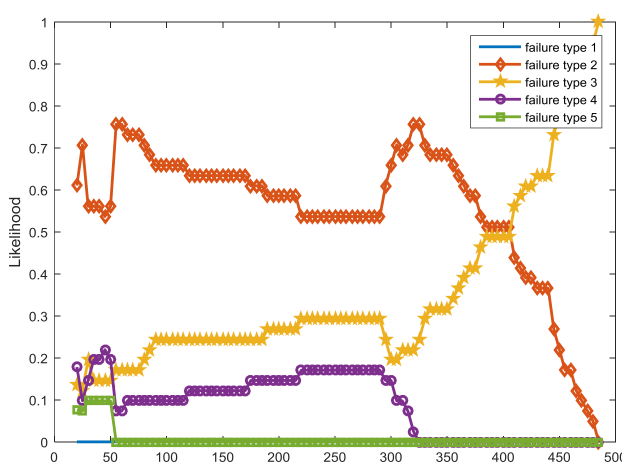

Figure 7. Likelihoods that the fourth observed scenario falls into the different classes with degradation data becoming available at different times t, as estimated by traditional fuzzy similarity.

Given the stochasticity of the degradation process, the error of the prognostic method on one specific failure scenario is not representative of the accuracy of the method. We, then, refer to the physical model (PDMP) that generates the average RUL of the observed degradation. The error of the proposed method compared to the RUL generated by the physical model is more reliable and informative.

Table 2. MSE of the predicted RUL with different methods.

Observed scenario	Fuzzy similarity	Fuzzy-cluster	Difference
1 (type 4)	184.32	145.85	38.47
2 (type 1)	479.93	313.70	166.23
3 (type 1)	634.58	325.74	308.84
4 (type 3)	460.96	322.60	138.36
5 (type 3)	279.80	265.78	14.02
6 (type 1)	503.05	292.73	210.32
7 (type 1)	829.22	799.09	30.13
8 (type 1)	4155.2	3038.3	1115.9
9 (type 5)	225.89	177.26	48.63
10 (type 5)	242.75	199.50	43.25
11 (type 2)	1512.5	1212.4	300.1

Table 2 shows the Mean Squared Error (MSE) between the predicted RUL given by the fuzzy similarity and fuzzy-cluster, and that generated by the physical model. Differences between the MSE given by the fuzzy similarity and fuzzy-cluster are also given in Table 2. For the ten observed scenarios, the proposed fuzzy-cluster method always give better result than the traditional fuzzy similarity.

The price to pay for this improvement is the computation time which is longer for the proposed method than for the traditional fuzzy similarity, as the Monte Carlo simulation takes time for calculating the membership likelihoods. Yet the time is still much less than the computation time for PDMP. For example, the computation time of PDMP for scenario 11 is 5996.6s.

Table 3. Computation time (s) of different methods for RUL prediction.

Scenario	Fuzzy similarity	Fuzzy-cluster
1 (type 4)	0.47	20.73
2 (type 1)	0.26	11.78
3 (type 1)	0.10	4.18
4 (type 3)	0.41	17.43
5 (type 3)	0.41	20.24
6 (type 1)	0.26	10.58
7 (type 1)	0.32	13.90
8 (type 1)	0.14	4.29
9 (type 5)	0.42	24.86
10 (type 5)	0.42	24.27
11 (type 2)	1.36	16.72

4. CONCLUSION

Fuzzy similarity-based prognostic methods are widely used. The RUL prediction stands on the RULs of reference scenarios selected from a library. The diversity of the reference scenarios is not guaranteed, when the reference scenarios are clustered depending on external characteristics of operation, environment, failure type. In this paper, the fuzzy similarity is combined with hierarchical clustering to inject diversity in the selected reference scenarios while keeping the accuracy of the predicted RUL. Monte Carlo simulation and SVC are integrated to calculate the class membership likelihood of the observed scenario. The reference scenarios are proportionally selected from different classes. A real case study concerning a stochastic degradation process of a sub-system in a nuclear power plant is considered. The predicted RUL of the fuzzy similarity is compared with that generated by the physical model. The proposed method gives better results than the traditional fuzzy similarity-based prognostics in the case study.

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BIOGRAPHIES

Jie Liu (B.Sc. in Mechanical Engineering, Beihang University, China, 2009; M.Sc. in Physics and Engineer in Nuclear Energy, Ecole Centrale Pekin, Beihang University, China, 2012; Ph.D. in Industrial Engineering, Ecole Centrale Paris, France, 2015) He is now a post-doc researcher in the Chair on Systems Science and Energetic Challenge, Foundation EDF, CentraleSupélec, Université Paris-Saclay France. His current research interests concern kernel-based methods for Prognostics and Health Management (PHM), economic value quantification of PHM approaches, adaptive online learning under nonstationary environment and maintenance optimization, dynamic reliability assessment, multi-agent system for prognostics.

Enrico Zio (M.Sc. in nuclear engineering, Politecnico di Milano, 1991; M.Sc. in mechanical engineering, University of California, Los Angeles, UCLA (1995); Ph.D., in nuclear engineering, Politecnico di Milano, 1995; and Ph.D., in Probabilistic Risk Assessment, Massachusetts Institute of

Technology, MIT (1998)). His research and academic activities include Full professor, Politecnico di Milano (2005-); Director of the Chair on System Science and Energetic Challenge at CentraleSupelec, Foundation EDF (2010-); Adjunct professor, University of Stavanger, Norway (2010-); Rector's Delegate for the Alumni Association, Politecnico di Milano (2011-); President of the Alumni Association, Politecnico di Milano (2012-); President of Advanced Reliability, Availability and Maintainability of Industries and Services (ARAMIS) srl (2012-); Adjunct professor, City University of Hong Kong, Hong Kong, China (2013-); Rector's Delegate for Individual Fund Raising, Politecnico di Milano (2015-); Adjunct professor, Beihang University, Beijing, China (2015-); Director of the Center for REliability and Safety of Critical Infrastructures (CRESCI) at Beihang University, Beijing, China (2015-). His research topics are: analysis of the reliability, safety and security, vulnerability and resilience of complex systems under stationary and dynamic conditions, particularly by Monte Carlo simulation methods; development of soft computing techniques (neural networks, support vector machines, fuzzy and neuro-fuzzy logic systems, genetic algorithms, differential evolution) for safety, reliability and maintenance applications, system monitoring, fault diagnosis and prognosis, and optimal design and maintenance.