Fault Prognostics in Presence of Event-Based Measurements

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In practice, fault prognostics has often touched with incomplete and noisy data collected at irregular time steps, e.g. in correspondence of the occurrence of triggering events in the system. Under these conditions, we investigate the possibility of predicting the Remaining Useful Life (*RUL*) of industrial systems using a properly tailored Echo State Network. A synthetic case study is used to show the effectiveness of the developed *ESN*-based methods and its superior performance with respect to traditional feedforward neural networks.

Keywords: Prognostics, Remaining useful life, Incomplete event-based data, Echo state network.

1. Introduction

Prognostics aims at predicting the degradation of equipment for estimating the Remaining Useful Life (*RUL*) (Zio and Di Maio, 2010; Zio, 2012; Liao and Köttig, 2014; Baraldi *et al.*, 2017; Lei *et al.*, 2018). Among data-driven techniques for *RUL* prediction, Recurrent Neural Networks (*RNNs*) (Zio, Broggi and Pedroni, 2009; Malhi, Yan and Gao, 2011; Zio *et al.*, 2012; Guo *et al.*, 2017) are gaining attention due to their capability of representing the degradation evolution by incorporating dynamic temporal behaviors. Various types of *RNNs* have been used with success in prognostic applications. A *RNN*-based model has been developed for predicting machine deterioration evolution using vibration data (Tse and Atherton, 1999). A Long Short-Term Memory (*LSTM*) *RNN* has been used to predict the remaining useful life of lithiumion batteries (Zhang *et al.*, 2018). A *RNN* Encoder-Decoder network, which transforms multivariate time series subsequences into fixed-dimensional vectors, has been used to define health indicators and, then, to predict the *RUL* of turbofan engines (Gugulothu *et al.*, 2017). A health indicator defined by using a *RNN* has been used for the prediction of bearing *RUL* (Guo *et al.*, 2017). Infinite impulse response locally recurrent neural networks has been employed for forecasting failures and predicting the reliability of components and systems(Zio *et al.*, 2012).

The main challenge for practical *RNNs* applications is the slow and computationally intensive training procedure, which cannot guarantee the final convergence of the algorithm towards an accurate and robust model (Lukoševičius and Jaeger, 2009).

To overcome this challenge, the Reservoir Computing (*RC*) paradigm has been proposed (Lukoševičius and Jaeger, 2009). *RC* involves randomly creating a *RNN*, called Reservoir, which remains unchanged during the training and is passively excited by the input signals. Among *RC* approaches, Echo State Networks (*ESNs*) have shown intrinsic dynamic properties, generalization capability and ability to handle noisy data (Jaeger, 2004). However, that there are few applications of *ESNs* to prognostic problems. An example is the use of *ESNs* for predicting the *RUL* of a fleet of turbofan engines (Rigamonti, Baraldi, Zio, Roychoudhury, *et al.* 2016). An ANalysis Of VAriance (*ANOVA*) method has been applied for predicting the proton exchange membrane fuel cell ageing based on an *ESN* (Morando *et al.*, 2015). *ESNs*

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have also been employed for prognostics of an industrial Fuel Cell (*FC*) (Morando *et al.*, 2017).

In this work, we consider a case in which the measurements are collected only when triggering events occur, such as individual components faults or extreme operational conditions. These "snapshot" datasets are often encountered in industrial applications, dominated by the necessity of cost saving in storing and managing the databases (Weijters and van der Aalst, 2003; Li and Zio, 2017), and of reducing energy consumption and bandwidth sources (Tsividis, 2010). Since failure events rarely occur during the lifetime of a system, event-based datasets are dominated by the presence of a large number of missing measurements (Fink, Zio and Weidmann, 2015).

The objective of the present work is to develop a data-driven method for predicting the *RUL* of a system of non-repairable interconnected components, where the data is collected only at the occurrence of triggering events. The main difficulty is that, contrarily to the typical applications of *ESNs*, the time intervals at which the data become available are not constant. We propose a method based on the idea of exciting the reservoir at each time step. If an event has occurred, the reservoir states are excited both by the previous reservoir states and the measured signals, whereas, if an event has not occurred, they are excited only by the previous reservoir states. Therefore, it is expected that the connection loops in the reservoir allow reconstructing the dynamic degradation behavior of the system at those time steps in which events do not occur.

The proposed method is applied to a synthetic case study, properly designed to mimic run-to-failure trajectories of a system of non-repairable interacting components, in which the measurements are collected when events occur. The accuracy of the method is evaluated considering the Cumulative Relative Accuracy (*CRA*) and Alpha-Lambda (α-λ) metrics (Saxena *et al.*, 2010), and compared to that of a traditional feedforward neural network.

The remaining of this paper is organized as follows: Section 2 illustrates the work objectives and problem setting; Section 3 describes the proposed method for fault prognostics; Section 4 introduces the synthetic case study and discusses the obtained results; finally, some conclusions and remarks are drawn in Section 5.

2. Problem Setting

We assume the availability of the measurements of P signals collected in correspondence of the occurrence of events in the monitored system, during R run-to-failure degradation trajectories. The generic r-th trajectory is formed by the measurements collected at the occurrence of n^r events before the failure of the system. The time of occurrence of the j-th event of the r-th trajectory, $j = 1,\ldots,n^r$, will be referred to as τ_j^r and the corresponding measurement vector $\boldsymbol{z}^r(\tau_j^r)$. The objective of this work is to develop a direct data-driven prognostic method for the prediction of the ground truth *RUL* of a test system at time t, $RUL^{test}(t) = t_f^{test} - t$, with t_f^{test} indicating the ground truth failure time of the system, on the basis of the signal measurements $\boldsymbol{z}^{test}(\tau_j)$ collected in correspondence of the occurred events $j = 1,2,\ldots,n^{test}$, with $\tau_n^{test} < t$ indicating the last time at which signal measurements have been acquired. The *RUL* prediction at time t is indicated as $\widehat{RUL}(t)$.

3. Methodology

An *ESN* is a *RNN* characterized by recurrent loops in its synaptic connection pathways (Jaeger, 2004). Differently from traditional *RNNs*, the internal neurons, which form the *ESN* reservoir, are sparsely connected (Lukoševičius and Jaeger, 2009). This architecture, which mimics the biological neural networks, allows maintaining an ongoing activation of the neurons even in absence of input to the *ESN* and, thus, it provides dynamic memory (Inubushi and Yoshimura, 2017).

We consider an *ESN* architecture characterized by P input neurons, a reservoir with $N_x >> 1$ internal neurons and one output neuron representing the system *RUL* (Figure 1). Matrix $\boldsymbol{W}_{in}$ of size $N_x \times P$ contains the weights of the connections from the input neurons to the internal neurons, matrix $\boldsymbol{W}$ of size $N_x \times N_x$ contains the weights of the connections among the internal neurons, matrix $\boldsymbol{W}_{ofb}$ of size $N_x \times 1$ contains the weights of the connections from the output back to the reservoir internal neurons and matrix $\boldsymbol{W}_{out}$ of size $1 \times (P + N_x)$ contains the weights of the connections from the input and the reservoir internal neurons to the output. We consider a reservoir with leaky-integrator neurons, whose state is updated according to:

$$\boldsymbol{x}(t) = (1-a)\boldsymbol{x}(t-1) + f(\boldsymbol{W}_{in}\,\boldsymbol{u}(t) + \boldsymbol{W}\boldsymbol{x}(t-1) + \boldsymbol{W}_{ofb}y(t-1)) \quad (1)$$

where $\boldsymbol{x}(t)$ is the activation vector of the reservoir neurons at the generic time t, $f(\cdot)$ is the internal neurons activation function, which is typically $tanh(\cdot)$, $\boldsymbol{u}(t)$ is the P dimensional input vector $\boldsymbol{u}(t) = \boldsymbol{z}^{test}(t)$, and $y(t) = \widehat{RUL}(t)$ is the output vector. The leaky rate $a \in [0,1]$ is a hyper-parameter controlling the decaying potential of neurons (Jaeger, 2005).

The output provided by the *ESN* at time t is:

$$y(t) = f_{out}(\boldsymbol{W}_{out} \cdot [\boldsymbol{u}(t)|\boldsymbol{x}(t)]) \quad (2)$$

where $f_{out}(\cdot)$ is the output neuron activation function, which is typically the identity function, $f(x) = x$ and the symbol $\cdot|\cdot$ represents the vertical concatenation operation.

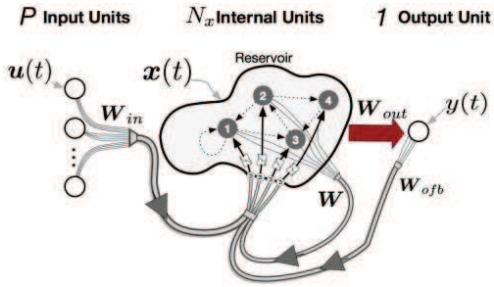

Fig. 1. Echo State Network architecture.

The elements of $\boldsymbol{W}_{in}$, $\boldsymbol{W}$ and $\boldsymbol{W}_{ofb}$ are randomly sampled from uniform distributions according to the *RC* principles. To ensure the *Echo State Property* (Jaeger, 2004; Yildiz, Jaeger and Kiebel, 2012;), which implies that the effect of the current states of the reservoir internal neurons and of the input on a future state vanishes gradually as time passes and does not amplify or persist, the reservoir connection matrix is typically scaled as $\rho/|\lambda_{max}| \cdot \boldsymbol{W}$, where $|\lambda_{max}|$ is the magnitude of the largest eigenvalue of $\boldsymbol{W}$ and $\rho \in (0,1)$ is a model hyper-parameter indicating the desired spectral radius.

The *ESN* training aims at finding optimal values for $\boldsymbol{W}_{out}$ and is performed by minimizing the quadratic error between the target output and the *ESN* output, which requires solving the corresponding linear regression problem.

3.1 *Method proposed to deal with event-based measurements*

The reservoir neurons are excited at each time step $t = 1,2,\dots,\tau_{n^{test}}$, independently from the occurrence of events in the system. In particular, if at time t the event has not occurred and, therefore, the signal values $\boldsymbol{z}^r(t)$ are not measured, Eq. (1) becomes:

$$\boldsymbol{x}(t) = (1-a)\boldsymbol{x}(t-1) + f(\boldsymbol{W}\boldsymbol{x}(t-1) + \boldsymbol{W}_{ofb}y(t-1)), \quad (3)$$

whereas, if at time t an event has occurred, i.e. $t = \tau_j^r, j = 1,\dots,n^r$, Eq. (1) is applied. Notice that Eq. (3) is used in the different context of *RNN* training by the teacher forcing method (Williams and Zipser, 1989; Lamb *et al.*, 2016) to speed up the convergence by forcing the reservoir to stay close to the ground truth sequence. The training set is obtained by concatenating the input-output data according to the scheme shown in Figure 2.

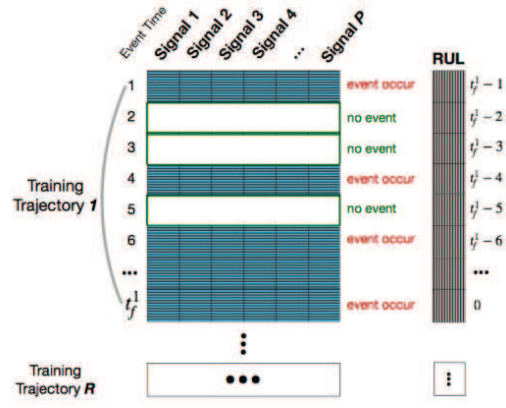

Fig. 2. Input-Output training set concatenation method. t_f^1 indicates the ground truth failure time of trajectory 1.

4. Case Study

4.1 *Simulation step and data description*

We consider a system made by four non-repairable components sharing a common load (Figure 3). The system load, L, is equally shared by the healthy components, i.e. the load sharing factor is:

$$LS = L/(4 - n_f) \quad (4)$$

where $n_f \in \{0,1,2,3\}$ is the number of failed components. The system fails when the last operating component fails.

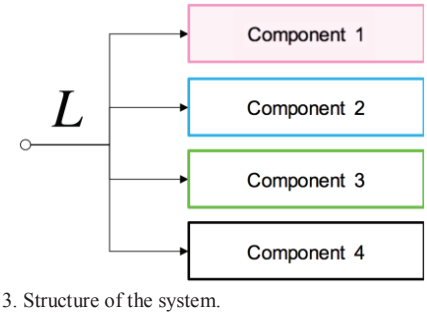

Fig. 3. Structure of the system.

The degradation of the i-th component of the system is simulated by using (Rigamonti, *et al.*, 2016):

$$d_t^i = d_{t-1}^i . e^{LS_{t-1} * C(T_{t-1})} + w_{t-1} \quad (5)$$

where d_t^i represents the i-th component degradation level at time t, LS_t the load sharing factor of the i-th component at time t, w_t the process noise describing the degradation process stochasticity, and $C(T_t)$ is a function of the temperature experienced by the component at time t. Eq. (5) is taken from (Rigamonti, *et al.*,

2016) where it is used to describe the degradation process of electric components. Function $C(T_t)$ is based on the Arrhenius law (Rigamonti, *et al.*, 2016):

$$C(T_t) = \frac{ln(2)}{Life_{norm} \cdot \exp\left[\frac{E_a}{k} \cdot \frac{273 - T_t}{273 \cdot T_t}\right]} \quad (6)$$

where E_a is the activation energy of the component, k is the Boltzmann constant, and $Life_{norm}$ is the nominal life of the component aged at the constant nominal temperature 273 K.

The simulation of a system run-to-failure trajectory starts assuming at $t = 1$ a degradation level $d^i = 1$ (in arbitrary units) for all the system components, $i = 1, \dots, 4$, and proceeds by randomly sampling the noise w_{t-1} from a zero-mean Gaussian distribution with standard deviation σ_w and applying Eq. (5). The temperature T_t experienced by the components at time t is influenced by the environment temperature T_t^{env} and the effect of the operational condition, which is represented by an additive temperature term Γ_t:

$$T_t = T_t^{env} + \Gamma_t \quad (7)$$

The environmental temperature is assumed to have a periodic triangular wave behavior, which reproduces its seasonality:

$$T_t^{env} = 2(T_{max}^{env} - T_{min}^{env}) \left| \frac{t}{p} - floor\left(\frac{t}{p} + \frac{1}{2}\right) \right| + T_{min}^{env} \quad (8)$$

where T_{max}^{env} and T_{min}^{env} are the maximum and minimum annual environment temperatures, respectively, and p is the period of the environment temperature cycle. The term Γ_t is sampled from a uniform distribution in the range (1,9].

A component fails when its degradation level d_t reaches the failure threshold, which is set to 1.25, 1.50, 1.75 and 1.77 for components 1, 2, 3 and 4, respectively. Different failure thresholds have been used to represent the heterogeneity of the components (Patricks *et al.*, 2007). Table 1 reports the parameter values used for the system run-to-failure trajectory simulations, which are taken from (Rigamonti, *et al.*, 2016b).

The events in correspondence of which the measurements are taken are:
1) when the temperature T_t^{env} experienced by the system exceeds either a lower or an upper temperature bound, set to 320 K *and* 380 K respectively;
2) when the degradation level of any one of the components exceeds the thresholds of 1.25, 1.50, 1.75, 1.77.

The following 6 measurements are assumed to be available in correspondence of events:

$$\boldsymbol{z}_i(\tau_j) = d_{m,\tau_j}^i = d_{\tau_j}^i \cdot \left(\alpha + \beta e^{-\frac{(T_{\tau_j} - 273)}{\gamma}}\right) + \eta_{\tau_j}, i = 1, \dots, 4, j = 1, \dots, n^r \quad (9)$$

$$\boldsymbol{z}_5(\tau_j) = T_{\tau_j},\ \boldsymbol{z}_6(\tau_j) = \Gamma_{\tau_j} \quad (10)$$

where η_{τ_j} represents the measurement noise, which is sampled from a zero-mean Gaussian distribution with standard deviation σ_η, and α, β and γ are parameters characteristics of the component. Table 1 reports the values of these parameters.

We have generated 150 run-to-failure simulation trajectories, which are partitioned into three sets: the training set (50 trajectories), the validation set (50 trajectories) and the test set (50 trajectories). On average, an event generates the measurements of the 6 quantities every 55 time units. Thus, the dataset is characterized by a fraction of missing data equal to nearly 98%.

Table 1. Parameters for the system run-to-failure trajectory simulations.

Parameters	Value
Standard deviation of w (σ_w)	0.002
Activation energy (E_a)	6.48×10^{-20}J
Boltzmann constant (k)	1.38×10^{-23}J/K
Component nominal life ($Life_{norm}$)	87600
Period of the environment temperature cycle (p)	8760
Standard deviation of η (σ_η)	0.002
Component characteristics (α)	0.0817
Component characteristics (β)	0.037
Component characteristics (γ)	30.682

4.2 *Results and Discussion*

The hyperparameters of the *ESNs* have been set by applying the random search algorithm proposed in (Bergstra and Yoshua Bengio, 2012) The validation results have been computed using the 50 run-to-failure trajectories of the validation set. A reservoir washing out procedure (Jaeger, 2005) is applied each time a new degradation trajectory is processed to avoid the influence of data collected from different systems on the neuron states (Lukoševičius and Jaeger, 2009).

Figure 4 shows the *RUL* predictions obtained by the obtained *ESN* on two different run-to-failure trajectories. Table 2 reports the average values of the accuracy prognostic metrics CRA and $\alpha - \lambda$ (indicated as $\overline{CRA}$ and $\overline{\alpha - \lambda}$) of the *ESN*, and of a Feedforward Artificial Neural Network (*FANN*), computed on the 50 run-to-failure trajectories of the test set. The *FANN*

predicts the *RUL* at time τ_j, using the collected signal measurements $\boldsymbol{z}(\tau_j)$. The *FANN* network architecture has been optimized using a grid-search approach on the validation set. Notice that *ESN* provides more accurate predictions than *FANN*. Figure 4 shows that the *RUL* predictions of *FANN* are less satisfactory at the end of the system life when the use of the historical degradation information becomes more relevant.

Table 2. Comparison of the performance of the proposed *ESN* method and of a *FANN*.

Method	$\overline{CRA}$	$\overline{\alpha-\lambda}$
ESN	**0.492±0.209**	**0.498±0.169**
FANN	0.0193±0.225	0.4639±0.199

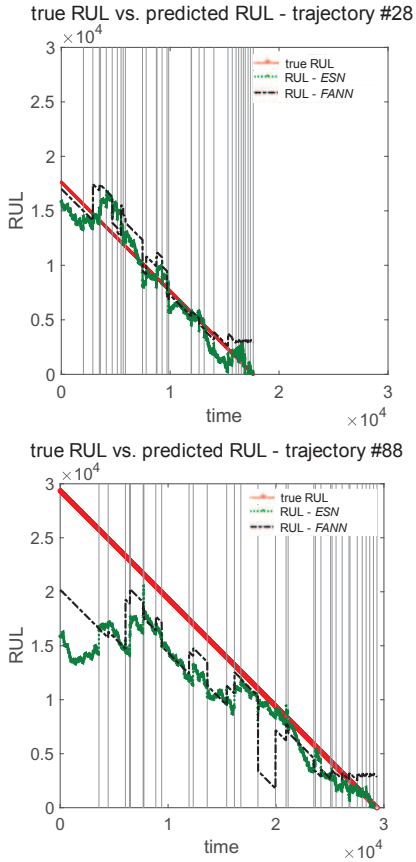

Fig. 4. Remaining Useful Life (*RUL*) predictions on two run-to-failure test trajectories. The vertical lines indicate the time at which the measurements are taken.

5. Conclusion

We have developed a method for predicting the remaining useful life of a system of non-repairable interacting components using a *ESN* properly tailored to deal with data collected at irregular time steps. When signal measurements are not collected, reservoir neurons internal states are excited only by the previous time internal states. The proposed *ESN* method has been verified using a synthetic case study, which mimics the behavior of a system in which measurements are collected only when events occur. The results obtained have shown that the proposed *ESN*-based method overperform a *FANN*.

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