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Failure and Reliability Predictions by Infinite Impulse Response Locally Recurrent Neural Networks

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In this paper, Infinite Impulse Response Locally Recurrent Neural Networks (IIR-LRNNs) are employed for forecasting failures and predicting the reliability of engineered components and systems. To the authors' knowledge, it is the first time that such dynamic modelling technique is used in reliability prediction tasks. The method is compared to the radial basis function (RBF), the traditional multilayer perceptron (MLP) model (i.e., the traditional Artificial Neural Network model) and the Box-Jenkins autoregressive-integrated-moving average (ARIMA). The comparison, made on case studies concerning engine systems, shows the superiority of the IIR-LRNN with respect to both the RBF and the ARIMA models, whereas a similar performance is obtained by the MLP.

1. Introduction

Reliability modeling and forecasting have received increasing attention over recent years, due to the growing use of reliability indices in engineering decision making.
Successful reliability prediction generally requires developing a reliability model of the system. Several reliability modelling approaches are available depending on the problem (e.g. reliability block diagrams, fault tree analysis, state-space methods, failure rate prediction methods (Siewiorek and Swarz, 1982)). Although these methods are widely used, they bear some limitations when used for predicting the evolution of reliability with time. The limitations derive from the need to make assumptions on the failure processes and distributions, which render the reliability models little realistic.
In general, reliability changes with time and the changes can be treated as a time series. However, the complexity and nonlinearity of the process poses strong challenges to the standard time series analysis methods. On the other hand, artificial neural networks have received increasing attention in time series forecasting, due to their general nonlinear function mapping capabilities: Liu et al. (1995) used neural network models to estimate the parameters of a reliability distribution when a small data set is available; Su et al. (1997) combined ARIMA models with neural network techniques to predict engine reliability; Amjady and Ehsan (1999) proposed a neural-network-based expert system for evaluating the reliability of power systems; Cai et al. (2001), Ho et al. (2003), Tian and Noore (2005a and b), Hu et al. (2007) used both classical and recurrent neural networks to forecast software reliability.
Whereas feed-forward neural networks can model only static input/output mappings, the structure of recurrent neural networks allows reproducing the behavior of dynamic systems by implementing temporal dynamic feedbacks into the widely used multi-layered feed-forward neural network. By adding recurrent feedback connections, a multilayer feed-forward network can be provided with system state

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memory and thus transformed into a recurrent network which is potentially capable of modeling dynamic systems and time series (Ho et al., 2002; Xu et al., 2003).
In this paper, an Infinite Impulse Response Locally Recurrent Neural Network (IIR-LRNN) modeling approach (Back and Tsoi, 1991) is proposed for forecasting the reliability and failures of hardware components. To the authors' knowledge, it is the first time that such type of recurrent neural network is used for this task. To investigate the IIR-LRNN capabilities in reliability prediction, the predictive performance of various time series models including MLP, ARIMA and RBF, are evaluated in comparative studies regarding engine failure processes.

2. Neural networks for time series prediction

Time series are samples of the behaviour of a process over discrete time values. The prediction of the evolution over time of a process implies the prediction of the future values of the time series describing the process (Charfield, 1991).
Time series prediction with classical methods relies on successive steps which include the design of the model, its identification and finally the parameters estimation. Let $\bar{x}_t \equiv (x_1, x_2, \ldots, x_{t-1}, x_t)$ be the time series data collected up to time *t*, in order to build the model. The data are samples of the process variable *x,* taken with a given time step. The prediction of the time series values can be made a single-step ahead to estimate x_{t+1} or multi-step ahead to estimate x_{t+p}, p>1.
The predictive model is then a mapping function of the form:

$$x_t = f(x_{t+p-1}, x_{t+p-2}, \cdots, x_t) \tag{1}$$

where *p* is the dimension of the input vector, i.e. the number of past observations in the time series which relate to the future value x_t, and *f* is the model function.
The most difficult processes to predict are (Mandic and Chambers, 2001): i) those with insufficient amount of data in the series (for instance chaotic signals); ii) those whose data series are obtained through observations and measurements (in this case the data are affected by measurement errors); iii) processes whose behaviour varies in time.
On the contrary, the application of artificial neural networks for time series analysis relies purely on an 'automatic training' procedure of parameters (weights) tuning, based on the data observed. This training aims at finding the approximating function *f*, which is uniquely determined by iteratively adjusting the weights of the network. Because multilayer feed-forward networks with at least one hidden layer and a sufficient number of hidden units are capable of approximating any measurable function (Hornik et al., 1989), an artificial neural network has the capability of representing any form of time series, even in the case of noisy and/or missing data. Furthermore, the neural networks ability to cope with nonlinearities, their speed of computation, their learning capacity and their accuracy make neural networks valuable tools of prediction and give them an advantage over linear models like the ARIMA technique (Box and Jenkins, 1976).
When neural networks are used for time series forecasting, the data series is usually divided into a training set and a test set. The training set is used for the construction and training of the neural network whereas the test set is used for measuring the predictive ability of the model.
As already said, classical feed-forward networks are in general capable of representing only static input/output mappings and suffer from the drawback of not being able to characterize higher order dynamics of a system. For this reason, in order to improve performance, delayed feedback links can be designed to obtain recurrent architectures. In this way, the network is capable of storing previous knowledge on the input patterns. Hence, these recurrent structures can learn temporal sequences better as time evolves (Ho et al., 2003).

3. The Infinite Impulse Response-Locally Recurrent Neural Network (IIR-LRNN)

A LRNN is a time-discrete network consisting of a global feed-forward structure of nodes interconnected by synapses which link the nodes of the *k*-th layer to those of the successive (*k*+1)-th layer, *k* = 0, 1, …, *M*, layer 0 being the input and *M* the output. Differently from the classical static feed-forward networks, in an LRNN each synapse carries taps and feedback connections. In particular, each

synapse of an IIR-LRNN contains an IIR linear filter whose characteristic transfer function can be expressed as ratio of two polynomials with poles and zeros representing the Auto Regressive (AR) and Moving Average (MA) part of the model, respectively.
During the forward phase, at the generic time t = 1, 2, …, T the generic neuron j = 1, 2, …, N^k belonging to the generic layer k = 1, 2, …, M receives in input the quantity $y_{jl}^{k}(t)$ from neuron l = 1, 2, …, N^{k-1} of layer (k – 1):

$$y_{jl}^{k}(t) = \sum_{p=0}^{L_{jl}^{k}-1} w_{jl(p)}^{k} \cdot x_{l}^{k-1}(t-p) + \sum_{p=1}^{I_{jl}^{k}} v_{jl(p)}^{k} \cdot y_{jl}^{k}(t-p) \qquad (2)$$

The quantities $y_{jl}^{k}(t)$, l = 1, 2, …, N^{k-1}, are summed to obtain the net input $s_{j}^{k}(t)$ to the nonlinear activation function $f^{k}(\cdot)$, typically a sigmoidal, Fermi function, of the j-th node, j = 1, 2, …, N^k, of the k-th layer, k = 1, 2, …, M:

$$s_{j}^{k}(t) = \sum_{l=0}^{N^{k-1}} y_{jl}^{k}(t) \qquad (3)$$

The output of the activation function gives the state of the j-th neuron of the k-th layer, $x_{j}^{k}(t)$:

$$x_{j}^{k}(t) = f^{k}\left[s_{j}^{k}(t)\right] \qquad (=1 \text{ for the bias node, } j=0) \qquad (4)$$

For simplicity of illustration, and with no loss of generality, an example of a network constituted by only one hidden layer, i.e. M = 2, is depicted in Figure 1.
Further details about the IIR-LRNN architecture and forward calculation may be found in (Campolucci et al., 1999) and (Cadini et al., 2007).

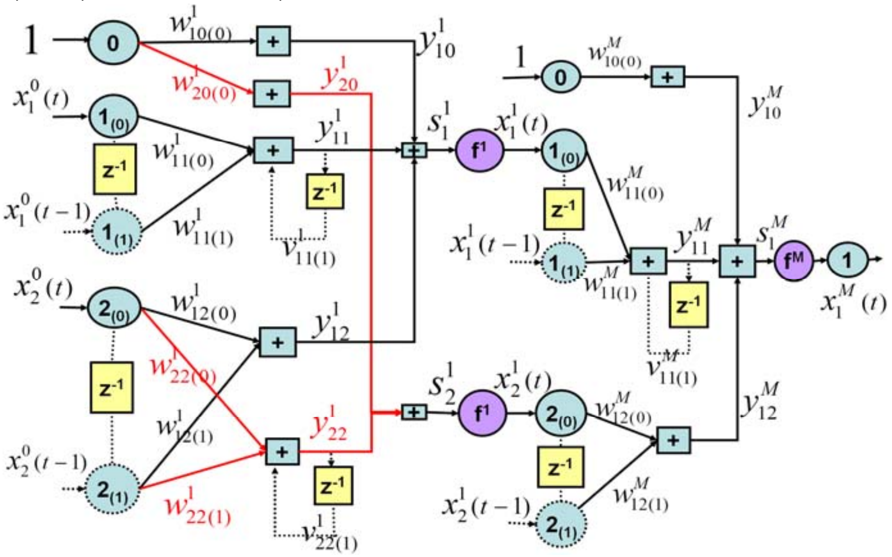

Figure 1. Scheme of an IIR-LRNN with one hidden layer

The IIR-LRNN is trained with the Recursive Back-Propagation (RBP) training algorithm (Campolucci et al., 1999), a gradient-based minimisation algorithm which makes use of a particular chain rule expansion for the computation of the necessary derivatives. For brevity, the RBP algorithm is not presented in this paper; the interested reader may refer to (Campolucci et al., 1999) and (Cadini et al., 2007) for details.

4. Failure and reliability prediction by IIR-LRNN

In the following, the dynamic modelling power of IIR-LRNN is challenged with the task of failure and reliability prediction. To verify the potential of the technique, two literature case studies concerning engine systems are considered and a comparison is made against other traditional and neural paradigms of time series modelling.

4.1 Forecasting the failure time of turbochargers in diesel engines

Most modern diesel engines are equipped with a turbocharger, for increased power output. Capturing the trends of the failure data of this component is of paramount importance for predicting its reliability.

The data set used in this paper is composed by the failure times observed in 40 turbochargers from a set of 100 units of a specific type: see (Xu et al., 2003) for details.

With reference to the general time series mapping function (1), the observed x_t is the time-to-failure T_i, whereas the discrete observation time t is the failure order number i.

Two IIR-LRNNs have been developed. The first one builds a single-step ahead predictive function by using the i-th unit time-to-failure as input to predict the (i+1)-th time-to-failure as output. The second makes a two-step ahead prediction of the (i+2)-th time-to-failure, using the same input.

Both IIR-LRNNs are composed of three layers: the input, with two nodes (bias included); the hidden, with nine and eight nodes (bias included) for the single- and two-step-ahead predictions, respectively; the output with one node. Hence, both networks have a single node for the variable time-to-failure in the input layer, which is fed with the lagged observations of the data series. The single node in the output layer provides the future values of the time-to-failure series.

The number of hidden nodes, as well as the number of taps and delays have been chosen experimentally to obtain a satisfactory modelling performance of the trained IIR-LRNNs, measured in terms of the Normalized Root Mean Square Error (NRMSE) defined as $NRMSE = \sqrt{\sum [x(t) - \hat{x}(t)]^2 / \sum x^2(t)}$, where $\hat{x}(t)$ is the prediction of $x(t)$.

As in (Xu et al., 2003), the data corresponding to the first 35 failures are used to construct the training patterns and those corresponding to the last 5 failures as the testing patterns, for a total of 40 patterns. The training has been carried out for 6000 iterations; on each iteration, the 35 training patterns are reprocessed and the network parameters adjusted so as to reduce the prediction error.

Figure 2 shows the comparison between the actual and predicted failure times for both single and two-step ahead IIR-LRNNs respectively. The IIR-LRNNs predictions are in satisfactory agreement with the real failure times.

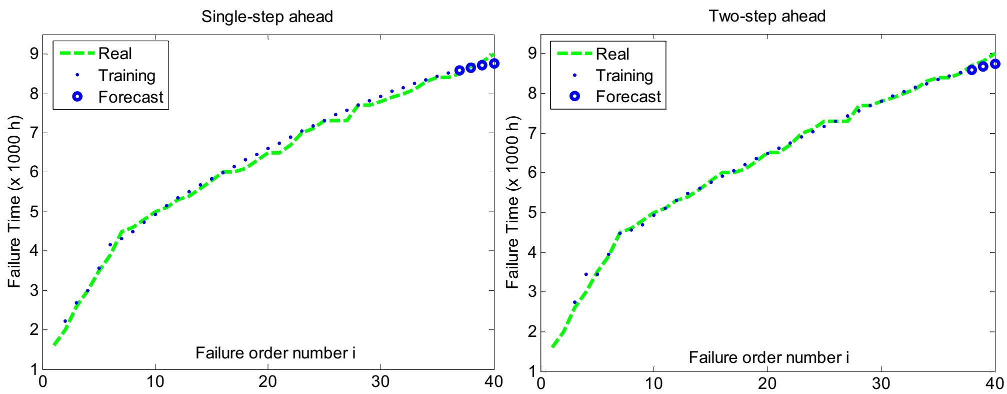

Figure 2. Predictive performance of the two IIR-LRNNs.

The IIR-LRNN predictions have been analyzed further in terms of the component reliability $R(T_i)$ at failure time T_i, computed as $R(T_i) = 1 - (i - 0.3)/(n + 0.4)$, where i is the failure order number and n is the date sample size (i.e., n = 40) (Xu et al., 2003). The NRMSE values computed on the training and test data are found to be 0.0213, 0.0149, respectively, for the single-step-ahead IIR-LRNN and 0.0117 and 0.0199, respectively, for the two-step-ahead IIR-LRNN; the values confirm that both single- and two-step ahead IIR-LRNNs have good generalization capabilities, the error being less than two percent on the five test data.

4.2 Forecasting km-to-failure for car engines

In the automotive industry, the reliability performance of car components is often measured in terms of usage. In the application considered in the following, the distance covered by a car engine between consecutive failures measured in km-between-failures is taken as performance indicator.

The data set used in this paper is composed by the km-between-failures for 100 units of a specific brand of car engine: see (Xu et al., 2003) for details.

These data can be treated as a time-series in which the observed quantity *x(t)* is the km-between-failures and the time *t* is the number *i* of the failure. The objective is to forecast the remaining km-between-failures based on past failure observations.

One IIR-LRNN has been trained for the single-step ahead prediction. Hence, one pattern is given by the km-between-failures at failure number *i*, as input, and the corresponding value at failure number *i*+1. The IIR-LRNN has three layers: the input, with two nodes (bias included); the hidden, with eleven nodes (bias included) and the output with one node.

The training set is composed of patterns constructed by the first 90 data, where the last 10 data are used to build the testing patterns. The training is performed for 20,000 iterations. The graphical plot of the actual and predicted km-between-failures is presented in Figure 3. The predictive performance of the IIR-LRNN is summarized in Table 1: a comparison is made with the results obtained with MLP, RBF and ARIMA models (Xu et al., 2003).

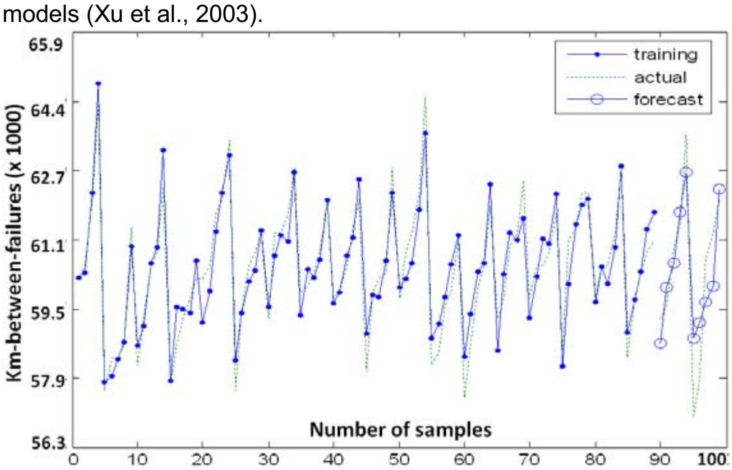

Figure 3. IIR-LRNN predictive performance on the km-between-failures of car engines.

Table 1. Prediction results of car engine km-between-failures using times series models (x 1000)

Number	km-between-failures (actual)	IIR-LRNN	MLP (logistic activation)	MLP (Gaussian activation)	RBF (Gaussian activation)	AR
91	59.3142	58.7302	59.5862	59.5311	59.7209	60.1151
92	59.6211	60.0342	60.8605	60.3476	60.7569	58.4521
93	61.0005	60.6075	60.8729	60.7599	61.1570	59.6419
94	61.4607	61.8008	62.0301	61.8350	61.0426	61.6380
95	63.6063	62.7250	62.4743	63.4594	61.4867	62.2930
96	57.0159	58.8506	58.7650	58.1193	59.4444	63.2554
97	57.9354	59.2221	58.6996	58.4238	58.4614	55.0012
98	60.6948	59.6933	59.3018	59.4691	59.3503	58.4445
99	61.3070	60.0779	61.0613	60.0134	60.0062	61.7482
100	62.0732	62.3274	62.3102	61.7686	61.4402	64.6621
NRMSE		0.0158	0.0156	0.0122	0.0211	0.0422

5. Conclusions

In this paper, the dynamic modelling power of recurrent neural networks is employed to map the past failure data series into future failure occurrences. In particular, single- and two-step ahead IIR-LRNNs have been set up for forecasting failure times of engine systems. To the authors' knowledge, this is the first time in which the properties of IIR-LRNNs are exploited for failure and reliability prediction. In the application presented, a novel formulation of the problem has required that the failure order numbers be considered as the time instants in a time series framework. The significance of the adopted neural modelling approach is that no a priori specifications of parametric failure distributions need to be made and verified. The results obtained show that the use of neural network models for failure forecasting is an effective way for tackling such problem. More precisely, a comparative study of IIR-LRNN, MLP, ARIMA and RBF models has shown that neural networks in general provide a promising alternative for complex time series modelling, leading often to better predictive performances than the ARIMA models. In particular, the proposed IIR-LRNN architecture has been shown capable of achieving comparable or lower prediction errors than traditional feed-forward MLP and RBF network models.

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