The Application of Recurrent Neural Networks for the Diagnosis of Industrial Systems

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Abstract: The complexity of industrial equipment is constantly increasing, which makes the task of monitoring more and more complex. In this context, the use of artificial intelligence techniques offers very practical solutions to deal with this task, especially artificial neural networks, because thanks to their learning capacity and their automatic and intelligent algorithms, they can handle perfectly industrial system monitoring problems. In these papers, we are mainly interested in recurrent neural networks, which are a specific kind of artificial neural network, which provides excellent dynamic behaviour. In the literature, several architectures of recurrent neural networks have been proposed and implemented, and each one offers some strengths and weaknesses. Therefore, in the following papers, we present state of the art as well as a comparative study between the most relevant architectures that can be used to ensure the operation of the diagnosis, which is considered a significant phase of industrial system monitoring.

1 INTRODUCTION

The neural networks have represented extraordinary progress in the field of artificial intelligence so that, the consequences of this progress extend to several industries and applications (T. Cambrai, 2019), especially in form recognition, which has been widely applied in various engineering fields, mainly industrial systems monitoring (Msaaf and Belmajdoub, 2015), especially the dynamic and static diagnosis (Koivo, 1994), (H. Wang and P. Chen, 2011), (R. Patton, J. Chen, and T. Siew, 1994) as well as the prognosis (DePold and Gass, 2014),(Tobon-Mejia et al., 2012).

According to Lefebvre (Lefebvre D., 2000), the principle of monitoring is to detect and classify failures by observing the system's evolution, than to diagnose them by locating the faulty elements and identifying the primary causes. Therefore, the application of neural networks in the diagnosis can be considered as a kind of classification or form recognition (Msaaf and Belmajdoub, 2015), so that each observed failure is associated with its probable fault class. From the different sensor signals generated by the desired system, the neural networks provide an output that indicates the probably current state (Zemouri et al., 2003). In practice, the sensor's outputs changes during the system functioning (Palluat et al., 2005). Therefore it can be considered as a time series dataset. In this context, the use of recurrent neural networks (RNNs), which are dedicated to treating this kind of data, seems interesting. These papers aim to present an overview and a comparative study of the relevant recurrent neural network architectures, which can be used to ensure industrial system diagnosis.

The rest of these papers will be as follow: In the next section, a general context about neural networks will be presented. The third part gives an overview of recurrent neural networks and a classification of the several architectures of RNNs, as well as a comparison between the different architectures to justify the choice of the appropriate architecture to accomplish the diagnosis function.

2 FORMAL NEURONE

In 1943, Mc. Culloh et al. developed the first mathematical and computer model that mimics the

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functioning of the biological neurons (Mcculloch and Pitts, 1943), which is the single neuron or formal neuron (figure 1). It consists of a binary neuron, i.e. whose output is 0 or 1. The behaviour of a formal neuron is composed of two main phases:

$-\ 1^{st}$Phase or the activation phase, in this phase; a weighted sum of the entries is calculated so that:

$$a_i = \sum_{j=1}^{n} W_{ij} * x_{ji} + b_i \qquad (1)$$

Such as W_{ij} represents the weights of the neuron and b_i the bias of the neuron.

$-\ 2^{nd}$ Phase is the phase of calculating the neuron output. From the value of a_i the output Y_i is calculated so that:

$$Y_i = f(a_i) \qquad (2)$$

Such as the function f is a transfer function (or activation function) applied to a_i.

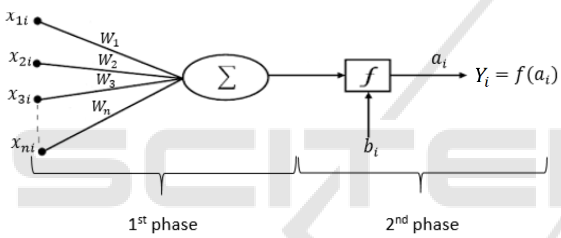

Figure 1: Formal neurone.

The activation function is the transfer function that connects the weighted summation to the output signal. There are different types of activation functions. Figure 2 shows the most commonly used ones (Msaaf and Belmajdoub, 2015).

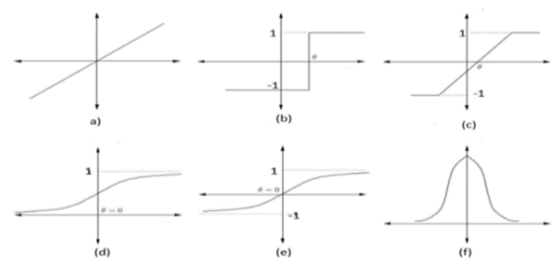

Figure 2: The most frequently used activation functions, A) Linear Function. B) Threshold function. C) Linear Function by Piece D) Sigmoid Function. E) Hyperbolic Tangent Function. F) Gaussian Function.

The formal neuron does not have a tremendous computational capacity, but this strength appears when it is interconnected with other formal neurons. A neural network is formed by a set of formal neurons connected and organized in layers. There are three main classes of layers: the input layer, the output layer and the hidden layer. Thus, each node is connected to the node in the next layer (in the case of a feedforward neural network), or can be linked to any other node or even to itself (in the case of a recurrent neural network).

3 RECURRENT NEURAL NETWORKS

3.1 General Context

The recurrent neural networks (RNNs) is a particular class of artificial neural networks dedicated to time-series datasets, i.e. a sequence of data that varies over time. The main feature of an RNN is that the network disposes on feedback connection or internal loop ("Recurrent Neural Network - an overview | ScienceDirect Topics," 2020), which permits continuing information related to past knowledge so that it handles sequences by iterating through the elements of the series and maintaining a state, which contains information relative to all the details presented to the network (Chollet, 2017), which give to the RNN the ability to treat the current element while keeping memories of what came before. In the literature, several architectures of RNNs have been proposed to ensure different operations. In the next section, we will present the main relevant ones, which can be used to guarantee industrial systems diagnosis.

3.2 Recurrent Neural Networks Architectures

3.2.1 Jordan's Architecture

In (Jordan M. I., 1989), the author proposed one of the first architectures of recurrent neural networks, which is the Jordan architecture. In this architecture, the units of the output layer are duplicated on a context layer. The units of this layer also consider their state at the previous state, which gives the neural network a dynamic or individual memory (Zemouri, 2003). The output of this layer is calculated according to the following equation:

$$C(k) = \alpha C(k-1) + Y(k-1) \qquad (3)$$

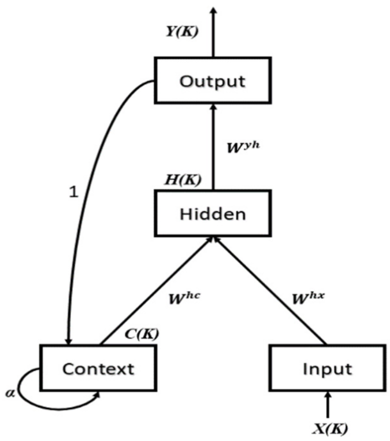

Figure 3: Jordan's architecture

3.2.2 Elman's Architecture

Elman's architecture (Elman J. L., 1990) is inspired by a large part of Jordan's architecture; this time, instead of duplicating the network output, it is the hidden layer units that are reproduced in the context layer.

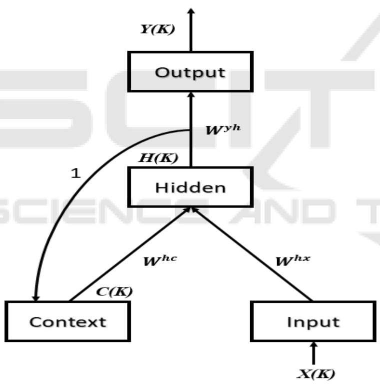

Figure 4: Elman's architecture

Remarque

Elman's and Jordan's architecture are considered simple recurrent neural networks (Dinarelli and Tellier, 2016).

3.2.3 Recurrent Radial Basis Function (RRBF)

Contrary to Jordan's and Elman's architecture, the RRBF neural network (Zemouri, 2003) obtains its dynamic aspect by a recurrence of the connections at the level of the neurons of the input layer, which provide the input neurons with a capacity to take into account the different data already presented (Zemouri et al., 2003), (Zemouri et al., 2006). As a result, The RRBF disposes of two types of memory:

- Dynamic memory that takes into account the dynamics of the input data.
- Static memory for prototype storage.

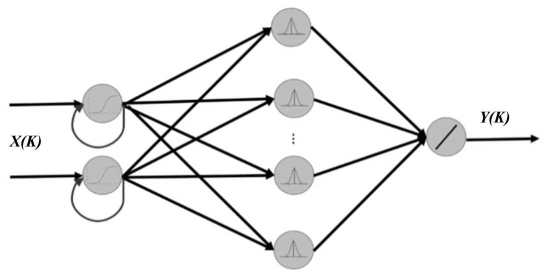

Figure 5: RRBF's architecture

3.2.4 Recurrent Radial Basis Function (R2BF)

The R2BF (Frasconi et al., 1996) model has been developed to have a behaviour comparable to a finite state automaton. This network is composed of 4 layers: Input, output, and two hidden layers, the first hidden layer has Gaussian neurons, which are fully connected to the second one that has sigmoid neurons, the production of these neurons is connected to the output layer and at the same time reinjected to the first hidden layer as the input of this layer is represented by two vectors, which are the current input and the output of the second layer of the previous state.

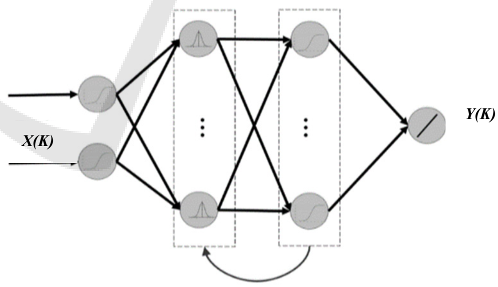

Figure 6: R2BF's architecture

3.2.5 Dynamic General Neural Network (DGNN)

This architecture is considered as the combination of two neural networks: the multi-layer perceptron and the radial basic function (Palluat et al., 2005), (Ferariu, L. and T. Marcu, 2002) (For further information about these two architecture show (Msaaf and Belmajdoub, 2015)). This architecture is composed of three layers: input and output layer and a hidden layer (Scarselli et al., 2009), which contains two types of neurons

(Sigmoid neurons and Gaussian neurons), this network has recurrent internal connections in the neurons of the output and hidden layer.

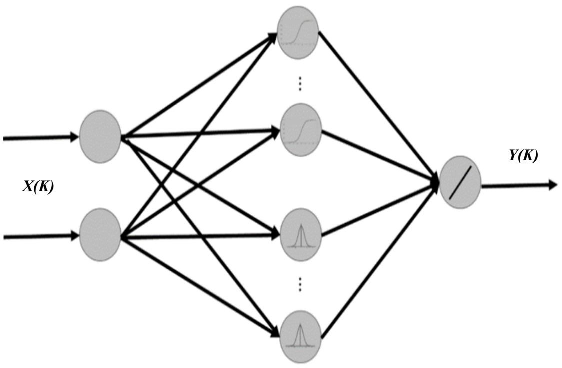

Figure 7: DGNN’s architecture.

3.2.6 Jordan’s/Elman’s architecture variant

In (Dinarelli and Tellier, 2016), the authors have proposed a variant of Jordan’s and Elman's architecture. In this architecture, the authors proposed that the outputs predicted by the network at the stages of the sequence processing are returned to the input of the network, which allows the returned data to traverse the network in its entirety.

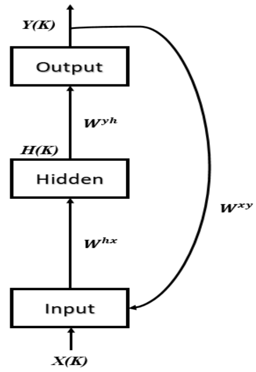

Figure 8: Jordan’s/Elman’s architecture variant.

In practice, each of these architectures presented above shows some advantages and disadvantages. Therefore, based on a thorough analysis of the several case studies presented in the following researches (Zemouri et al., 2003), (Palluat et al., 2005), (Dinarelli and Tellier, 2016), (Zemouri et al., 2006), (Wysocki and Ławryńczuk, 2015), and (Tong et al., 2009) it was possible to extract the several strengths and weaknesses, which provides each method in practice (table1).

Table 1: The advantages and disadvantages of some recurrent neural networks architectures.

Neuronal Architecture	Author(s)/Date of Publication	Recurrence type	Advantages	Disadvantages
Jordan	Jordan M. I./1989	Between the output layer and the context layer.	- Simple architecture -Fast learning -Adapts to several tasks that consist of predicting sequential information. -Use the label predicted in the current state.	-Sometimes, the context layer exhibits forgetting behaviour. -Only a part of the network is affected by the recurrent information, which results in more or less inefficient learning. -Vulnerable to error propagation.
Elman	Elman J. L./ 1990	Between the hidden layer and the context layer.	-Simple architecture. -Fast learning. -Adapts to several tasks that consist of predicting sequential information. -Avoid the forgetting behaviour presented to Jordan's architecture.	-Only a part of the network is affected by the recurrent information, which results in more or less inefficient learning.

Table 2: The advantages and disadvantages of some recurrent neural networks architectures (cont.).

Neuronal Architecture	Author(s)/Date of Publication	Recurrence type	Advantages	Disadvantages
RRBF	Zemouri, R., Racoceanu, D. and Zerhouni, N./2003	Recurrence of the connections at the input layer.	-Architecture is easy to understand and to implement. -The recurrent information traverses the entire network, affecting all the network layers, resulting in efficient learning. -Fast learning with high accuracy. -Architecture dedicated to industrial system diagnosis and prognosis. -Simple and stable learning algorithm.	-Complex learning. -Require a high computation capacity.
R2BF	Frasconi, P., Gori, M., Maggini, M., Soda, G./1996	Between the outputs of the neurons of the hidden layer and the one.	-R2BF have a very intriguing relationship with high order recurrent networks (The "order" of a neural network refers to the dimensionality of the product terms in the weighted sum (Frasconi et al., 1996)). -Fast learning with high accuracy but lower than RBBF's accuracy.	-Require a high computation capacity. - Only a part of the network is affected by the recurrent information, which results in more or less inefficient learning.
DGNN	Scarselli, F., Gori, M., Tsoi, A. C.,Hagenbuchner, M., Monfardini, G./2009	Internal recurrent connections in the neurons of the hidden layer and the output layer.	-Simple architecture with good accuracy and capacity for generalization. -Interesting results may be obtained with a high number of hidden layers. - Interesting results may be obtained by using genetic algorithms or other artificial intelligence algorithms.	- High response time. - Sometimes it is necessary to do several training on different bases to obtain interesting results. - Only a part of the network is affected by the recurrent information, which results in more or less inefficient learning.
Jordan/Elman variant	Dinarelli, M. Tellier, I./2016	-Recurrence between output and input layer	-The information traverses the network in its totality, which allows more effective learning. -The recurrent connection between the output and input layers makes the model much more robust.	-Require a high computation capacity. -Significant learning time.

This comparative study shows that:

-The extension of Jordan and Elman's architecture and the RBBF have a recurrence between the output of the network, which allows the recurrent information to traverse the entire network, affecting all the layers without exception, which provides much more efficient learning. In the other architecture, only a part of the network is affected by the recurrence, which results in more or less inefficient learning. Besides, the forgetting behaviour of Jordan's architecture cannot be tolerated because most of the industrial systems are complicated systems, which generate very long sequences, directly affecting the reliability and accuracy of the diagnosis result.

-RRBF, R2BF, and DGNN provide a good capacity of generalization and a fascinating accuracy; however, RRBF is distinguished by its architecture that is dedicated to industrial system diagnosis, in addition to its high accuracy in comparison to the others; also the use of an increased number of hidden layer in the case of DGNN affects directly the training and response time, which may be incompatible for the online diagnosis, the DGNN requires in some applications to perform several pieces of training with several training databases to obtain interesting results, which is not possible in some problems of industrial diagnosis, because sometimes the data are minimal.

-Concerning the high computing capacity required by the RRBF, R2BF, and Jordan/Elman variant's architectures, there is no longer a real problem thanks to the potent processors developed in the last few years.

The outcome of this comparison shows that the RRBF provides some advantages, which another architecture cannot deal with. Thanks to its high accuracy and its simple architecture, which is dedicated directly to industrial systems diagnosis, in addition to its easiness of understanding and implementation, make it the recurrent neural network architecture, which can deal perfectly with the diagnosis operation.

4 CONCLUSIONS

The implementation of a diagnosis module for an industrial system imposes different requirements to be taken into consideration. In these papers, we highlight the use of recurrent neural networks to ensure the diagnosis operation; through a comparative study between the relevant architectures presented in the literature, we found the RRBF could deal perfectly with industrial system diagnosis, which another cannot deal with, thanks to the strengths offered by this architecture. As an extension of this work, we will use the RRBF neural network to elaborate a diagnosis module to ensure discrete event system diagnosis, which is considered an important class of industrial systems.

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