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A Feed-Forward Backpropagation Neural Network Method for Remaining Useful Life Prediction of Francis Turbines

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Abstract **-** In this paper, a method based on feed-forward backpropagation artificial neural networks is developed to achieve a more accurate prediction of the useful life of the Francis turbines, subject to the monitoring of the condition. Predicting the remaining life of the Francis turbine components is critical to an effective condition-based maintenance to improve reliability and reduce overall maintenance costs. With the correct instrumentation it is possible to periodically measure and calculate the necessary operating parameters and, in the present investigation, having input data, the vibration severity in speed magnitude and the turbine efficiency, there will be trained a feed-forward backpropagation neural network in such a way as to obtain the Weibull failure rate function of the Francis Turbine. A two-element input vector is introduced with 100 samples for each input; the targets (100 samples) of Weibull failure rate function are also introduced. The method developed, for its consistency and effectiveness, can be generalized to systems and rotating equipment.

Keywords**:** neural network, Weibull distribution, Francis turbine, remaining life

1. Introduction

The Agoyán Hydroelectric Power Station was conceived to take advantage of the flow of the Pastaza River; it is in the Province of Tungurahua in Ecuador, at 180 km southeast of Quito and 5 km east of the city of Baños. It has a dam of gravity concrete of 43 m height and 300 m length, with bottom drainage, landfill and take. It has a pressure pipe of 170 m with a drop of 150 m. The engine room is underground to accommodate 2 groups of turbo-generators of 85,000 kVA each. The consumption flow is 60 m3 / s, its installed capacity is 156 MW, with 2 Francis units with vertical axis of 78 MW each, with a speed of 225 rpm.

The two Francis type reaction turbines are subject to heavy wear and tear in their constituent parts as a result of the erosive effect of the waters of the Pastaza river and that has been strongly complicated with the eruptions of Tungurahua volcano that has been in eruptive process for over 16 years, and whose ash is largely entrained by the waters of the Pastaza River, hydroelectric plants using water with volcanic ash for power generation suffer from severe metal wastage due to particle-induced erosion and cavitation that decreases the efficiency of the Francis turbines and the Mean Time Between Failures (MTBF), increasing the maintenance cost and, in general, affects both the operational reliability and the energetic efficiency of the generation plant.

Many studies have been conducted problem; our research group had been conducting studies on the water-sand flow through a rectangular tunnel with a step using the Particle Image Velocimetry (PIV) [1], [2], obtaining the following conclusions:

- The particles produce a biphasic micro flow that produces abrasive wear and additionally cavitation wear.
- The particles with high density should not be used as tracers for PIV studies with changes in the cross section.
- Downstream step, the velocity increases due to a change of section as a step is higher for sand than for water and is not influenced by a low sand concentration variation.

- The sand velocity is 5 % higher than water velocity for a reduction of 25% in the cross section and the water velocity profiles do not change due to variation of low concentrations of sand.

Also, some studies have been made on High-Velocity Oxy-Fuel process (HVOF)-based coatings given its application to improve the erosion life of the Francis turbines [3], [4]. The properties such as porosity, hardness, indentation toughness, and cavitation resistance are being investigated.

However, of these improvements, it has been determined the need to predict the failure time (predictive maintenance strategy) by the erosion and cavitation of the Francis turbines with due anticipation, avoiding not planned stops by vibrations of very high severity and a critical decrease in the efficiency of the generation. If you can perform a planned and optimal repair, minimizing the Mean Time to Repair (MTTR).

The high costs in maintaining today's complex and sophisticated equipment makes it necessary to enhance modern maintenance management systems. Conventional condition-based maintenance reduces the uncertainty of maintenance per the needs indicated by the equipment condition. The intelligent predictive decision supports system model, based on the artificial neural network (ANN) approach, was developed and tested and run for the critical equipment of a power plant [5].

In recent years, many researches have been successfully made, developing methods of artificial neural networks to very accurately predict the remaining life of rotating equipment [6], [7], [8], [9].

In this research, a method based on feed-forward backpropagation artificial neural networks is developed to achieve a more accurate prediction of the useful life of the Francis turbines, subject to the monitoring of the condition. Predicting the remaining life of the Francis turbine components is critical to an effective condition-based maintenance to improve reliability and reduce overall maintenance costs.

2. Weibull failure rate function

In maintenance engineering, there are related concepts such as: reliability, failure rate, mean time between failures (MTBF), mean time to repair (MTTR). Weibull distributions can be used to accurately model failure behaviors of a wide range of critical systems such as the critical equipment of a power plant [10], [11].

The Weibull reliability function is given by:

$$R(t) = e^{-(\frac{t-\gamma}{\delta})^{\beta}} \tag{1}$$

Where:
R(t) is the reliability
β is the shape parameter, also known as the Weibull slope
δ is the scale parameter
γ is the location parameter
The Weibull failure rate function $\lambda(t)$ is given by:

$$\lambda(t) = \frac{\beta}{\delta}\left(\frac{t-\gamma}{\delta}\right)^{\beta-1} \tag{2}$$

This is one of the most important aspects of the effect of β on the Weibull distribution. As is indicated on Fig. 1, Weibull distributions with $\beta < 1$ have a failure rate that decreases with time, which are also known as infantile or early-life failures. Weibull distributions with β close to or equal to 1 have a fairly constant failure rate, indicative of useful life or random failures. Weibull distributions with $\beta > 1$ have a failure rate that increases with time, also known as wear-out failures. These comprise the three sections of the classic "bathtub curve". An example of a bathtub curve is shown on Fig. 1 as follows:

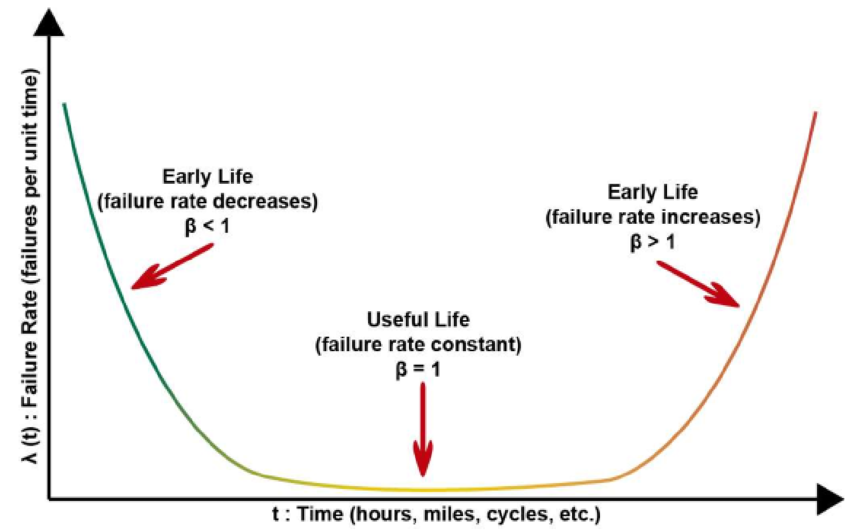

Fig. 1: Bathtub curve of Weibull failure rate function $\lambda(t)$.

Operative parameters generally can be found in general systems and mechanical equipment, whose measurement, allows determining the operating conditions of this equipment, to establish normal operating conditions and to predict failures in these systems. In the case of Francis turbines, in this research, the following operating parameters will be used to monitor the operating conditions of these turbines over time:

- The vibration severity in speed magnitude $V(t)$ (RMS speed), given that the wear caused in a turbine, by cavitation and abrasion, implies an increase in the value of vibrations in speed magnitude. In this case, we have as a pattern or reference the vibration severity chart which is based on ISO 10816, where, for the turbine speed in rpm, we can use as a reference the values of $V(t)$ in RMS speed for normal operation, with acceptable wear and failure conditions.
- The turbine efficiency $\eta(t)$, given the wear caused in a turbine by cavitation and abrasion, implies a decrease in the value of this efficiency. In this case, the pattern or reference is the theoretical curve calculated from the equations of turbomachinery and the real curve supplied by the designer and manufacturer of the turbine; in which also, the values of $\eta(t)$ can be referenced for normal operation, with acceptable wear and for failure conditions.

With the correct instrumentation it is possible to periodically measure and calculate the necessary operating parameters and, in the present investigation, having input data $V(t)$ and $\eta(t)$, there will be trained a feed-forward backpropagation neural network in such a way as to obtain the Weibull failure rate function $\lambda(t)$ of the Francis turbine.

3. Feed-forward backpropagation neural network

An elementary neuron with R inputs is shown below on Fig 2. Each input is weighted with an appropriate w. The sum of the weighted inputs and the bias forms the input to the transfer function f. Neurons can use any differentiable transfer function f to generate their output [12], [13].

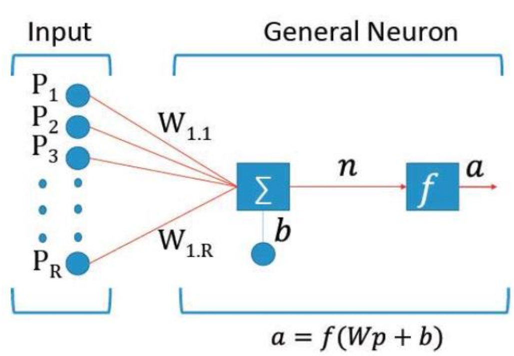

Fig. 2: Elementary neuron with R inputs.

An artificial neural network is composed of several artificial neurons that are linked together according to a specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs. Artificial neural networks are also called neural nets, artificial neural system, parallel distributed processing system and connectionist system.

A single-layer network of S logsig neurons having R inputs is shown below on Fig 3 in full detail on the left and with layer diagram on the right.

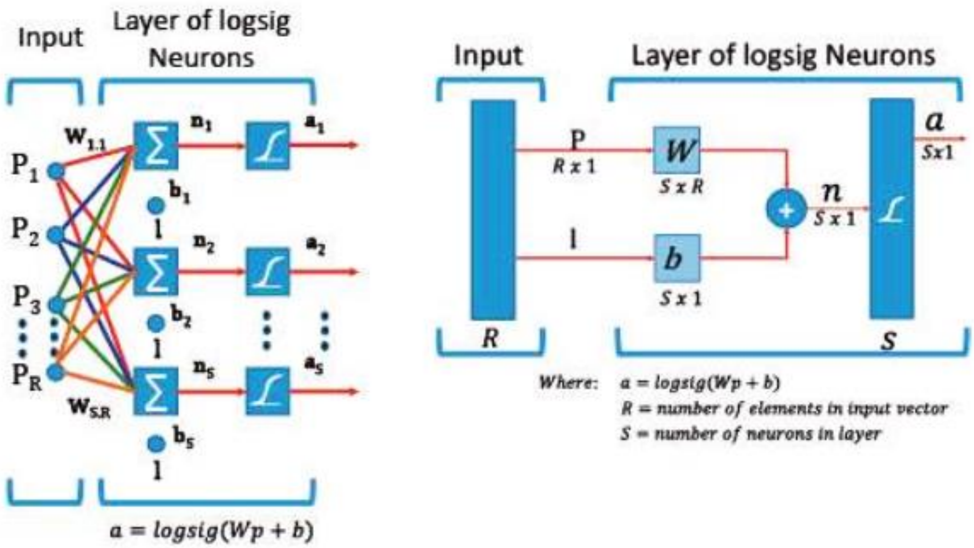

Fig. 3: Single-layer network of S logsig neurons having R inputs.

Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons, as it is shown in Fig 4.

Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors.

The linear output layer lets the network produce values outside the range -1 to +1. On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig).

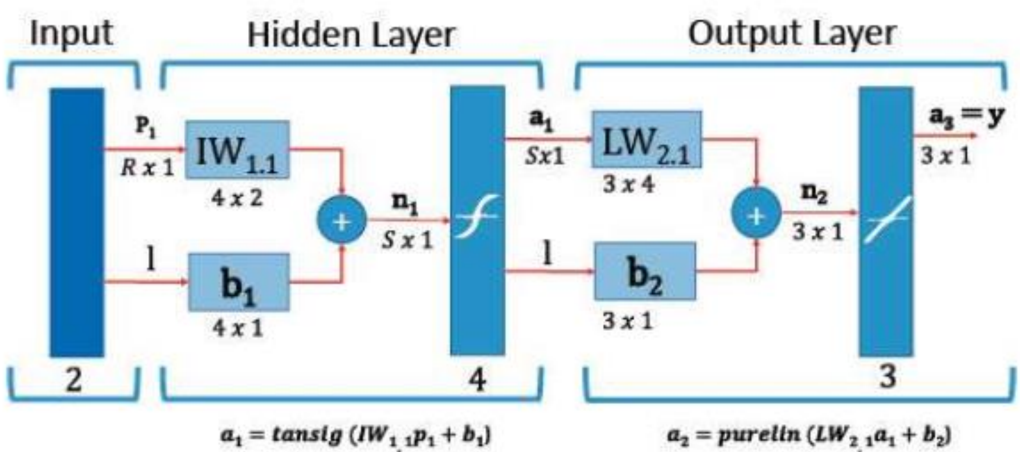

Fig. 4: One or more hidden layers of sigmoid neurons followed by an output layer of linear neurons.

Learning with backpropagation [14], [15]:

- Calculate first the changes for the synaptic weights of the output neuron;
- Calculate the changes backwards starting from layer p-1, and propagate backwards the local error terms.

4. Development Method

At this point, a method based on feed-forward backpropagation artificial neural networks is developed to achieve a more accurate prediction of the useful life of the Francis turbines, subject to the monitoring of the conditions.

In the Agoyán Hydroelectric Power Station, as it happens in this type of stations, the necessary instrumentation is available to monitor the main operating parameters and of diagnostics of the condition, inclusively with the operative parameters the distributed automatic control is referred. The corresponding SCADA system is also available, which allows performing a supervision control and the corresponding acquisition of the values of these parameters

Specifically, for the Francis turbines of the Agoyán Hydroelectric Power Station, two parameters, among others, are currently monitored for diagnose of the turbine operations: the vibration severity in magnitude of speed V(t) (RMS) measured in the supports (bearings) of the axes and; the efficiency of the turbines $\eta(t)$ which is obtained from measuring the electric generation variables.

Therefore, we define the input of our feed-forward backpropagation neural networks with a vector of two elements [V(t); H(t)] and an output vector of a Weibull failure rate function $\lambda(t)$.

A training set of 100 samples is used per input and output parameter, generated as follows:

- The samples (training inputs) of vibration severity in magnitude of speed V(t) are generated for the speed of the turbine in rpm, taking as standard or reference the vibration severity chart of the Norm ISO 10816, in the range of normal operation and the fault condition. The value of V(t) for failure is also determined from this chart.
- The samples (training inputs) of turbine efficiency $\eta(t)$ are generated by taking as a standard or reference the theoretical curve calculated from the Turbomachinery equations, in the normal operating range and the fault condition. The value of η (t) for failure is also determined.
- The targets (training outputs) of Weibull failure rate function $\lambda(t)$ have been developed based on the measurement of the vibrations taken on one of the Francis turbines of the Agoyán Hydroelectric Power Station, taking year 2015 and 2016, with which it was possible to verify the β values the shape parameter, δ the scale parameter and γ the location parameter y therefore, the Weibull distributions with $\beta = 1$ have a fairly constant failure rate, and Weibull distributions with $\beta > 1$ have a failure rate that increases with time.

With this data it is necessary to define in the neural network: training function, adaption learning function, performance function, number of layers, number of neurons on each layer and transfer function.

The neuron network must be trained and watch how the minimum synaptic weights converge; and, once the network has been trained, proceed to perform the corresponding simulations to determine the validity and effectiveness of the learning network predicting the remaining life of the Francis turbine.

5. Results

For the implementation of the developed method the Neural Network Toolbox is used to use with MATLAB [16]. A two-element input vector is introduced [V(t); H(t)], with 100 samples for each input; the targets (100 samples) of Weibull failure rate function $\lambda(t)$ are also introduced.

The training of feed-forward backpropagation neural networks for different transfer functions is performed: log-sigmoid, linear and tan-sigmoid. The results of these simulations are presented bellow on Fig. 5:

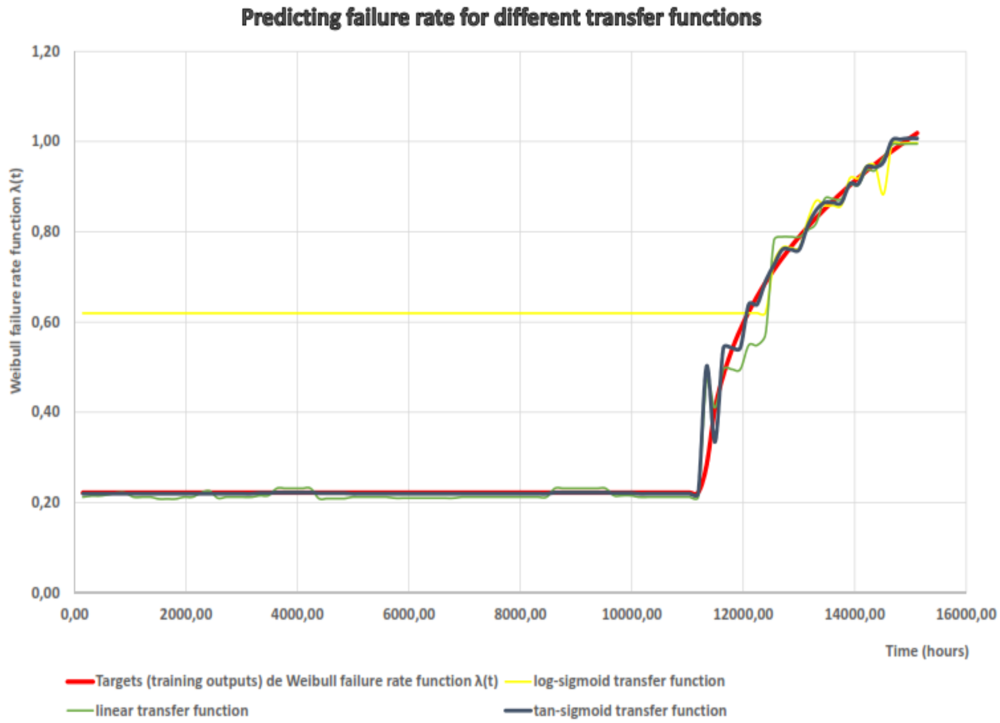

Fig. 5: Predicting failure rate for different transfer functions.

Equally, with the same data, the training of several neural networks is performed: feed-forward backpropagation, layer recurrent and feed-forward time delay. The results of these simulations are presented bellow on Fig. 6:

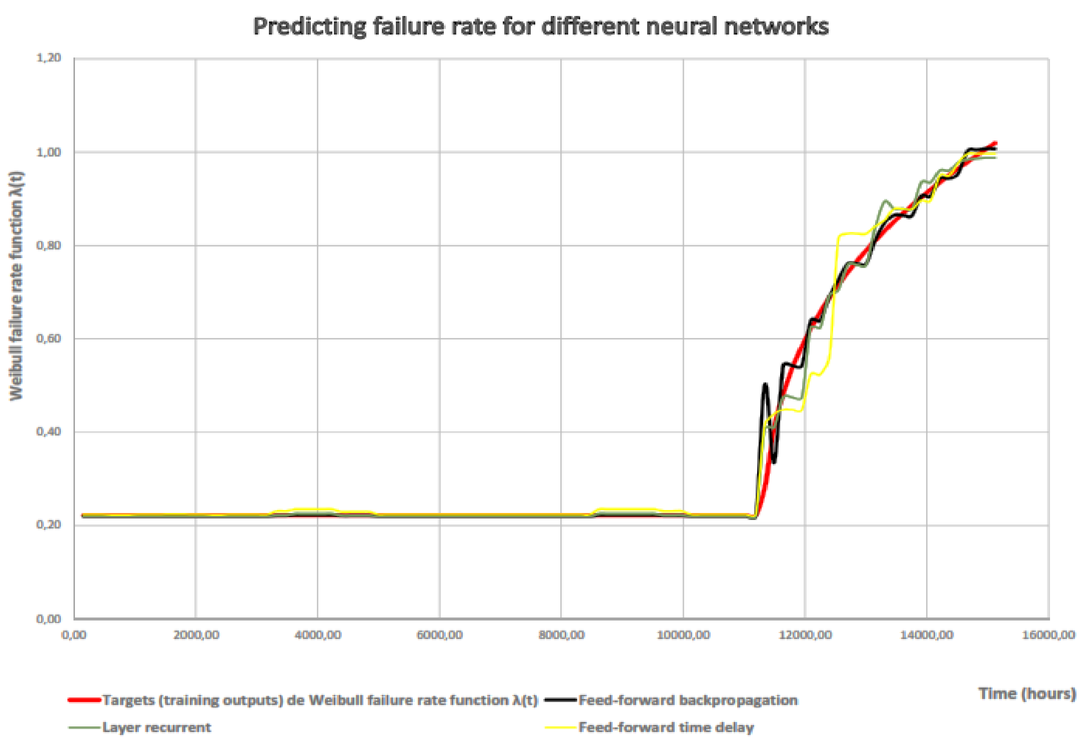

Fig. 6: Predicting failure rate for different neural networks.

6. Discussion

The calculated values of β the shape parameter, δ the scale parameter and γ the location parameter, based on the data measured in the Francis turbines of Agoyán Hydroelectric Power Station, that allowed to define the targets (training outputs) of Weibull failure rate function $\lambda(t)$, have some degree of error with respect to the traditional curve of $\lambda(t)$ for rotary machines; However, what matters is that the learning results of the neural networks follow closely the curve of $\lambda(t)$, which is what matters in the developed method. Further research is recommended to improve sampling including values from other Francis turbines.

It is also considered that an increase of neural network inputs would improve the effectiveness and precision of the neural network for this application.

In this research only the supervised neural networks have been used, it is considered important to extend the investigation by verifying the behavior of the unsupervised neural networks for this application.

7. Conclusions

- The developed method, in this research, using on feed-forward backpropagation artificial neural networks based on Weibull distribution, allows to improve the accurate prediction of the useful life of the Francis turbines, which makes it possible to perform an effective condition-based maintenance to improve reliability and reduce overall maintenance costs.
- The feed-forward backpropagation artificial neural network has been proven to be the most effective and accurate between the supervised neural networks, analyzed in this paper.
- The tan-sigmoid transfer function, it turns out to be the most suitable for predicting the remaining life of the Francis turbine, the log-sigmoid transfer function, it is not applicable for this purpose.
- The method developed, for its consistency and effectiveness, can be generalized to systems and rotating equipment.

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