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“Artificial Intelligence for Concentrated Solar Plant Maintenance Management”

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Alfredo Arcos Jiménez
Ingenium Research Group, Universidad de Castilla-La Mancha
Alfredo.Arcos@alu.uclm.es

Carlos Quiterio Gómez Muñoz
Ingenium Research Group, Universidad de Castilla-La Mancha
CarlosQuiterio.Gomez@uclm.es

Fausto Pedro García Márquez
Ingenium Research Group, Universidad de Castilla-La Mancha
FaustoPedro.Garcia@uclm.es

Long Zhang
Faculty of Engineering and Physical Sciences School of Electrical and Electronic Engineering
University of Manchester, United Kingdom

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Chapter 1
Artificial Intelligence for Concentrated Solar Plant Maintenance Management

Alfredo Arcos Jiménez, Carlos Quiterio Gómez Muñoz, Fausto Pedro García Marquez and Long Zhang

Abstract Concentrated Solar Power (CSP) is an alternative to the conventional energy sources which has had significant advances nowadays. A proper predictive maintenance program for the absorber pipes is required to detect defects in the tubes at an early stage, in order to reduce corrective maintenance costs and increase the reliability, availability, and safety of the concentrator solar plant. This paper presents a novel approach based on signal processing employing neuronal network to determine effectively the temperature of pipe, using only ultrasonic transducers. The main novelty presented in this paper is to determine the temperature of CSP without requiring additional sensors. This is achieved by using existing ultrasonic transducers which is mainly designed for inspection of the absorber tubes. It can also identify suddenly changes in the temperature of the CSP, e.g. due to faults such as corrosion, which generate hot spots close to welds.

Keywords Fault detection and diagnosis · Electromagnetic sensors · Macro fiber composite · Wavelet transforms · Non destructive tests · Neuronal network

1.1 Introduction

Due to the continuous growth in electricity needs in the world, power production from renewable energy sources has been primarily used up to cover the energy demand. This need has caused significant growth and development of new Concentrated Solar Power. Fig. 1.1 shows the growth of solar thermal power generation in Spain between 2007 and 2011.

A. A. Jiménez · C. Q. G Muñoz · F. P. G. Marquez (✉)
Ingenium Research Group, Castilla-La Mancha University
e-mail: FaustoPedro.Garcia@uclm.es

L. Zhang
Faculty of Engineering and Physical Sciences School of Electrical and Electronic Engineering
University of Manchester, United Kingdom

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CSP requires to improve the operational and maintainability of this plants because a failure can halt production of an entire power plant [5, 6, 21]. A proper condition monitoring system [17] is necessary to analyze those critical elements of the plant, such as the absorber tubes and welds [4, 11, 14, 18].

Non-destructive testing (NDT) for fault detection in structures such as pipes has gained significant attention in recent years due to noteworthy advances in instrumentation technology and digital signal processing. The capability of NDT to prevent the evolution of faults to catastrophic failures is one of its main advantages, increasing the reliability, availability and maintainability of the system.

Within the NDT field, guided waves are a technique widely employed for structural health monitoring. This technology is based on the excitation of ultrasonic waves that propagate through the pipe over long distances. It allows inspection of larges distances without relocation of the transducers [20].

Most of the absorber pipes are made of austenitic stainless steel, whose properties ca be exposed to large temperature ranges. The ultrasonic waves are sensitive to the temperature changes because it modify properties of the steel like: density, Youngs modulus and Poisson ratio. Temperature changes directly affect to the propagation velocity and attenuation modifying the waveform the ultrasonic pulses. These changes are difficult to detect with traditional methods of signal processing, so it has become necessary to seek for new techniques to find patterns within the signal at a certain temperature.

Neuronal networks have shown to be a very useful tool for pattern recognition within signals [15]. In this work, a type of neuronal network has been used to train and recognize temperatures ranges in a test rig that simulate the working conditions of a CSP.

1.2 Methodology

The aim of this work is to determine the temperature of the tubes only by using piezoelectric sensors. It can lead to cost savings and to optimize the number of structural health monitoring sensors of a CSP [14, 16]. It was carried out emissions

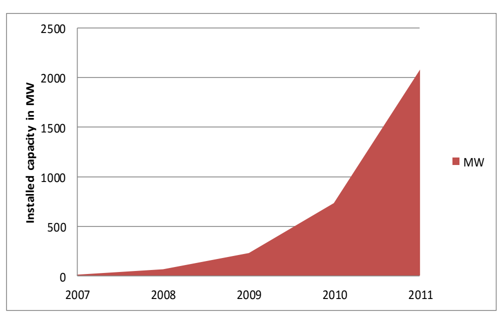

Fig. 1.1 Growth in installed solar thermal power generation capacity of Spain (projects in operation). An astounding total of 14,231 MW in potential solar thermal projects is currently under consideration in Spain [13]

of ultrasonic short pulses at different temperatures, and the signals were processed to train a neuronal network. The output of the neuronal network allows knowing the temperature of the pipe.

1.2.1 Data Collection

The experiment was carried out in a test rig (Fig. 1.3) consisting in 316 L austenitic stainless steel tubes, four meters long, similar to those used in CSP, whereby oil is circulated at high temperature. Two Macro Fiber Composite (MFC) transducers were placed in the test rig, where one acts as a transmitter and the other as receiver

Fig. 1.2 Process flow

Fig. 1.3 Test rig: austenitic stainless steel pipes

(pitch and catch). The transmitter transducer generates short pulses (6 cycles) of 250 kHz. The receiver transducer collects the ultrasonic wave, by converting the mechanical movement of the wave into electrical signal [7]. Also the temperature is collected by using a thermocouple on the pipe, in order to train the neuronal network.

The oil that circulates inside the pipes was heated from 25°C to 75°C and the external surface of the pipereached 55°C. During the heating of the experimental platform were collected 1100 ultrasonic signals with their respective temperatures.

1.2.2 Signal Pre-Processing

The signal obtained must be conditioned in order to properly train the neuronal network. For this purpose has been used wavelet transform to perform a signal denoising.Wavelet transform has been shown to be a powerful tool to remove noise and to extract the relevant information within the signal [3, 9, 10]. The Daubechies family of Wavelets was chosen to perform the signal denoising.

1.2.3 Feature Extraction from Ultrasonic Signal

110 signals are obtained for each temperature measurement and each signal contains 2000 samples. If each sample is considered an input of the neuronal network, in this case, to have a large number of inputs, would generate a high number of learning patterns and therefore, the error would be significant. Otherwise, it would be producing an over learning network, which degrades the generalization ability of the neuronal network. This is called the curse of dimensionality [1, 2, 8].

It is necessary to use a technique that allows reducing the number of inputs while maintaining the characteristic signal information. The characteristic coefficients of each ultrasonic signal were extracted by using the autoregressive model AR, by employing the Yule-Walker equations [12].

The ultrasonic signals provide different parameters, such as waveform, peaks, energy, amplitude, etc., that are used for pattern recognition. The knowledge in this field aids to select such parameters. The results obtained have been verified with trial and error.

Different classical approaches have been employed in order to achieve adequate results for neural networks, e.g. time domain (time of flight of the ultrasonic echoes of the signal, maximum amplitude, peak position, rise time and descent time, energy, etc.) or frequency domain (arithmetic mean, mode, standard deviation or variance). However, the outcomes of these methods are not accurate enough.

The method autoregressive (AR) of Yule-Walker are an example of parametric approaches. They calculate the power spectral density estimating the linear coefficients of a hypothetical system that generates the first signal. These methods tend to produce better results than conventional techniques, when the length of the available signal is relatively short.

In the spectral analysis used in this document a parametric estimator based on the model used Yule-Walker.

1.2.4 Pattern Recognitionby Neuronal Network (Multilayer Perceptron)

For pattern recognition has been used a Neural Network Unidirectional supervised through a Multilayer Perceptron (MLP) with training by back propagation algorithm [25]. The inputs of the NN are the AR coefficients of the ultrasonic signal and the outputs are the temperature rages of the experiments. It has been stablished 11 ranges between 25°C and 55°C, whereby each range comprises 2.7°C.

The structure is three layers of processing units as you can see (Fig. 1.4) and mathematically expressed by:

The Eq. (1.1) is the general equation of the neuronal network,

$$z_k = \sum_j w'_{kj} y_j - \theta'_i = \sum_j w'_{kj} f\left(\sum_i w_{ji} x_i - \theta_j\right) - \theta'_j, \tag{1.1}$$

where: x_i is input neural network; x_i is output of the hidden layer; z_i is output final layer; t_k is output targets; $w_j i$ is weight hidden layer; w'_{kj} is weight final layer; θ_j is bias hidden layer; θ'_k is Bias final layer.

And the chosen activation function of the neuronal network is the sigmoid function. The sigmoid function is shown in Eq. (1.2), and plotted in Fig. 1.5.

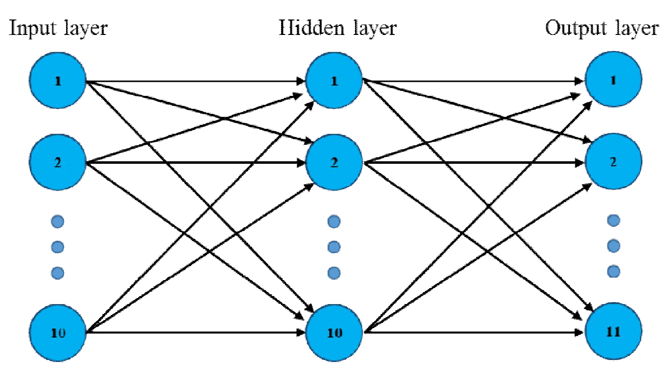

Fig. 1.4 Multilayer perceptron scheme, where the inputs are the AR parameters, and the outputs are the temperature

$$f(x) = \frac{1}{1+e^{-x}}. \tag{1.2}$$

The steps used to achieve the results with the neuronal network are described.
(1) Set of samples

As mentioned in the previous section, in the input of the neuronal network is introduced the extracted characteristics of the signal. The architecture of the neuronal network, and the configuration of the hidden layer, depending on the structure of the input data. In this work it has been tested the following input parameter of the signal: AR (2), AR (5), AR (10), AR (15) and AR (20).

(2) Extraction of the training set, test and validation

Samples the set of signals we performed in order to generalize the network (cross validation) apart in sets:

Training: 70%; Validation: 15%; Test: 15%

On the other hand we have selected another set of signals (15%) to perform a check on the external network to test modes.

(3) Architecture design of multilayer Perceptron

It has been designed a neural network with one hidden layer because it has been found empirically that networks with multiple hidden layers are more prone to getting caught in undesirable local minima. Therefore we have proceeded to use with a single hidden layer.

It has tested different neural network architectures based on patterns obtained in the experimental phase. First it was tested with a Multilayer Perceptron 05/02/11 (first layer with two input neurons, hidden layer with five neurons and output layer of 11 neurons). Later we were increasing the number of inputs, the number of hidden neurons, to achieve the desired objectives.

(4) Learning process

Back propagation is one of the simplest and most general methods for supervised training of multilayer neural networks. Other methods maybe faster or have other desirable properties, but few are more instructive.

We have used two training modes back propagation algorithm:

- Gradient descent with momentum and adaptive learning rate back propagation and performance mean square error (MSE) [24, 26].
- Scaled conjugate gradient and performance Cross Entropy [19, 23].

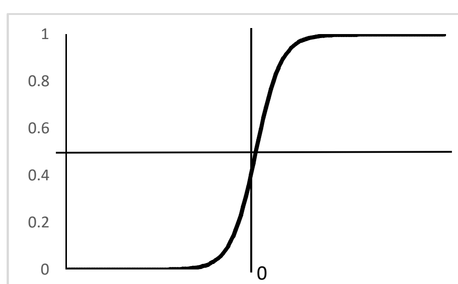

Fig. 1.5 Sigmoid activation function

In the second case we obtained best results with higher performance.

We have used a second-order analysis of the error in order to determine the optimal rate of learning through algorithm conjugate gradient based on performing gradient descent using also information provided by the rate of change of slope. It is the second derivative of the error:

$$H = \frac{\partial^2 E(W)}{\partial w_{ij} \partial w_{kl}} (\text{Hessian matrix}). \tag{1.3}$$

This algorithm uses different approaches that avoid the hard work that represents the direct calculation.

During the learning process, the MLP goes through stages in which the reduction of the error can be extremely slow. These periods of stagnation can influence learning times. In order to resolve this problem we propose to replace the mean square error (MSE) by cross entropy error function. Simulation results using this error function show a better network performance with a shorter stagnation period.

(5) Early stopping

One way to dealing with the overfitting problem is to extract a subset of samples of the training set (note that the whole test previously extracted) and use of auxiliary way during training [22].

This subset is called validation set. The role of the validation set is to evaluate the network error after each epoch (or after every few epochs) and determine when this starts to increase. Since the validation set is left outside during training, the error about is a good indication that the network error will commit on the test set. Consequently, the procedure to stop the workout at the time the validation error and increase the values of the weights of the previous epoch are preserved.

1.3 Results

During the design of the architecture of neural network, it has been determined the following parameters:

(1) Number of inputs to define the neural input layer: The original signals with the relevant information of the received ultrasonic pulses is composed by 2000 samples: The number of inputs is significantly reduced after extracting the characteristics of the signal through the method of autoregression (AR). Network has been tested with different inputs as can be seen in Fig. 1.6, and the AR-10 method provides better results.

(2) Numbers of outputs. A neuronal network with fewer outputs have better results that with more outputs. It was decided to have more outputs for the range of temperature range were lower. Thus, each range has a range of 2.7°C, corresponding to eleven outputs elected.

(3) The numbers of neurons in the hidden layer is treated by many authors problem. There is criteria based on the number of inputs and training patterns. This is one

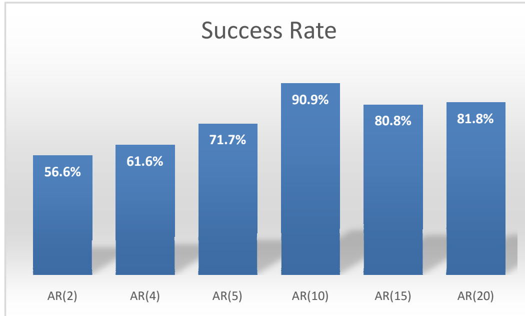

Fig. 1.6 Success rate of the AR employed

of the main problems of MLP. For the calculation of the hidden neurons we've had on one hand the network performance through the mean square error and on the other the number of patterns to train.In this study we have trained, validated and tested with ultrasonic 990 signals, leaving 110 signals for further test in order to generalize the neural network.

(4) Scaled conjugate gradient and performance Cross Entropy has been training mode chosen as the best performance.

The established neural network architecture has been trained with the following results (Fig. 1.7):

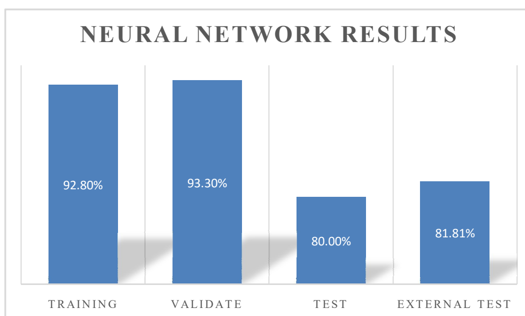

Fig. 1.7 Success rate of the neural network to determine the temperature range

1.4 Conclusion

The paper presents a novel methodology that allows increasing the reliability of a condition monitoring system analysing the temperature of the absorber tubes employing ultrasonic waves in a Concentrate Solar Plant (CSP). The approach can detect a temperature due to a potential failures, such as hot spots in defects in welds. This technique allows avoiding redundancy of sensors, since a specific number of ultrasonic transducers can determine the structural condition of the tube and its temperature, using guided waves. A test rig, that simulates the working conditions of the absorber pipes of a CSP, was built to carry out the experiments. The oil inside the pipes was heated and circulated in the installation, while the pitch and catch of ultrasonic pulses were carried out. A neuronal network has been designed for signal processing and pattern recognition in order to identify the conditions. In order to reduce the inputs of the neuronal network, the ultrasonic signals have been pre-processed and their characteristic parameters have been extracted employing autoregressive methods. The trained neuronal network can determine the temperature of the test rig with an accuracy of 2.7 Celsius degrees.

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Alfredo Arcos Jiménez, 1

Carlos Quiterio Gómez Muñoz, 1

Fausto Pedro García Marquez, 1

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