Available online at www.sciencedirect.com

ScienceDirect

Procedia Structural Integrity 5 (2017) 997–1004

Structural Integrity Procedia

www.elsevier.com/locate/procedia

2nd International Conference on Structural Integrity, ICSI 2017, 4-7 September 2017, Funchal, Madeira, Portugal

Neural networks and genetic algorithms for the evaluation of coatings thicknesses in thermal barriers by infrared thermography data

H.Halloua[a], A.Elhassnaoui[b], A.Saifi[a], A. Elamiri[a], A.Obbadi[a], Y.Errami[a], S.Sahnoun [a,*]

[a]*Laboratory of Electronics, Instrumentation, and Energetic, Faculty of Sciences, B.P 20. 24000 El Jadida, Morocco.*
[b]*Industrial Engineering Laboratory, Faculty of Science and Technology, BP: 523,Beni Mellal, Morocco*

Abstract

In the context of using non-destructive thermal control methods for the coatings thicknesses evaluation in thermal barriers. We have treated the laser-pulsed thermography data with the neural networks to model the relationship between the thermal response and the coating thickness. The algorithms based on the error gradient computation are used during the learning step. Indeed, the initial weights of the network found and the number of data processed facilitated the convergence of these algorithms. In this work we presented a neural network training method using pre-processing of data by principal component analysis(PCA) to optimize the number of network inputs and the genetic algorithm for the optimum initial weights determination in the network training by the back propagation algorithm. The two algorithms recombination allowed the thicknesses evaluation with deviations less than 5%.

Peer-review under responsibility of the Scientific Committee of ICSI 2017

Keywords: Non-destructive testing, pulsed laser Infrared thermography, artificial neural network, genetic algorithms, principal component Analysis, finite element method.

1. Introduction

Thermal barrier coatings systems are deposited on hot parts in order to insulate them thermally and protect them from heat (Clarke & Phillpot (2005)). The coating thicknesses evaluation in these structures is very important in the integrity control of these parts. The latter are used in many industrial sectors using non-destructive testing methods

* Corresponding author. Tel.: +212-661-347-441.
E-mail address: ssahnoun@gmail.com

2452-3216 © 2017 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of the Scientific Committee of ICSI 2017
10.1016/j.prostr.2017.07.153

and they are the subject of several studies, where several models and approaches have been proposed in the literature of coatings thickness estimating (Bu et al. (2016); Tang et al. (2016); Zhang et al. (2016)). Neural networks represent an alternative to conventional non-destructive testing methods. They have proven their effectiveness in several applications, in particular in thermal control (Waqar & Demetgul (2016); Usamentiaga et al. (2013); (Wang et al. (2014)).

The neural network's training is an important step to develop the neural model. Gradient error backpropagation variants such as the backpropagation of Levenberg-Marquart (Marquardt (1963); Hagan & Menhaj (1994)) and Bayesian regularization (MacKay (1992)) are the most used in the neural network phase training. Despite these successful applications, the backpropagation algorithms have disadvantages related to the synaptic weights research in the training phase. They do not guarantee a global minimum because it is a local search algorithm that uses gradient error descent. Genetic algorithms represent a promising alternative to backpropagation algorithms. In this work, we will use neural networks to establish a relation between the temperature variation of a controlled part and the thickness of its coating. We are going to do a pre-processing by principal component analysis of the network inputs from the pulsed laser infrared thermography data, and also an optimization of its structure as well as an optimization of its initial weights by a genetic algorithm.

2. Pulsed laser infrared thermography

In the active thermal control by pulsed laser thermography (Mezghani et al. (2016)), a very localized heating spot is used in the form of a pulse (radius r and power P) for heating the controlled part. The inspected sample response is recorded with an infrared camera in digital form for meticulous analysis to characterize existing defects. The laser spot usage allows a punctual inspection. Full control of the surface can be carried out point by point or by continuous movement of the laser spot to determine the variations in the coating thickness.

3. The used model

The studied sample is a homogeneous and isotropic thermal barrier coating with thickness *e,* deposited on a substrate (Fig. 1), with a dimension of 100 mm × 100 mm × 10 mm. The samples lateral faces are insulated. Their initial temperatures is $T_0 = 25$ ° C and the convective transfer coefficient h_f=10 W/m^2 C°. The coatings are ideally fixed to the substrate, their thicknesses varying between 10 μm and 3000 μm. The heating source is a laser of power P = 20 W, with a radius r = 3 mm for a duration τ = 20 ms (Bu et al. 2015). The coating and the substrate thermal parameters are shown in table 1.

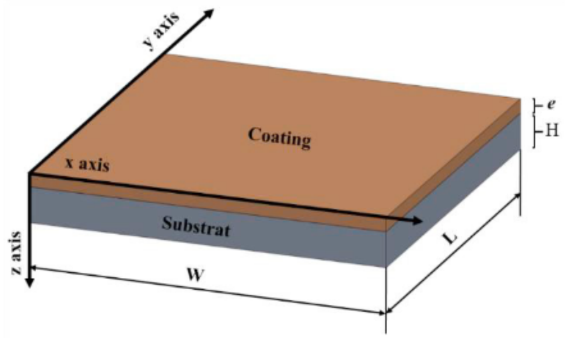

Fig. 1 : Schematic representation of the three-dimensional model

Table 1. Thermal properties and physical parameters (Zhang et al. (2016))

Layers	Density [kg m^{-3}]	Specific heat capacity J/(kg.degC)]	Conductivity [W/(m.K)]
Coating	2160	1378	0.78
Substrate	1200	1297	0.152

The equation governing the heat transfer by conduction in the material is expressed in the cartesian coordinate system by the following relation:

$$\rho c_p \frac{\partial T}{\partial t} = k_x \frac{\partial}{\partial x}\left(\frac{\partial T}{\partial x}\right) + k_y \frac{\partial}{\partial y}\left(\frac{\partial T}{\partial y}\right) + k_z \frac{\partial}{\partial z}\left(\frac{\partial T}{\partial z}\right) \quad (1)$$

Initial and boundary conditions that translate natural convection and radiation between the sample surfaces and the external environment are translated by the following equations:

$$-k_z \frac{\partial T(x,y,z,t)}{\partial z}\Big|_{z=H} = Q + h_f(T_{am} - T(x,y,H,t)) \quad (2)$$
$$-k_z \frac{\partial T(x,y,z,t)}{\partial z}\Big|_{z=0} = h_f(T_{am} - T(x,y,0,t)) \quad (3)$$
$$-k_x \frac{\partial T(x,y,z,t)}{\partial x}\Big|_{x=0} = -k_x \frac{\partial T(x,y,z,t)}{\partial x}\Big|_{x=W} = 0 \quad (4)$$
$$-k_y \frac{\partial T(x,y,z,t)}{\partial y}\Big|_{y=0} = -k_y \frac{\partial T(x,y,z,t)}{\partial y}\Big|_{y=L} = 0 \quad (5)$$
$$T(x,y,z,t)|_{t=0} = T_{am} \quad (6)$$

The resolution of the heat diffusion equation with these boundary conditions by finite element software gave the controlled surface temperature distribution (Fig. 2). We reported in Figure 3 the temperature variations with time of the heated region center (controlled by the laser) for coating thicknesses ranging from 0.4 to 3 mm. We can distinguish a correlation between the coatings thicknesses and the controlled zone temperature value; In fact, the temperature reaches important values, passing through maximums for small thicknesses of the substrate.

We will use neural networks to model the relationship between the temperature and the coating thickness to apply it in the non-destructive thermal control. Therefore, a network inputs pre-treatment by principal components and the structure optimization with the initial weights will be presented in the following sections.

4. Artificial neural networks

Artificial neural networks are highly connected systems of elementary processors that mimic biological neurons. By learning, the network is impregnated with the conclusions to be given in a new situation. The neural networks general architecture consists of representing neurons in successive layers. If it is theoretically possible to build networks with a very large number of layers, a three-layer network architecture with a single hidden layer using sigmoidal type activation functions is usually sufficient to approximate any nonlinear function (Cybenko (1989)).

Supervised learning has been chosen because it is most suitable for functions approximation. In most cases, neural network training is formulated as an optimization problem by seeking the synaptic weight matrix W which minimizes

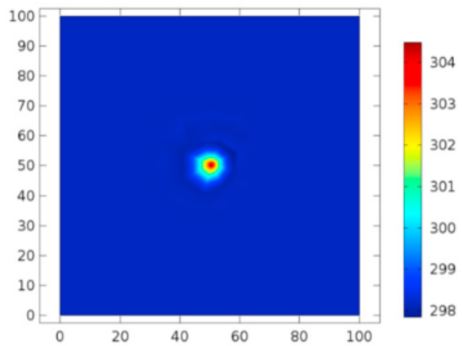

Fig. 2 : Simulated temperature field results of a sample with a 3mm thickness at the time t=0.2s on the sample's upper side

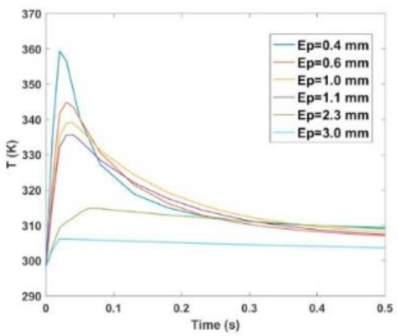

Fig. 3 : Temperatures according to coating thicknesses Ep

the error difference between the desired output and the network response. The network learning is achieved by modifying the synaptic weights until the desired result is achieved, where the synaptic weights are no longer modified. Optimization algorithms based on a gradient descent, such as backpropagation are the conventional training algorithms to iteratively adjust the network connections weights. These algorithms start generally from a random starting point and descend along the largest local slope. Therefore, the use of these algorithms does not guarantee to find a global minimum and can be blocked in a local optimum of the function to be optimized. Indeed, the starting research point of these algorithms conditions the convergence to the solution; that is to say, to find the optimal synaptic weights combination that gives the smallest gap. We propose the use of a genetic algorithm, it is a global stochastic research algorithm and a good alternative to backpropagation algorithms. It will be used to optimize the initial synaptic weights of the neural network. This has allowed us to converge more quickly towards the most optimal solutions.

5. Genetic algorithms

Genetic algorithms are commonly used in optimizations (Yang (2014)). They rely on techniques derived from genetics and natural evolution (Fig 4). The genetic algorithm aims to iteratively select the best set of parameters minimizing an objective function. It works by modifying a set of potential solutions to the problem to optimize (population of individuals) according to certain rules called "operators". The individual is represented by a chromosome composed of genes that contain the hereditary properties. The adaptation of every individual to the criterion to be optimized (fitness) is evaluated by the objective function value. The algorithm generates iteratively individual generations by using selection, crossing and mutation operators: The selection aims to promote the choice of the most suitable individuals in the population. The crossing allows the reproduction by mixing of the chosen individual's particularities, and the mutation ensures the random alteration of an individual's particularities. The process is completed if the maximum generation number is reached or when the population is no longer evolve.

6. The proposed hybrid algorithm

The proposed hybrid algorithm tries to combine the neural network qualities and the global search advantages of the genetic algorithms for the thermal barrier-coating thickness evaluation. We have represented in Figure 5 the coating thicknesses determination steps, where we used neural networks to link the inspected point temperature to its coating thickness. The genetic algorithm allows evolving the synaptic weights to find the most optimal starting weights for the neural network training.

The first part of the proposed method consists in obtaining the network training data in the vectors form. To form them we carried out a parametric study on a 3D simulation software by finite elements, where we have varied coating thicknesses between 10 and 3000 µm with a step of 5µm. This allowed us to obtain 582 vectors which represent the temperature evolution for each instant of the acquisition time. Each input vector obtained consists of N=59 temperature values (Fig. 6). To reduce the neural network input data number a pre-processing was carried out by applying the Principal Component Analysis (CPA) to form M input vectors of the network.

In the training phase, the cross-validation method was used to solve the network over-learning problems (Prechelt (1998)); Where we divided the 582 input couples according to the percentage 70% for the network training, 15% for the validation and 15% for the network test.

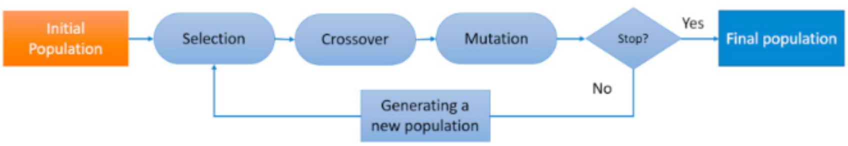

Fig. 4 : Genetic algorithm principle

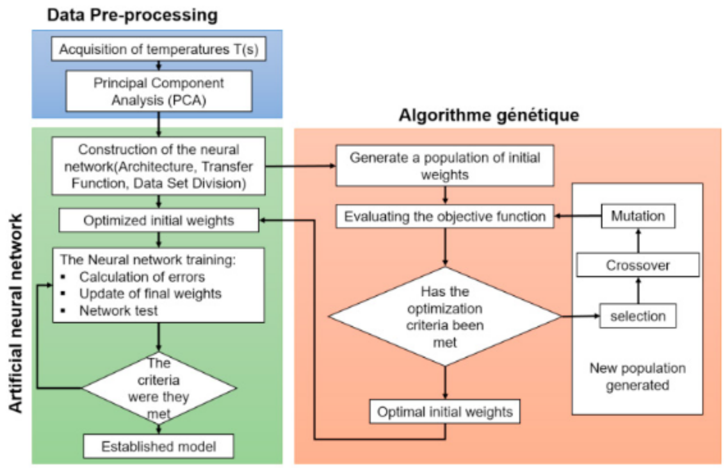

Fig. 5 : The proposed hybrid method structure

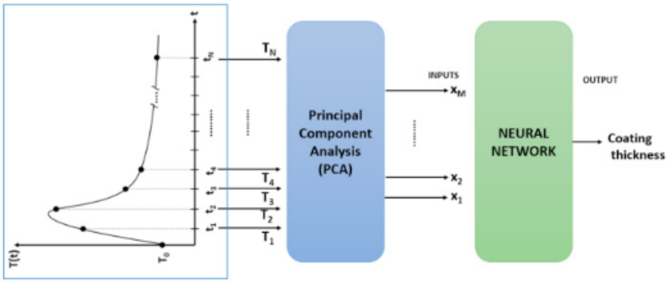

Fig. 6 : acquired data pre-processing

Five principal components were selected to represent the original data of the input temperature vectors, so the input layer contains five neurons. The network has one output representing the sought coating thickness. To set the neurons number in the hidden layer we did several tests showing that twelve neurons gave the best approximation during training. So, to process this data the final architecture is 5-12-1. The lavenberg Marquardt algorithm which gave better performances in previous searches was used to adjust the neural network final weights after the initial weight optimization procedure by the genetic algorithm.

3.1. Initial weights Optimization

Initially, a set of random weights are generated in the neural network and then coded in the individual's chromosomes in the genetic algorithm. Figure 7 shows the coding principle from the network weights and the biases. The obtained chromosome total length is 85 (12 + 60 + 1 + 12). From this population, the genetic algorithm makes it evolved to minimize an objective error function *f(W)* defined in equation (11).

A Matlab program has been established to optimize the weights by the genetic algorithm. The input parameters of this program are the network architecture, the synaptic weight vector, the input and output vectors. At each iteration and for each individual, the algorithm assigns the synaptic weights to the network and then calculates the network output and evaluates the mean squared error defined from output values compared to target ones:

$$f(W) = \frac{1}{N}\sum_{i=1}^{N}(outputs(W) - targets)^2 \qquad (7)$$

The initial weight vector W is determined by the objective function *f(W)* minimization.

$$\min\{\mathrm{f}(W)\} = \min\{\frac{1}{\mathrm{N}}\sum_{i=1}^{N}(outputs(W) - targets)^2\} \qquad (8)$$

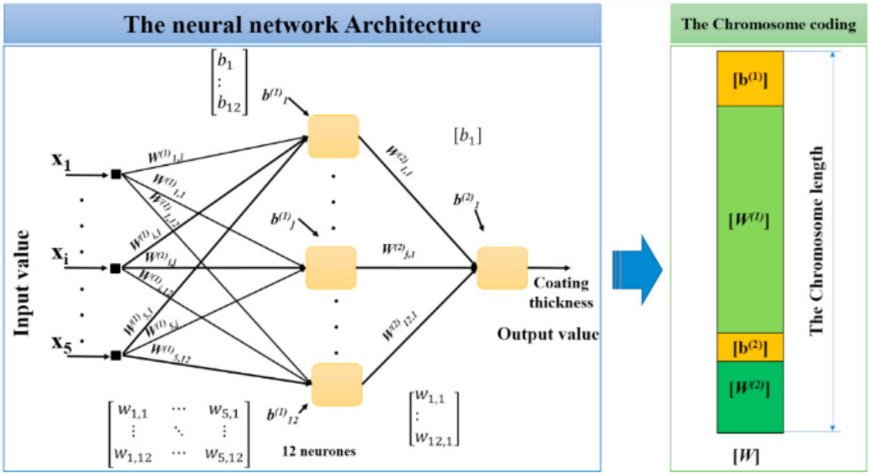

Fig. 7 : The coding of an individual structure W

7. Results and discussion

Figure 8 shows the objective function variation in the weight optimization process. The best solution was obtained after 490 generations. After the initial weights determination, they are transferred into the neural network to carry out the training by the Levenberg Marquardt algorithm. We have plotted in figure 9 the mean squared error variation that we obtained for the three data sets: training, test, and validation. We noted that the neural network gave a good result (Mse = 0.0088) after just eight iterations; It is a very small iterations number. This result shows that the initial weights optimized by the genetic algorithm gave a good convergence of the final algorithm.

The training step performance of the formed network was, furthermore, measured by means of a regression and a linearity analysis between the obtained thicknesses by the network and the corresponding targets. In this task, the "Linear regression method" function implemented in Matlab was used as well as the linear correlation coefficient of Person R.

We have reported in Figures 10, 11 and 12 the obtained thickness values by the network for the three datasets; training, validation, and testing. In the three figures, the regression analysis and the obtained Pearson coefficients (R=0.99571 for training, R=0.99532 for validation, R=0.99401 for testing) show a good linearity and an almost perfect correspondence between the obtained thicknesses (output) and the target thicknesses.

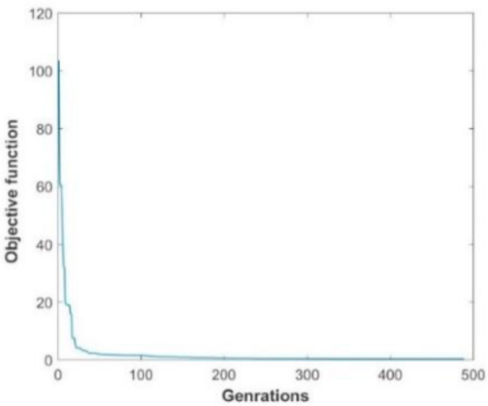

Fig. 8 : Initial weights optimization results by the genetic algorithm

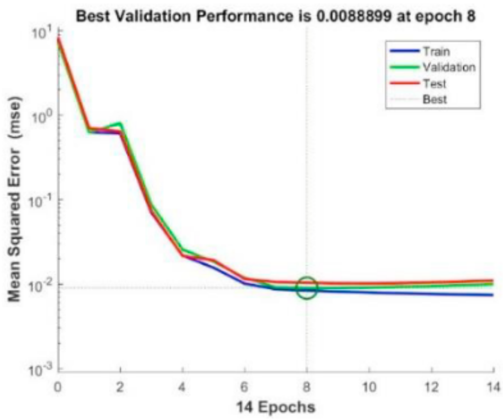

Fig. 9: The mean squared error variation in the learning phase

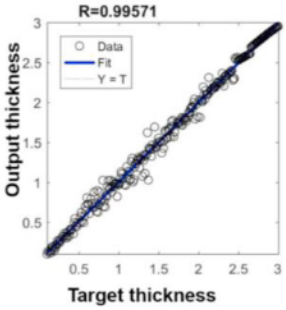

Fig. 10 : The network training phase results

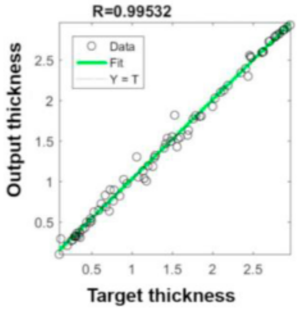

Fig. 11 : The network validation phase results

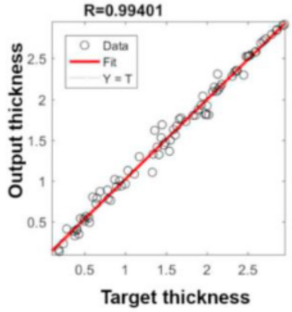

Fig. 12 : The network test phase results

These results show that the chosen network has been well trained and confirm the good approximation of the established hybrid neural algorithm in thermal barrier-coating thickness prediction.

Once the learning was complete, we generated several tests on coating thicknesses that were not used in the learning process to validate the obtained model by the neural network. Table 2 shows the results of these tests. It is found that the predicted thicknesses by the neural network are close to the real thickness with deviations less than 2%.

Table 2. Coating thickness values estimated by our neuronal algorithm.

Target Thicknesses (µm)	67	117	536	1087	2788	2867
Estimated thicknesses (µm)	68.25	116.23	534.97	1085.34	2789.48	2866.06
Gaps %	1.86	0.65	0.19	0.15	0.05	0.03

Table 3 shows the comparison results between the established neural network convergence with and without initial weights optimization. It is noted that the genetic algorithm usage makes it possible to improve the network performance by reducing the iterations number and the mean square error value Mse.

Table 3. Comparison between convergence with and without initial weight optimization.

Results	Trials	Mean square errors (Mse)	Iterations number
Without initial weight optimization	1	0.0265	59
	2	0.0165	65
	3	0.1185	230
With initial weight optimization	1	0.0082	17
	2	0.0093	10
	3	0.0095	13

8. Comparison with other methods

Following the obtained results, it is necessary to compare our method results with those of other methods for the thermal coatings thickness determination in order to better evaluate and validate its performance. A comparison with the proposed method by Zhang et al. (2016) was performed, where Zhang proposes to measure the thickness of the coating by lock-in infrared thermography from the thermal response phase. Four samples were modeled with the following coating thicknesses: 0.32mm-0.51mm-0.71mm-0.97mm.

The results of this comparison are shown in table 4. We can notice that the proposed method has a deviation from the exact values of 3%; This result is an improvement of the coatings thicknesses estimation: Zhang found the thicknesses with a gap of 7%.

Table 4. Results comparison in coating thicknesses determination

		Exact sample thicknesses (mm)			
		0.32	0.51	0.71	0.97
Jin-Yu results	Estimated thicknesses (mm)	0.307	0.490	0.664	0.925
	Gaps (%)	4.06	3.92	6.48	4.64
Obtained results	Estimated thicknesses (mm)	0.316	0.518	0.687	0.981
	Gaps (%)	1.25	1.56	3.34	1.13

9. Conclusion

In the coatings thermal barriers control framework, we proposed a hybrid method combining neural networks and genetic algorithms for the coating thicknesses determination by laser-pulsed thermography data. In the proposed hybrid model, five components were selected in the pre-processing of the network input data by principal components analysis. The genetic algorithm is used to optimize the neural network initial weights. This optimization allowed improving the network performance compared to the standard neural network in terms of iteration numbers and means squared errors. The proposed hybrid model gave a good accuracy in estimating the thin thicknesses of thermal barrier coatings with deviations less than 3%. This result is better than the one found by Zhang et al. (2016).

References

Bu, C. et al., 2015. Infrared Physics & Technology A theoretical study on vertical finite cracks detection using pulsed laser spot thermography (PLST). *Infrared Physics & Technology*, 71, pp.475–480.

Bu, C. et al., 2016. Quantitative detection of thermal barrier coating thickness based on simulated annealing algorithm using pulsed infrared thermography technology. *Applied Thermal Engineering*, 99, pp.751–755.

Clarke, D.R. & Phillpot, S.R., 2005. Thermal barrier coating materials. *Materials Today*, 8(6), pp.22–29.

Cybenko, G., 1989. Correction: Approximation by Superpositions of a Sigmoidal Function. *Mathematics of Control, Signals, and Systems*, 2, pp.303–314.

Hagan, M.T. & Menhaj, M.B., 1994. Training Feedforward Networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks*, 5(6), pp.989–993.

MacKay, D.J.C., 1992. A Practical Bayesian Framework for Backpropagation Networks. *Neural Computation*, 4(3), pp.448–472.

Marquardt, D.W. & Marquardtt, D.W., 1963. An algorithm for least-squares estimation of nonlinear parameters an algorithm for least-squares estimation of nonlinear parameters. *Source Journal of the Society for Industrial and Applied Mathematics J. Soc. Indust. Appl. Math*, 11(2), pp.431–441.

Mezghani, S. et al., 2016. Evaluation of paint coating thickness variations based on pulsed Infrared thermography laser technique. *Infrared Physics & Technology*, 76, pp.393–401.

Prechelt, L., 1998. Automatic early stopping using cross validation: Quantifying the criteria. *Neural Networks*, 11(4), pp.761–767.

Tang, Q. et al., 2016. Theoretical and Experimental Study on Thermal Barrier Coating (TBC) Uneven Thickness Detection Using Pulsed Infrared Thermography Technology. *Applied Thermal Engineering*.

Usamentiaga, R. et al., 2013. Feature extraction and analysis for automatic Automatic detection of impact damage in carbon fiber composites using active thermography. *Infrared Physics & Technology*, 58, pp.36–46.

Wang, H., Hsieh, S. & Stockton, A., 2014. Evaluating the performance of artificial neural networks for estimating the nonmetallic coating thicknesses with time-resolved thermography.

Waqar, T. & Demetgul, M., 2016. Thermal analysis MLP neural network based fault diagnosis on worm gears. *Measurement*, 86, pp.56–66.

Yang, X.-S., 2014. Chapter 5 – Genetic Algorithms. In *Nature-Inspired Optimization Algorithms*. pp. 77–87.

Zhang, J.-Y., Meng, X. & Ma, Y., 2016. A new measurement method of coatings thickness based on lock-in thermography. *Infrared Physics & Technology*, 76, pp.655–660.