NEW APPROACH FOR THERMAL SPRAY PROCESS CONTROL WITH AN ARTIFICIAL NEURAL NETWORK IN AERO-ENGINES

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ABSTRACT

Thermal spray coatings on basic materials of aero-engine components are indispensable for prolonging life and improving efficiency. Thermal spray processes are extremely complex; therefore it is impossible to represent them accurately enough in a traditional model, hence some reliable simulation. In this research work it will be shown how such processes can be represented with an artificial neural network that allows the thermal spray process to be controlled automatically. Data from plasma spray processes on turbo-compressor casings is used to train and verify the neural network. The results of the first prototype for a closed loop are very promising.

KEYWORDS: Artificial neural network, Aero-engines, Thermal spray, Coating, process control.

1. INTRODUCTION

Basic materials of aero-engines are mechanically, thermally and chemically highly stressed so that for extending their life coatings are applied using thermal spray processes. For efficiency improvement reasons thermal spray coatings are also used as abradables and sealing fins as well as thermal barriers.

The functions of coatings on aero-engine materials are demonstrated in this work using the operating behaviour of a compressor as an example. Modern compressors are characterised by a high efficiency. This is only achievable, if the hot tip clearance is tight enough and if it can be kept tight during all flight manoeuvres. A tip clearance that is correctly adjusted for steady-state operation may – during certain flight manoeuvres – cause the blades to rub into the casing and thus the tip clearance to increase due to material wear. This effect can be reduced by thermal spraying of suitable abradable coating systems on the compressor casing.

In order to save weight modern engines have thin casing walls, which may lead to a mismatched dilatation between blades and casings. During transient operation the tip clearance may increase, resulting in efficiency η and air mass flow losses of e.g. the compressor. In the compressor map it is clearly noticeable that the speed lines move to a smaller air mass flow and a lower efficiency as in Figure 1. As a result, the losses through migration of the operating line in the compressor map intensify the losses through the increased tip clearance. As illustrated in Figure 2, a thrust hole thus occurs, which adversely affects the flight manoeuvrability. This problem can be partially avoided by the use of thermal barrier coatings on the compressor casing.

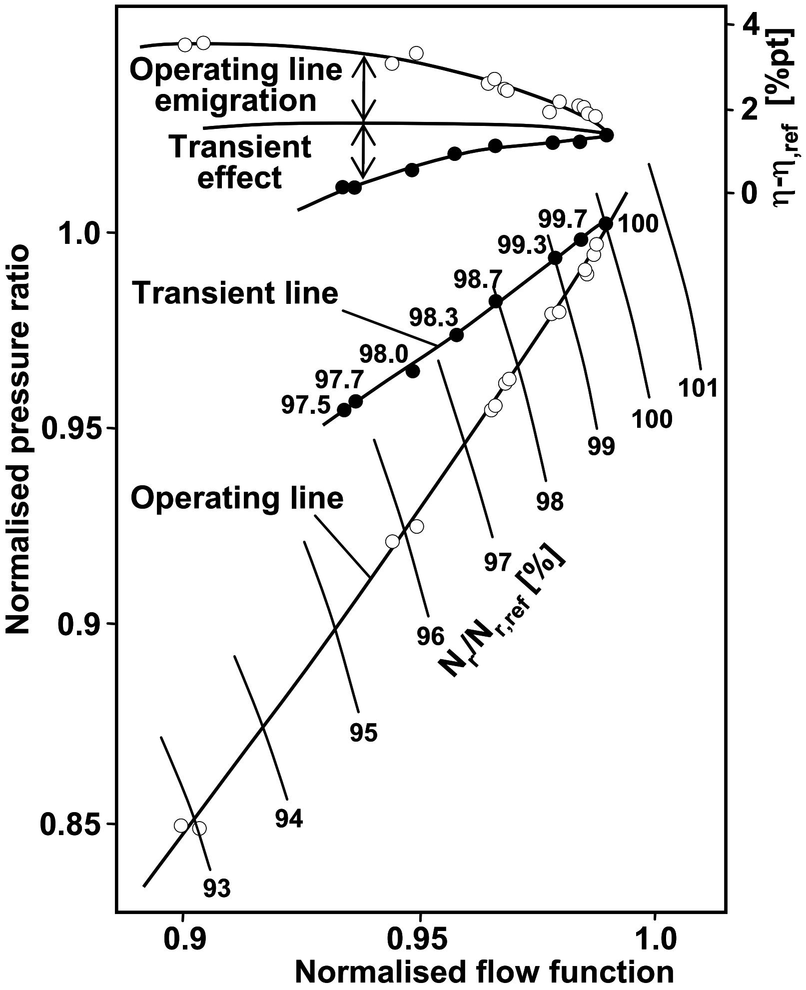

Figure 1: Compressor map – efficiency and flow function loss during engine acceleration

In this paper the plasma spray process is briefly described. The process influence parameters for one coating system are analysed. The development of an artificial neural network including training, validation and testing with real test data sets is presented. Finally, the results of the research work are presented and discussed.

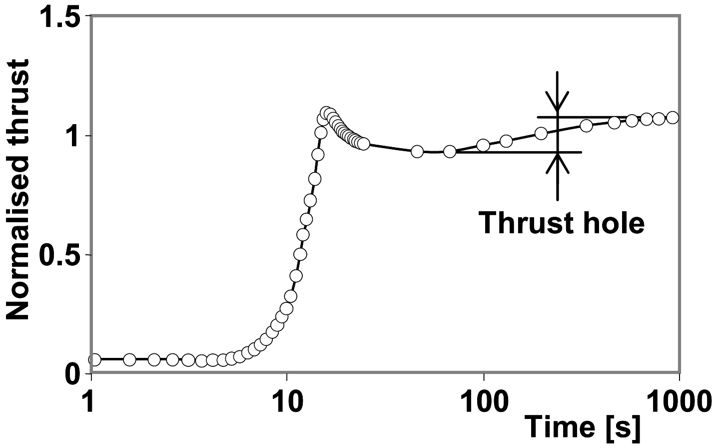

Figure 2: Possible thrust loss during engine acceleration due to tip clearance increase.

2. PLASMA SPRAY PROCESS

There are a number of thermal spray methods. One of them that is often applied in aero-engines is plasma spraying. The facility and process can be described in principle as follows: the plasma torch comprises an anode and a cathode, and an electric arc is generated between them as an electric current is applied. The electric arc brings a mixture of inert gas like argon, helium, hydrogen and nitrogen or a mixture of them into plasma condition. Depending on the gas mixture used, dissociation (hydrogen, nitrogen) and ionisation (argon, helium, hydrogen, nitrogen) occur. Recombination of the gases produces a heat of over 20,000 °C. Due to the expansion the gas is accelerated to a high speed through the nozzle of the spray torch.

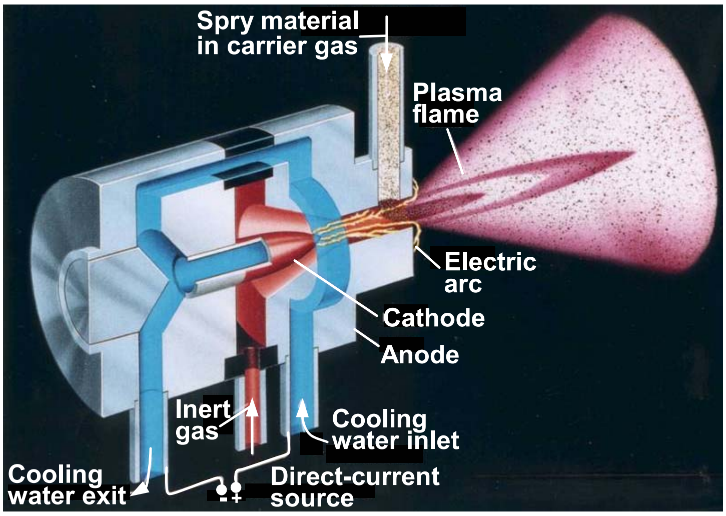

Figure 3: A principle plasma spray facility with its main components

Depending on the torch design the metallic or ceramic coating powder is fed to the gas inside the torch or in front of the nozzle. Because of the high temperature the coating powder is partly or completely melted and it is projected onto the engine basic material at the high speed of the gas. To protect the torch against the high temperature water cooling is used. Depending on the requirements for the coating the plasma spray processes are carried out in a normal, an inert atmosphere, in a vacuum or in a liquid. Figure 3 is a schematic representation of the plasma spray facility. [1-3] depict further details about thermal spray processes.

3. PROCESS INFLUENCE PARAMETERS

Coating properties have to fulfil various requirements. The mechanical strength and the deposition efficiency are two main requirements of the plasma spray process investigated in this research work. In order to achieve certain values of mechanical strength and deposition efficiency accurately and repeatably, the influence parameters of the process have to be controlled accordingly. This is not possible to date, as the number of the influence parameters is too large and the relationships between these and the coating properties are not all known. Publications mention that more than 200 parameters may influence the plasma spray process [2], a large part of them being unquantifiable; Table 1 illustrates some of the plasma spray process parameters.

Measurable	**Unquantifiable**
Primary gas flow	Coating powder charge
Secondary gas flow	Nozzle tolerances
Carrier gas flow	Electrode
Electric current intensity	Wear of powder tube
Electric current voltage	Air circulation in spray cabin
Powder feed rate	Arc fluctuation
Torch parameter *A*	Torch tolerances
Coating hardness *H*	Argon ring tolerances
Deposition efficiency *AL*	Powder humidity
Substrate material *ST*	Torch aging
	…

Table 1: Some influence parameters of the plasma spray process

In addition, process control is difficult, as the mechanical strength and the deposition efficiency are not measurable online. But one possible way of process control is to use the online measurable parameters during spraying as control parameters, while the properties of the plasma and the powder particle will represent the required coating properties. The plasma and particle properties are quantifiable through the so-called Particle Flux Imaging *PFI* method [4]. A digital camera with two different optic filters captures the light density distribution of the plasma and particle jet. The plasma jet, which is located directly at the nozzle, shines more intensively than the particle jet which is further away from the nozzle. The light densities are evaluated and the contours with the same light densities are approximated to ellipse. The *PFI* method thus provides the ellipses parameters for a chosen light density for the plasma jet $(a, b, x, y, \alpha)_{\mathrm{Pl}}$ and the particle jet $(a, b, x, y, \alpha)_{\mathrm{Pa}}$, as shown in Figure 4. The idea here is to use the values of the ellipse parameters as substitutes for coating strength and the deposition efficiency. This permits an online control of the plasma spray process.

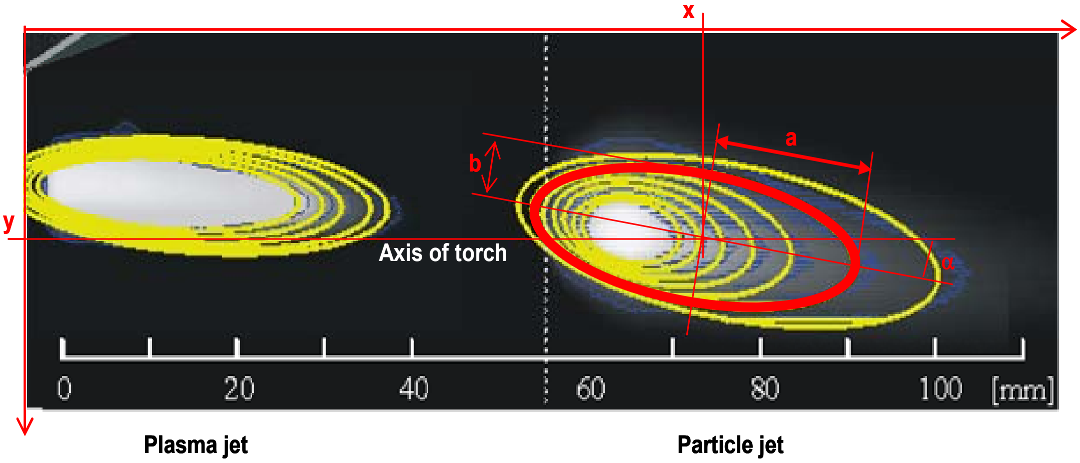

Figure 4: Visualisation of the Particle Flux Imaging PFI parameters of a plasma spray process

4. ARTIFICIAL NEURAL NETWORK

The task is to establish a relationship between the control parameters and the required coating properties. This should become possible through the use of an artificial neural network. An artificial network is an adaptive, error-tolerant and learning system, which consists of nodes, also called neurons, and a network that should simulate the function of the human brain. The network is characterised by the arrangement of the nodes, network pattern, learning algorithm, network weights and network bias. The error tolerance relates to the problem description on the basis of inaccurate and uncertain information. With these characteristics it is possible to solve problems that are intuitively described, as it is the case with the plasma spray process.

A network can consist of several layers and every layer can in turn have several neurons. Each neuron has an input signal a_j^{l-1} and output signal a_i^l, which are connected through the weights $w^l_{i,j}$ and the bias b_i^1. For training of the network the backpropagation algorithm is used which has proven its worth in solving of various problems. The function of the backpropagation algorithm is demonstrated using the network shown in Figure 5.

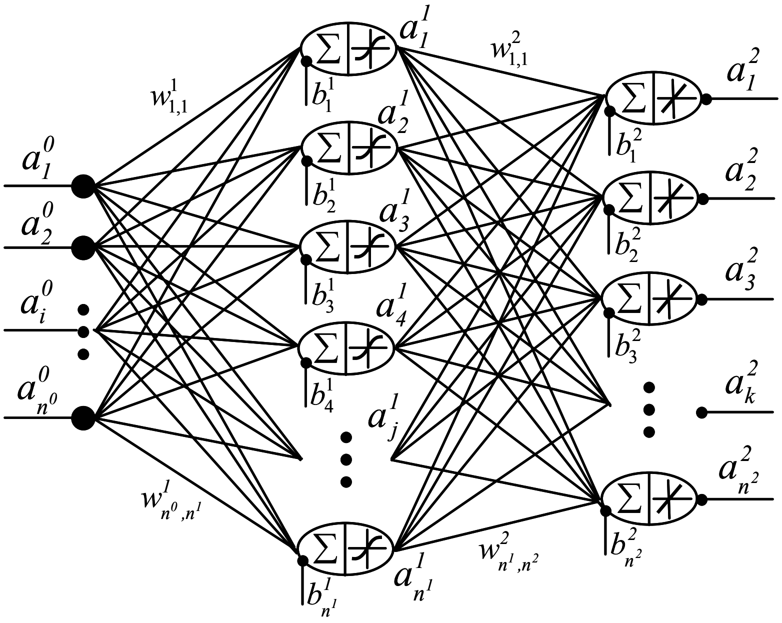

Figure 5: A feed-forward network with two layers, the neurons of the first layer have sigmoid, and of the second layer linear transfer functions

The output vector of the layer l is calculated from its input signal using a transfer function, the weight matrix and the bias vector as arguments:

$$a_i^l = f\left(\sum_{j=1}^{n^{l-1}} w_{i,j}^l a_j^{l-1} + b_i^l\right) \tag{1}$$

In order to calculate a_i^l it is necessary to determine the unknowns first, i.e. the weights and the bias. For this purpose the network is trained with many data sets consisting of the input data x_i, i.e.

$$a_i^0 = x_i \tag{2}$$

and the desired output data d_k. At the beginning of the training, the weights and bias are set to random values. To finally determine their actual values, many iterations are necessary which minimise the error function:

$$E = \frac{1}{2}\sum_{k=1}^{n^2}\left(d_k - a_k^2\right)^2 \tag{3}$$

According to the backpropagation algorithm the update of the weights and bias follows the descending gradient of the error function:

$$\Delta w_{i,j}^l = -\frac{\partial E}{\partial w_{i,j}^l}; \quad \Delta b_i^l = -\frac{\partial E}{\partial b_i^l} \tag{4}$$

The use of a sigmoid like

$$f(\sigma)=\frac{1}{1+e^{-\sigma}} \text{ with } \sigma=\sum_{j=1}^{n^{l-1}} w_{i,j}^{l} a_{j}^{l-1}+b_{i}^{l} \tag{5}$$

as a transfer function in conjunction with the adoption of the abbreviations

$$\delta_{k}^{2}=a_{k}^{2}\left(d_{k}-a_{k}^{2}\right)\left(1-a_{k}^{2}\right) \tag{6}$$

$$\delta_{j}^{1}=a_{j}^{2}\left(1-a_{j}^{2}\right)\sum_{k=1}^{n^{1}} w_{j,k}^{2}\delta_{k}^{2} \tag{7}$$

and the introduction of the so-called learning rate λ result in the following relationships for determination of the weights and bias of the training step *k*:

$$w_{i,j}^{l}(k)=w_{i,j}^{l}(k-1)-\lambda\, a_{j}^{l-1}\, \delta_{j}^{l} \tag{8}$$

$$b_{i}^{l}(k)=b_{i}^{l}(k-1)+\lambda\, \delta_{j}^{l} \tag{9}$$

There are various variants of the backpropagation algorithm, which mainly differ from each other by their convergence acceleration. More details about the backpropagation methods can be found, for example, in [5-7]. The configuration of a neural network, i.e. determination of the number of layers and the number of neurons on each layer, is problematic as no method exists for this purpose. Another difficulty is related to the backpropagation algorithm, which cannot distinguish between main and secondary minima. Further more, the trained network may be over-fitted. In this case, the network does not generalize. It recognizes the data used for the training very well but it is unable to interpolate or extrapolate accurately.

5. TRAINING DATA SETS

To train the neural network used for this research work, over 440 data sets of one coating type applied to compressor casings by plasma spraying were available. They include the above-mentioned process parameters and the coating properties, of which only the plasma and particle ellipse parameters, coating strength, deposition efficiency and shape of the compressor casing are of interest. All other parameters are kept constant during the spray process. The shape of the casing influences the duration of cooling down and thus the properties of the coating. For control of the spray process it may be of interest to specify the required strength, to determine the required torch parameter from the substrate and to predict the corresponding process performance using the casing shape and the *PFI* parameters as input, as Figure 6 illustrates.

One can expect that extensive data sets which have been registered over a long period of time, represent all possible process changes, i.e. the whole process domain. So a network that was trained with this data may be capable of simulating the plasma spray process without exactly knowing each one of the influence parameters and their effects. But the values of the *PFI* parameters have to be representative of the effects of the influence parameters. Moreover the possibility exists that the network can be trained continuously whenever new data becomes available.

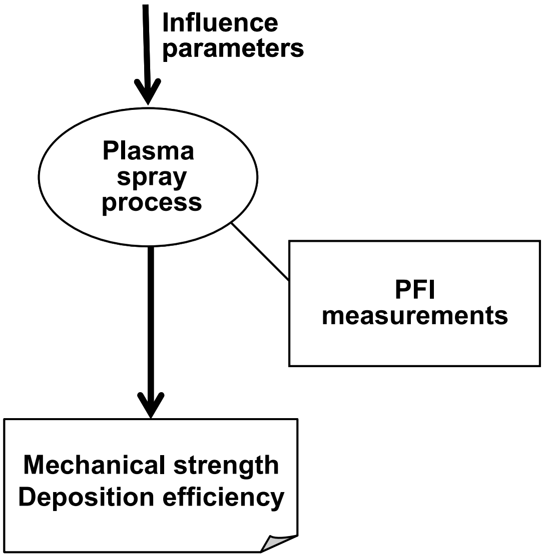

Figure 6: Illustration of the plasma spray process

For training purposes the data sets are divided into three groups. Each of these three groups should be representative of the whole process domain. The first group is used for the proper training to determine the weights and bias of the network by minimising the error function. The second group is used for the validation, i.e. the calculation of the error function value using the weights and bias determined during the training. The validation step is performed in parallel with the training step. Its error decreases continuously like that of training step until it reaches a minimum value, and then it begins to increase again. The increase of the error is an indication of the start of network over-fitting. This is the criterion for stopping the training.

The third group of data sets is used to test the training results. If the error resulting from the test data sets has its minimum at a number of training runs which differs from that of the validation data sets, this means that the partition of the data sets is not representative. Further more the test data sets serve to compare the different training results.

6. RESULTS AND DISCUSSIONS

Figure 7 shows the plot of the error function versus the training epochs, where an epoch means a single presentation of the group of training data sets to the network. At about 60 epochs the training target is achieved. To simulate the process, all 440 data sets are fed to the trained network; the results are shown in Figures 8a and 8b. Here the simulated values are compared with the real values (measured values). In Figure 8a the torch parameter A is plotted, while Figure 8b shows the deposition efficiency AL. The correlation coefficients R achieved are 0.932 and 0.935, respectively. This is, within reason, a good representation of the plasma spray process in the neural network.

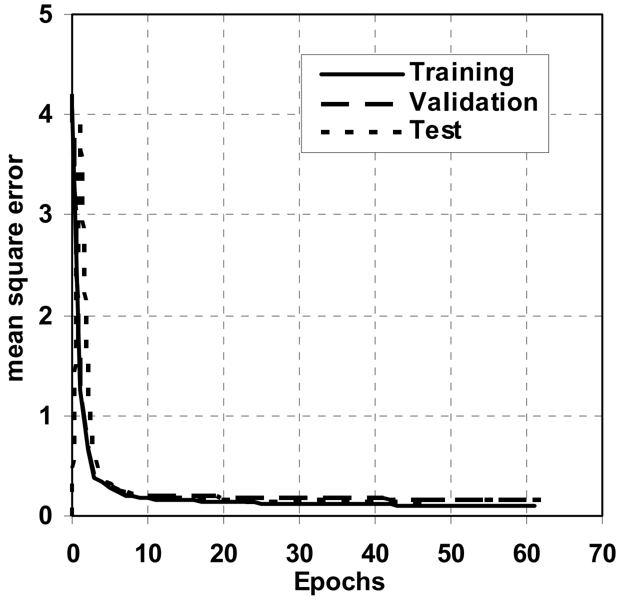

Figure 7: Error development during training, validation and test versus the iteration loops (epochs)

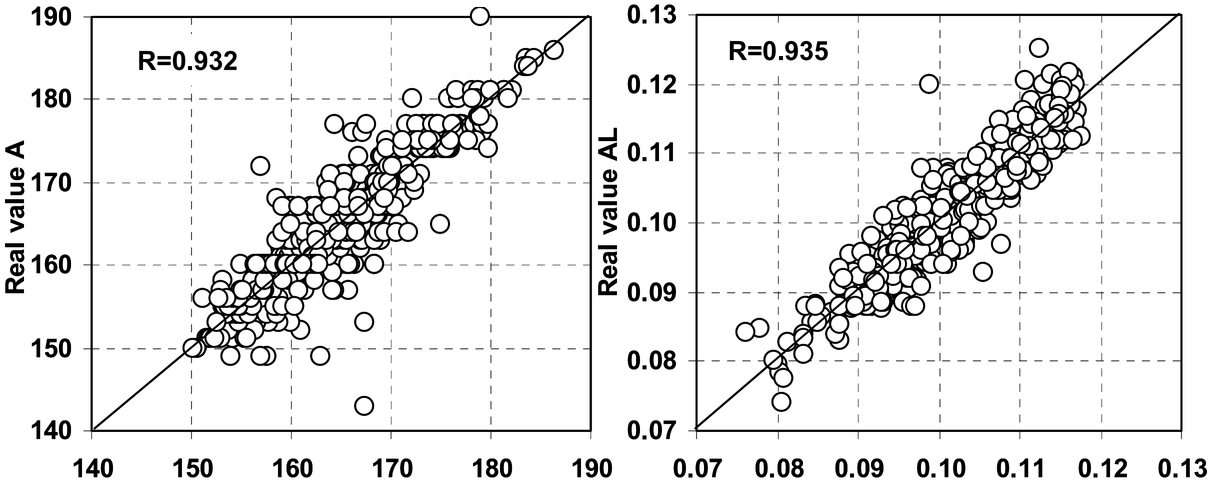

Figure 8: Comparison between network simulated values and real values from measurements of a) torch parameter, b) deposition efficiency

But beforehand it is necessary to clarify which network configuration, i.e. number of layers and number of neurons on each layers, is suitable for the control of the plasma spray process. For this purpose the following two network configurations were investigated. Each of them has 12 input and 2 output parameters, but they differ in terms of number of layers and of neurons. One network had two layers, where the number of the neurons on the first layer was variable. The other network had three layers, where the first two layers had variable numbers of neurons. Each network had the same number of the neurons on the last layer which has to be equal to the number of the network output parameters, i.e. two. In addition the transfer functions of the neurons were varied.

Criteria for comparison were the minimum value of the error function *E*, which resulted from the group of the test data sets, and the correlation coefficient *R* of *A* and *AL*. *E* and *R* are the average results of ten training samples, for which different minimum values were achieved in each run. This is due to the randomly chosen weights and bias at each iteration start. In this way the training prevents convergence only to secondary minima. Other comparison criteria like the number of training iterations and the training speed are possible, but due to the network configurations to be investigated here the training has a relatively low number of iterations and is very fast.

Figures 9a and 9b show the plots of *E* and *R* for the network with two layers versus the number of the first layer neurons. Above a certain number of neurons, i.e. ≥10, the *E* and *R* values change insignificantly. Figures 10a and 10b show the *E* and *R* plots for the three-layer network, in which the neurons on the first layer were fixed to 13 and the number of neurons on the second layer were varied. The introduction of a third layer does not result in further improvement.

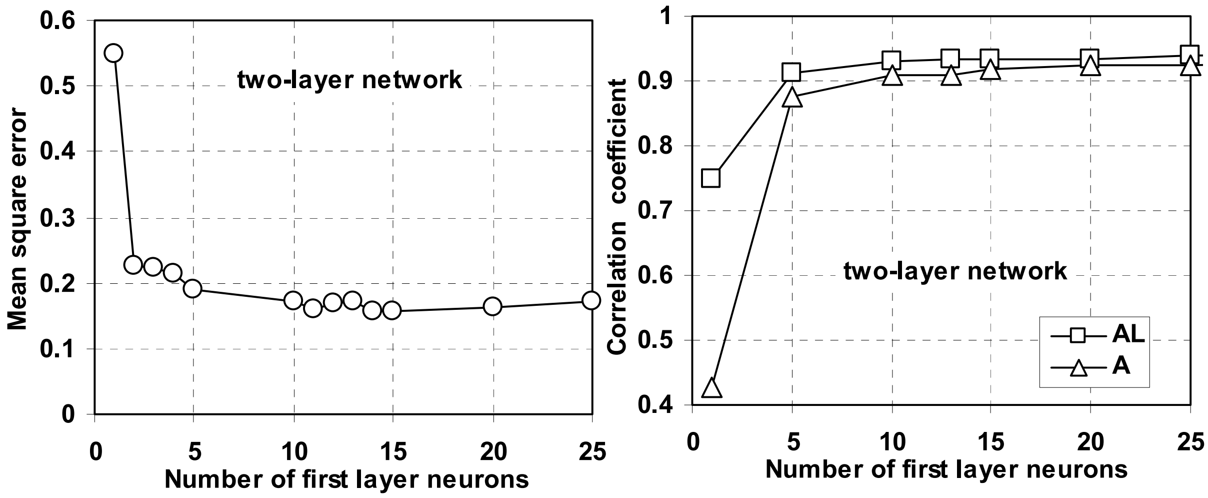

Figure 9: Network with two layers:
a) error development versus variation of the number of the first layer neurons
b) correlation coefficients for A and AL versus variation of the number of the first layer neurons

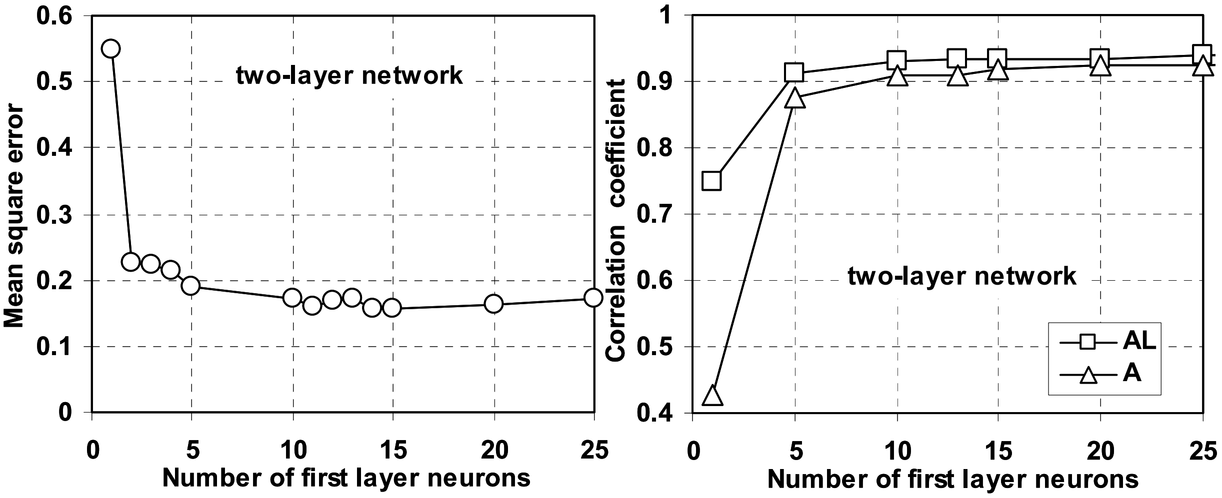

Figure 10: Network with three layer:
a) error development versus variation of the number of the second layer neurons
b) correlation coefficients for A and AL versus variation of the number of second layer neurons

Table 2 is a comparison between the use of linear and sigmoid transfer functions. According to the *E* and *R* criteria the adequate configuration should have sigmoid functions for the first layer neurons and linear functions for the second layer neurons. This corresponds to the configuration 2 in Table 2. The conclusion is that a network with two layers and 13 neurons on the first layer is suitable to simulate the plasma spray process accurately enough. The first results obtained with a prototype network created to control the plasma spray process are very promising. Figure 11 shows that on the basis of the measured *PFI* values the network is able to determine the necessary torch parameter for a specified coating strength and to predict the deposition efficiency. The deviations between simulation and measurement are within the accuracy of the measurement. Production application is planned for the next six months. A further development would be the online diagnosis of the plasma spray process, which enables suitable reaction to unexpected distortions so that the required coating properties are still achievable.

Configuration	1. Layer		2. Layer		E	R	
	sigmoid	linear	sigmoid	linear		A	AL
1	x		x		0.205	0.889	0.898
2	x			x	0.117	0.913	0.931
3		x	x		0.336	0.781	0.874
4		x		x	0.305	0.795	0.883

Table 2: Different configurations through variation of transfer functions for network with 2 layers and the effect on the error function and the correlation coefficient

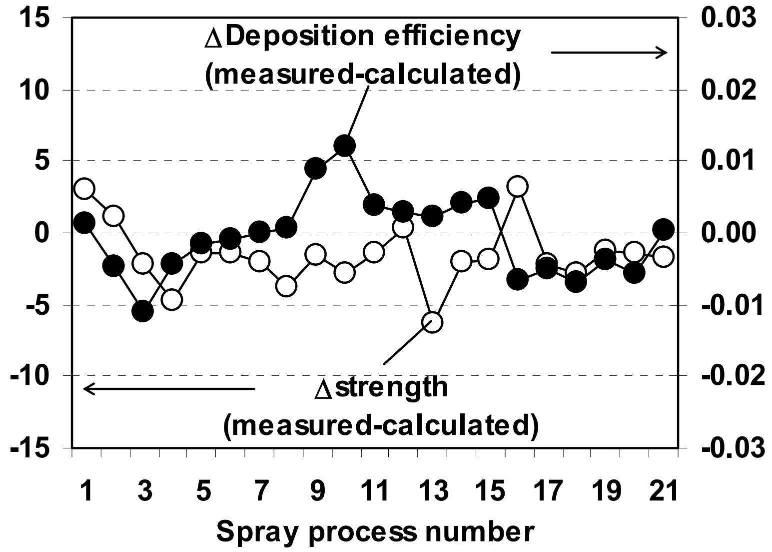

Figure 11: Prototype results of the plasma spray system with the neural network - a comparison between simulation and test

7. ACKNOWLEDGMENTS

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