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Procedia CIRP 62 (2017) 435 – 439

www.elsevier.com/locate/procedia

10th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16

Optimization of the sandblasting process for a better electrodeposition of copper thin films on aluminum substrate by feedforward neural network

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Abstract

The influence of a proper surface preparation is essential for a better adhesion of copper thin films on aluminum substrate. In this work, the surface properties of the aluminum substrate have been modified through sandblasting process, in order to influence the quality of electroplating. To evaluate the correct adhesion of the thin film to the substrate non-destructive measurements of diffusivity by infrared thermography have been made. A combining of a feedforward artificial neural network (FFANN) and an external optimized algorithm (EOA) is proposed to optimize the substrate surface preparation process. A FFANN model is developed to map the complex non-linear relationship between the surface process conditions of the substrate and the thermal diffusivity of the electroplated sample. A good performance of the FFANN model is achieved. An EOA is used for the optimization of the sandblasting process conditions, in order to maximize the adhesion of the thin film to the substrate.

Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Artificial neural networks; Process optimization; Thermo-graphic analysis; Electrodeposition.

1. Introduction

Artificial Neural Networks (ANNs) are information processing systems with their design inspired by the studies of the ability of the human brain to learn from observations and to generalize by abstraction [1]. They have been widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. ANNs have been used in many applications, such as: control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc., and they are particularly useful in system modeling [2, 3]. A neural network is a computational structure, consisting of a number of highly interconnected processing units called neurons. The neurons sum weighted inputs applies a linear or nonlinear function to determine the output, than this output is passed to the following neurons, which are arranged in layers and are combined through excessive connectivity. Neural networks are effective and efficient alternatives to conventional methods, such as: numerical modeling methods [4], which could be highly computationally expensive; analytical methods, which could be difficult to obtain for newly achieved devices; and empirical modeling solutions, due to huge range and limited accuracy [5]. In this work, a feedforward neural network has been developed to model the sandblasting process of aluminum samples, in order to enhance the electrodeposition of copper thin films on their surface. Copper is an active metal with low ionization energy, hence it does not readily plate onto a passivated surface, making direct plating on aluminum-based metals difficult. For this reason, aluminum substrate undergoes a surface pretreatment, thanks to which the copper can adhere. In this context, the level of surface finish required for the process of electrodeposition becomes a parameter of crucial interest, since the roughness profile, affecting the electrodeposition process, turn out to be decisive for the adhesion of the thin film to the substrate [6]. Through the use of various grains of sand

Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2016.06.036

at high pressure it is possible not only to completely eliminate the oxide layer on the surface, but also to change the level of surface finish simply varying the dimensions of the sand, the pressure and the time of the process [7]. The main goal of the work is to achieve a dynamic simulation system through ANNs, able to provide autonomously the best-input conditions, optimizing the adhesion of copper on the aluminum substrate. By combining the ANNs to an EOA is possible making the whole process dynamic and independent, able to reach the best possible conditions both during its planning phase, and during its execution.

2. Experimental procedure

1000-series aluminum was chosen for the samples. All the aluminum samples were obtained from the same block and manufactured with the same parallelepiped shape (30 × 20 × 5) mm. The surface preparation was carried out using a sandblasting machine, which exploits tiny corundum spheres, at high pressure, on the sample surface. The surface preparation has been led varying the particle size of the sand, the pressure and the time of execution of the test. In order to optimize this process the parameters employed have been, respectively:

- Grain: 46 (355-425 μm), 80 (180-212 μm), 120 (106-125 μm), 180 (63-90 μm);
- Pressure: 2 bar, 4 bar, 6 bar;
- Rate of execution: 3 sec, 5 sec, 7 sec.

This treatment enables to easily remove the oxide layer that is formed on the aluminum surface that is the cause of an imperfect and irregular coating. Moreover, this method allows to achieve the best adhesion of the coating, without the use of complex equipment and solutions harmful to the environment. After the sandblasting process, for each sample their roughness profile has been studied by profilometry [20]. The parameters of major interest, related with the consequent electroplating process and with the adhesive force of the thin film of copper to the substrate, have been: the average roughness (Ra) and the average inclination of the roughness peaks (Rdq). Ra allows to evaluate how the combined abrasive action of time, sand grain size and pressure, changed the general shape of the surface; while Rdq helps assess whether the geometrical shape of the roughness peaks has some influence on the subsequent electroplating process. Since the rate at which the oxide layer is regenerated is particularly high, the electrodeposition has been led immediately after the sandblasting process. For the process of copper plating, one of the most widespread acidic solutions was used: a copper sulfate based solution [8]. The sacrificial anode used for the process was composed of four copper plates connected to each other to form a hollow parallelepiped (50 x 30 x 5 mm), without upper and lower bases, in order to completely cover the sample, thus allowing the best possible results. The bath composition was studied and compared with those found in literature and consisted of: 1.25 M $CuSO_4$, 0.61 M H_2SO_4 and Cl^- 50 ppm. The presence of chloride is helpful in the polarization of anode and in the modification of the characteristic of the coating, whereas $CuSO_4$ and H_2SO_4 are obviously indispensable for the correct development of the process. The bath was kept in agitation with a magnetic agitator, located inside the electrolytic cell. On each sample the same amount of copper has been deposited, using for each electrodeposition the same electrolytic current (2.5 A) and the same time of process (5 minutes). In such a way, we could be sure that the thickness of the thin film of copper would have been the same for each sample. The evaluation of the adhesion of the copper thin film to the substrate has been crucial. Due to the thin thickness of the coating (24±0.1 μm) was impossible to perform peeling tests on the samples. Even scratch test was performed to evaluate the coating behavior at the interface, but without giving satisfactory results. During the scratch test, the high deformability of copper and aluminum didn't permit to discretize and evaluate the adhesion differences between different samples. For this reason, the adhesion at the interface has been determined through the indirect measure of the thermal diffusivity by flash method [9]. Considering an electrical analogy, for what concerns the thermal exchange through the electroplated sample, the presence of copper on the aluminum surface is a further resistance in series with that of aluminum and the contact resistance. From this point of view, the thermal conductivity of each electroplated sample results always lower than that shown by the bulk sample. Therefore, from the evaluation of the diffusivity can be understood which sample presents the highest contact resistance and which the lowest, and then the best adhesion on the substrate. For the modeling of the entire process, a multilayer feedforward neural network has been implemented. Thanks to its learning capability a well-trained neural network can produce more accurate outcomes, replacing empirical modeling solutions limited by range and accuracy [21].

3. Implementation of the Artificial Neural Network

The identification of all the main parameters is essential in order to determine which are the input neurons of the network, such as those of output, and how many networks are necessary for the correct modeling of the system [10, 11]. The sandblasting process has been modeled through the use of two networks, both having as input the parameters of the process (grain size of the sand, pressure and process time), and as output one of the roughness parameters (Ra or Rdq). Regarding the modeling of the flash method only one network was realized, having as input the roughness values (Ra and Rdq) and as output the diffusivity (α). In this way, the two networks that simulate the sandblasting process (working in parallel) were connected in series with the one that simulates the flash method. Regarding the two networks which model the sandblasting process, for both of them a FFANN with two hidden layers has been used: 6 and 5 neurons for the one which has as output Ra; 7 and 6 neurons for the one which has as output Rdq. The most important step during the development of an ANN is the training process, through which the network adapts itself to the process that it is modeling [12, 13, 14]. The algorithm chosen for their training has been a Resilient Backpropagation since it is more stable and accurate for the data at our disposal, as well as able to avoid the over-training problem and to minimize the error function used (mse, mean squared normalized error performance function). To model the thermal properties of the electroplated samples has been used a FFANN with two hidden layers. Due to the complexity of the problem, it has been necessary to use 8 and 7 neurons for the first and second layers respectively. The algorithm chosen for the training has been a Levenberg-Marquardt, as it was the only one, despite the increased computational heaviness, to arrive at extremely reasonable values of minimization of the error function. For all the networks created the transfer function used between the interlayers has been a hyperbolic tangent function. Once the network was built and trained it undergoes a validation process, by which the thinking capacity of the network is evaluated, providing the input data of which the answer is known, without providing the output [15, 16]. During this process the network is then evaluated for its ability to generalize, by comparing the response provided by the network and the real answer known. Generally a 20% of the entire data set is used for the validation but, due to the complexity of the system to model, it was necessary to use almost all of the data at our disposal for training rather than for validation, without which the network would not have had the ability to learn properly and generalize the problem [17]. The data subdivision used for the training and validation of the networks, has been:

- Training: 88% of the entire dataset;
- Validation: 12% of the entire dataset

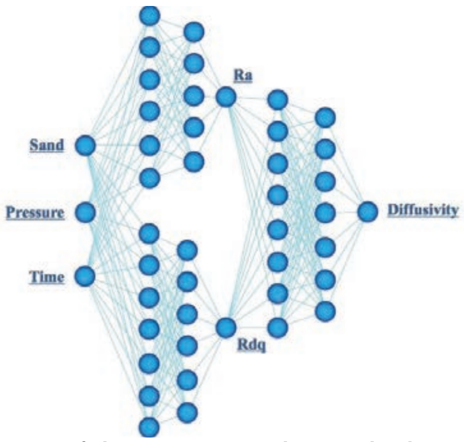

Fig 1. Image of the interconnections between the three neural networks created

Once the network has been trained and validated it is able to generalize the system that is shaping, namely to provide consistent answers according to input data which have never been provided [18]. In this regard an algorithm was created (first indicated by the acronym EOA) able to collect the networks created, and determine the conditions of sandblasting in order to maximize the thermal diffusivity. The algorithm works by analyzing all possible conditions for the sandblasting process, both as regards the type of sand, the pressure and the working time, needing only intervals in which it must look for the optimal solution. By the connection between the networks and the EOA we were able to model and optimize the entire system making it dynamic, namely able to varying the input values always maximizing the diffusivity, even when the process is taking place.

4. Experimental results

The roughness analysis has evidenced how the correlation between the main parameters of the sandblasting process is not linear. As shown in the following figure, we can clearly see how changes in the particle size of sand, or pressure, or blasting time allow some kind of assessments only for the same grain of sand. For example, if we consider the sand with grain 120 we can see how the abrasive capacity increase with pressure and time, while it is the opposite with grain 180. That because the increase of pressure from the nozzle ejector leads to a higher speed of the grain of sand, so the kinetic energy discharged on the surface ends up causing a higher abrasion. On the other hand, if we maintain the same pressure and time, varying the particle size, we obtain the opposite effect: less abrasion and higher work hardening.

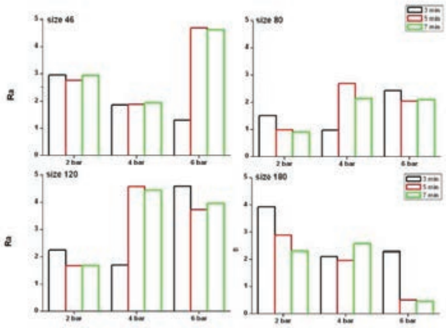

Fig. 2. Average Roughness Profile varying the sandblasting main parameters

As regards the measurement of the thermal diffusivity, the flash method is the most popular method used. It has the advantage of being fast, while providing values with excellent accuracy and reproducibility. The diffusivity of the electroplated samples has been determined according to Parker's law:

$$\alpha = 0.1388 \cdot \left(\frac{L^2}{t_{1/2}}\right) \tag{4.1}$$

Where L is the thickness of the sample, and $t_{1/2}$ the time that the thermo-gram takes to reach half of the maximum temperature increase [9]. All the diffusivities have been compared to the one measured for the bulk sample, in such a way we could be sure that we were measuring only the variations of contact resistance [19]. The thermal flow has been diagrammed for each sample, throughout the sample, as function of time (Fig. 4), by the use of a thermal imaging camera. As shown in the figure below we can clearly see how some samples present diffusivity values close to the one shown by the not-electroplated sample (there indicated simply as "Bulk"), while others present almost a constant trend.

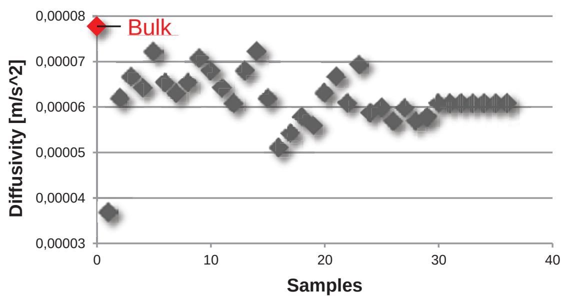

Fig. 3. Diffusivity values for each electroplated sample

As follows, we analyze three different characteristic samples by optical microscope. We choose the samples 9, 18 and 36, characterized by values of diffusivity respectively of 7.081·10-5 m2/s, 5.78·10-5 m2/s, and 6.09·10-5 m2/s. In order to highlight as much as possible the adhesion at the interface, the three samples were first cut, embedded in a thermosetting resin and then polished. The processes described have finished to alter the size (in terms of thickness) of the electrodeposited layer, while allowing analyzing accurately the interface. In the following picture (Fig. 4) we can clearly see how the adhesion on the 9th sample is the one with fewer imperfections, while in the 18th we incur in a partial separation of the thin layer. This ends up having a significant impact on the diffusivity and, consequently, on the thermal conductivity.

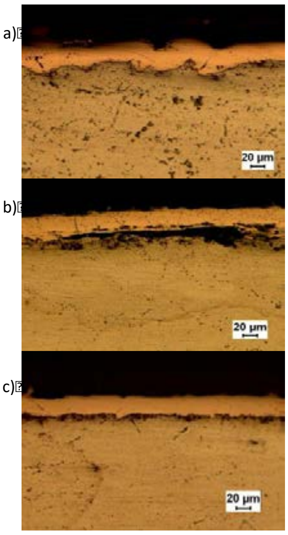

Fig. 4. Surface picture of the: a) 9th sample; b) 18th sample; c) 36th sample

5. Artificial Neural Network results

The training process of the neural network was carried out trying to avoid incurring the problem of over-training, while seeking to minimize the error function. As shown in the following tables and pictures, the performance of the three networks, i.e. the maximum deviations between the actual values (indicated with the "x" symbol) and the outputs generated by the neural network (indicated with the "o" symbol) in the learning phase, were all very low. Low values of mse-training performance have been reached, as a direct consequence of the high number of epochs realized in addition to the type of algorithm used.

Table 1. Epochs and Training performances of the three networks

Input	Output	Maximum Deviation	Epochs
Sand grain, pressure, Time	Ra	0.371%	10000
Sand grain, pressure, Time	Rdq	0.271%	10000
Ra, Rdq	α	2.59%	6000

As regards the validation process of the three networks, the deviations between the actual values and the outputs generated by the neural network were all superior to the ones shown during the training process. It demonstrates how the generalization ability of the network is mainly dependent on the complexity of the problem and on the amount of data provided during the training phase.

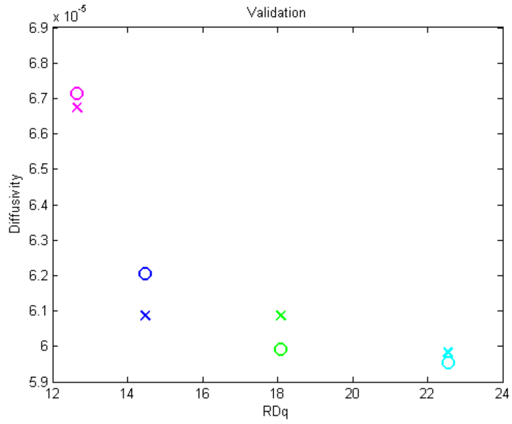

Fig. 5. Validation Process of the Network having as output the diffusivity

Table 2. Validation Performances of the three networks

Input	Output	Maximum Deviation
Sand grain, pressure, Time	Ra	10.3%
Sand grain, pressure, Time	Rdq	5.72%
Ra, Rdq	α	1.65%

As regards the EOA, the intervals where the algorithm had to look for the optimum sandblasting input values, were:

Table 3. Operative Intervals of the EOA

Sand	Pressure	Time
From grain 46 to 180	From 0 bar to 8 bar	From 0 sec to 20 sec

The optimization process has therefore led to the following results (all of them with the same value of α):

Table 4. Results of the Optimization Process

Sand	Pressure	Time
Grain 46	4 bar	5 sec
Grain 82	6 bar	8 sec
Grain 123	8.1 bar	2.1 sec

The results obtained represent the input parameters that permit to maximize the adhesion of the copper thin film to the substrate. The possibility of having different optimum conditions enables a dynamic control of the process conditions when it takes place, since it allows adapting the process parameters on-site, even when an unexpected occurs. This leaves the network to adapt autonomously its input parameters to changes, always minimizing the contact resistance. Obviously, optimization is very similar to reality if the training process of the neural network has been good, since it enables the network to properly simulate the entire process.

6. Conclusion

The use of the diffusivity as a tool for a non-destructively evaluation of the adhesion of the thin layer to the substrate was a successful choice, as demonstrated by the images obtained by the optical microscope. The use of a lower number of neuron on more hidden layers has allowed the network to generalize in a better way the problem proposed. A valid response to the validation phase, without incurring the problem of over-training, has been reached. The optimization carried out subsequently allowed the theoretical optimum conditions to be determined. The optimization has been based on actual data and on more distinct processes characterized by the absence of intrinsic correlations and then by non-linear behavior. The EOA realized allowed to evaluate every possible case, in times consistent with the computing power of the computer, allowing the realization of a dynamic process able to evaluate autonomously the input best conditions. The possibility to have a dynamic system, with respect to different operating situation, not only improves the stability of the process itself but also allows achieving considerable savings in terms of time, money and materials. Although there are never any guarantees of absolute accuracy when approximating unknown functions the ANNs can provide data and values consistent with the problems examined, in a reasonable time, with very high accuracies, which may represent a viable alternative to the current methods of simulation.

Acknowledgements

The author thanks Mr Massimiliano Della Millia of the Department of Engineering of the University of Studies of Rome "Tor Vergata", Rome, Italy, for his continuous support throughout the research work.

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