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ARTIFICIAL NEUTRAL NETWORKS APPLICATION FOR PLASMA CUTTING MODELING

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ABSTRACT

In order to obtain the required cut quality during the plasma cutting process, the particular regularities between the elements of the cutting quality and the process input parameters should be explored. This research should take into consideration the large number of the significant factors that influence the process output parameters. In this paper, the experimental research deals with the investigation of the impact of the plasma cutting current, cutting velocity and metal thickness on the kerf surface roughness.

Based on the experimental results, the sets of tests were done in order to determine the most favourable Artificial Neural Network structure and architecture. The particular Artificial Neural Network process modelling was applied for plasma cutting modelling. The results were verified by the simulation of the Artificial Neural Network, which was done by the set of data that was not used for the network training. The simulation was done for the purpose of verifying the experimental results, where the simulated data showed the good agreement with the experimental results.

KEYWORDS: Plasma cutting, artificial neural networks, kerf surface roughness

1. INTRODUCTION

During the plasma arc cutting, a high quantity of energy is focused on the small workpiece area, which implies an intense heating of its surface. The energy source is the ionized gas, characterized by high temperatures and velocities. The gas is ionized by the direct current, which is passing from the cathode (inside the nozzle) to the anode (the workpiece). When the plasma jet reaches the workpiece's surface, the energy used for its ionization is relieved, therefore, the material melts. The melted material is removed from the cutting area by the kinetic energy of the plasma jet. Due to the high temperatures, the heat transfer from plasma jet to the material accounts for most of the phenomena encountered, subsequently: shrinkage, residual stresses, structural and metallurgical changes, mechanical deformations, chemical modifications, etc. The plasma characteristics could be significantly changed, therefore controlled by changing the gas type, the gas flow, the cutting current, the nozzle size, etc.

The research of the plasma cutting process is usually focused on three separate fields: the generation of the plasma arc, the characteristics of the plasma jet and the interactions between the plasma jet and the material, together with phenomena which appear during the process. Most of the papers provide a quantitative description of the particular segments of the process, but generic models do not exist. The approaches depend on the selection of the process parameters, such as the gas type, the gas flow, the pressure, the distance between the nozzle and the workpiece, etc. and the segment of the process to be modelled. Extensive literature is also available for the assessment of the potential exposure of workers to the hazardous substances and the possibility to protect the working environment, due to the increasing concerns for human health and working conditions.

The development of Computer Aided Design (CAD) initiated the automation of the technological process designs and the elimination of its presumptions, in order to achieve a high-quality plasma cutting that is adaptive to small and large production plants. Working together on the technology developments, the companies that produce CNC machining centres and manufacturers of plasma equipment have optimized the machine control units in order to entirely utilise the advantages of speed and power of the plasma cutting, while CNC technologies enabled a unique maintenance of the cutting quality level. Therefore, the plasma cutting machines could be adjusted to automatic, whereby the setup time was dramatically reduced and almost eliminated the human error and so, the work efficiency was simply set forward as well as the production time and the work quality [1, 2]. Although the automation steps in the plasma cutting process appear quite simple, they are the result of an intense development of the modern technologies. The older plasma cutting systems, as well as many modern ones, do not utilise or partially utilise the advances of new technologies, and require precise manual adjustments in order to produce a satisfactory level of the cut quality [3].

The research on the Artificial Intelligence significantly contributed to the plasma cutting process automation. In the last two decades, this research has greatly improved the performance of both manufacturing systems and services. The complex processes, such as the plasma arc cutting, are particularly suitable for applying the Artificial Intelligence's methods for its modelling. This paper presents the application of one Artificial Intelligence's method - the Artificial Neural Networks for the plasma cutting process modelling, using data collected during the experimental research, tailored to the process modelling needs.

The relevance of the process modelling highly depends on the appropriate selection of the output process parameters, which will be modelled, as well as the input process parameters, which will be used to express the dependent variables in order to predict the process parameters. The plasma cutting is characterized by the big number of influential parameters, due to its complexity [4, 5]. However, for the purpose of this research, the selection of process parameters was supported by the analysis of the available literature and the manufacturers' manuals, as well as the data collected by interviewing the plasma cutting machine operators and the supervision engineers in the production facility, where the plasma cutting machine was located. Therefore, the number of the influential parameters was reduced through the previously undertaken analysis to three influential parameters: the cutting current (I), the cutting speed (v) and the material thickness (s). The kerf width was selected to be a dependant process variable (output process parameter) [6].

2. EXPERIMENTAL SETUP AND METHODOLOGY

The experiment, which provided data for the plasma cutting process modelling, was done on CNC machine HPm Steel Max 6.25 (produced by the Italian manufacturer High Performance Machinery). The plasma cutting unit used on this machine was Hypertherm HPR130, which can cut the material thicknesses up to 38 mm, for stainless steel.

The workpiece material used for this experiment was X10CrNiMn-16-10-2 (EN 10025), with the following chemical composition (wt): 0.1% C, 16% Cr, 10% Ni and 2% Mn.

The 99 rectilinear cuts were made by the above mentioned plasma cutting machine, varying the input parameters (the cutting current, the cutting speed and the material thickness) chosen as independent variables for the purpose of the process modelling. The samples prepared for examination are shown in Fig. 1.

Fig. 1: Samples prepared for examination

Five different workpiece thicknesses were used: 4 mm, 6 mm, 8 mm, 12 mm and 15 mm. The cutting current was 80 A or 120 A, while the cutting speed was ranging from 330mm/min to 2,800 mm/ min, depending on the material thickness and the chosen value of the cutting current. The values of those three parameters varied during 99 experiments and the samples were prepared for the examination. The kerf width, as independent variable in the model, was measured by the standard apparatuses.

3. PLASMA CUTTING PROCESS MODELLING

The Artificial Neural Networks represent the attempt to form an artificial system based on mathematical models, which will be, by its structure, function and information processing, similar to the biological nervous systems and, thus, able to intelligently process the information simulating the biological intelligence. The most important capability of the Neural Networks is learning on examples and the generalization of the problems after training [7, 8, 9]. For complex processes and systems, such as plasma cutting, whose structures and internal regularities are unknown, implementation of the black box model is appropriate. The input, controlled parameters are numerical values, able to be chosen and varied freely. In the particular case those parameters are: cutting current, cutting speed and material thickness. The output parameters (response, status characteristics) are values that can be measured or are result of input parameters action, such as kerf width, as chosen in this paper.

A very important step in process modelling using Artificial Neural networks is to determine its structure and architecture. This will determine the ability of the Neural Network to learn and to adapt to the particular problem. The Neural Networks are composed of a large number of neurons distributed in several layers and interconnected, operating in parallel. The neurons of the current layer receive data from the neurons of the previous layer, process them and forward them to the neurons of the next layer. The connections between particular neurons in layers are characterized by its interconnection weights. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Therefore, the basic principles of Neural Networks performance show the similarity with the performance of the human brain: the ability to learn during the training process and the interconnection weights that serve for memorizing the knowledge. The training of the Neural Network was performed by adjusting the values of the connections (weights) between elements, so that a particular input leads to a specific target output. For training the particular network for the kerf modelling, the set of data from 68 experiments was used. The software application Matlab was used for the network training and simulation, particularly its Neural Network Toolbox.

The network has three neurons in the input layer (one for each input parameter) and one neuron (for one measured output parameter) in the output layer. The number of the hidden layers is very important and influences the quality of the network output. Therefore, in order to select the proper number of the hidden layers and its neurons, six Neural Networks with a different number of hidden layers and a different number of its neurons were trained.

The following networks were trained: Ns-2, Ns-3, Ns_1-2 Ns_2-2, Ns_1-2 Ns_2-3, Ns_1-3 Ns_2-3 and Ns_1-3 Ns_2-2. The number following the sign Ns_1 represents the number of neurons in the first hidden layer, while the number following the sign Ns_2 represents the number of neurons in the second hidden layer. The training showed that the most suitable network structure was the network containing one hidden layer with three neurons Ns-3, as represented in Fig. 2.

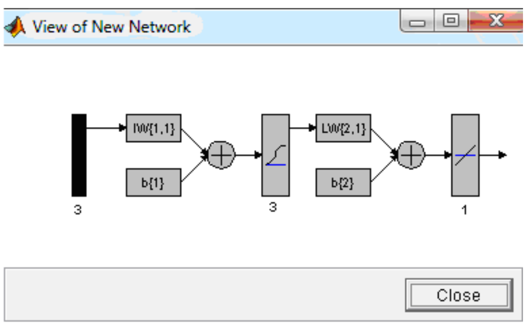

Fig. 2: A schematic representation of the selected Neural Network

The chosen Neural Network Ns-3 was a back-propagation network with forward data processing. The training process was supervised learning. Levenberg–Marquardt method with momentum was selected as a learning algorithm (the adoption learning function), which is assumed as the fastest for medium sized networks. This function proved the fastest convergence to the solution as compared to the other learning algorithms. The mean squared error, which should be reached during Neural Network training, was used as a criterion for optimization of interconnection weights. For the presented algorithm, it is commonly to choose the sigmoid transfer functions for all neurons in the hidden layer. The neurons in output layer had a linear activation function, which allows the network to generate output values outside the range +1 and - 1.

After the training, the network Ns-3 was simulated with the set of data from 32 experiments, which were not used for the network training. The selection of these data samples was carried out by a random number method. After the simulation of the previously trained network, these data were compared to the experimental results for the same experiments. Figure 3 presents the plotted experimental and network simulation results, with respect to the reference number of the experiment.

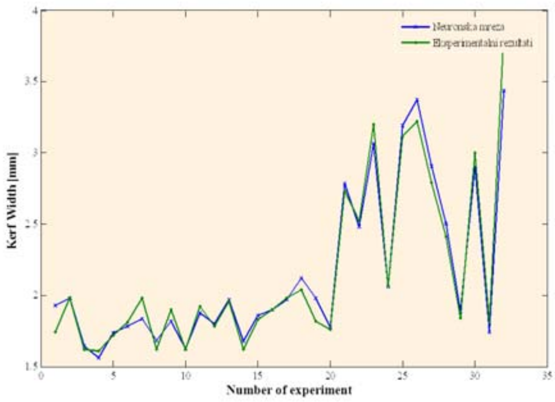

Fig. 3: The plotted experimental and the network simulation results

Figure 4 presents the comparison between the experimental values and the values obtained by the simulation of the previously trained network. The red line represents the best linear approximation of these data, whose equation is presented above the figure.

The dashed blue line represents the line that is angled at 45 degrees, for comparison purposes. The correlation coefficient was also calculated and amounts to 0.983, which is very close to 1. The average network error for the random data sample is 3.13%. However, besides the average error, the knowledge of the maximum and minimum errors is important. Therefore, the maximum error was 10.9%, while the minimum error was 0.01%. These results prove the good agreement between experimental results and the data obtained by the network simulation.

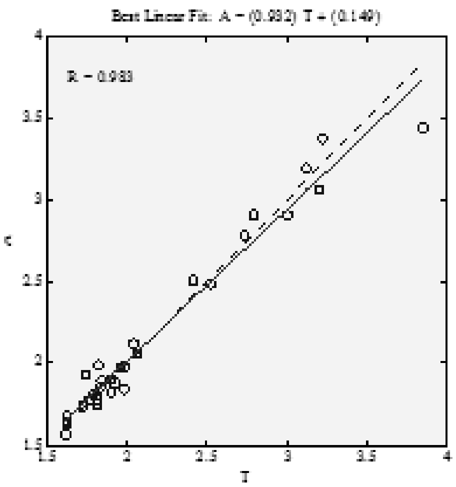

Fig. 4: Comparison between the experimental values and the values obtained by the network simulation

4. CONCLUSIONS

The results presented in this paper indicate the high potential of Artificial Neural Networks as a tool for empirical modelling of the plasma cutting process. The good agreement between experimental data and the modelled ones was obtained. The particular Neural Network Ns-3 represents the adequate plasma cutting model, while the generated output parameter (the kerf width) complies with the practical requirements at the satisfactory level. However, the network could be additionally improved by selecting the particular sets of input-output data for its training. Also, when the data generated by Neural Network shows a discrepancy with the experimental data, the experiment should be repeated for the particular number of experiment.

On the other hand, the Artificial Neural Network performance could be continually improved by additional data samples from direct manufacturing.

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