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OPTIMIZATION OF TOOL PATH DURING CNC DRILLING

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ABSTRACT
The paper applies the self-organizing neural network to optimization of tool path on the workpiece during drilling. The model shows the implementation of the artificial intelligence method on modern manufacturing system. The tool must make all drilled holes covering the shortest path between them. The locations of drilled holes to be made by the tool were represented with two-dimensional vectors of synaptic weights of neurons from the network. Due to the properties of the quantization stage during learning with equivalent algorithm of the self-organizing neural networks the vector of synaptic weights in the network became similar and, in the end, even identical to input vectors. The model correctly selects also the required tool for the individual drilled hole.
Keywords: intelligent manufacturing system, neural networks, optimization of tool motion

1. INTRODUCTION
Modern manufacturing systems require continuous changes and modernization and tend towards complete autonomy. To that end it is necessary to introduce intelligent systems with intelligence incorporated into the machine tool control and ensuring execution of activies with minimum required supervision of the human. Intelligent manufacturing systems want to imitate functioning and capability of the human brain in a way that would simply transfer the human logic and heuristics [1]. The human controls the manufacturing system on the basis of his knowledge and experience which cannot be converted into logical or algorithmic rules. By using inductive intelligent systems, such as artificial neural networks, the paper presents how the individual manufacturing system can work independently of the human. Recently, the neural networks have manifested great potential in solving complex optimization problems in the area of manufacturing systems. The neural networks with their capacity of learning from cases, their generalization capacity and general approximation capacity are used for the classification, modelling, prediction, optimization and managing in numerous areas of science and technology. This paper deals with the use of neural networks for optimization of the tool motion on the workpiece during drilling.

2. SELF-ORGANIZING ARTIFICIAL NEURAL NETWORKS
For solving our problem the self-organizing neural networks, whose structure and functioning are most related to real biological neural networks out of all types of artificial neural networks [2,3,4] were used.

2.1. Equivalent algorithm

The equivalent algorithm was used to implement the behaviour of the self-organizing neural networks without considering the side connections between neurons. Due to sophisticated mathematical operations in this algorithm the similarity to real biological neural networks was partly lost [5,6]. In fact, the equivalent algorithm of the self- organizing neural networks detects only which neuron responds to the used observation vector *x* to the maximum extent, only then changing of the weight of the winning neuron and its neighbours follows.

2.2. Travelling salesman problem

In our case the travelling salesman problem (TSP) was approached with the self-organizing network by the elastic tape method. That method was first presented by Durbin and Willshaw [7,8]. Their approach places the discrete optimization problem into the Euclidean space of locations of TSP. The algorithm is started with k points (nodes) on the imaginary "elastic tape", where *k* represents a number greater than the number of locations. Then, the nodes move in the Euclidean space and tighten the elastic tape so that it adapts to the positions of locations as much as possible. The problem is solved, when each location is covered with the node of the elastic tape. In the first group each neuron is connected to each neuron (also to itself) from that group and the weight depends on the distance between the two neurons. The weight *r(i,j)* between the two neurons *i* and *j* is expressed with the equation:

$$r_{(i,j)} = e\frac{-dist(i,j)^2}{2\cdot\Theta^2} \quad (1)$$

where *dist (i,j)* is the Euler's distance between the two neurons *i* and *j* , whereas *Θ* is the learning factor (>0).

In order to enter the data into the network still another group of neurons is needed. That group is subject to topological rules of the first group. Each neuron of this group is connected to each neuron from the first group. Further, the weights connecting those two groups are designated with *w*.

The equivalent algorithm of the TSP method is as follows:

1. Determine coordinates of locations.
2. Make a ring of neurons (first group).
3. Determine weights of each neuron (from the ring) up to the two input neurons (X and Y), where those weights are from the rank of coordinates of locations.
4. Determine the learning factor and its parameter.
repeat
5. Take coordinates of the random location (X_i and Y_i) and put them on the two input neurons.
6. Find the j-th neuron nearest to the randomly selected location (the Euler's distance between the selected location and the j-th neuron is smallest)

$$(X_i - w_{xj})^2 - (Y_i - w_{yj})^2 \quad (2)$$

where w_{xj} is the weight between the j-th neuron and the input neuron X. The same applies for w_{yj}.
7. Change the weights in the following way:

$$w_{xi} = w_{xi} + \phi\cdot r_{ij}\cdot(X_i - w_{xi}) \quad (3)$$

The same applies for w_{yi}. This is effected for all neurons of the first group. ø is the learning factor parameter.
8. Reduce the learning factor and its parameter.
9. Calculate again the weights r(i,j).
until the learning factor is sufficiently small.

2.3. Optimization of tool motion on workpiece

For building the neural network, solving our problem, a modern modular programme with graphic environment was used. With the tool NeurolSolutions [9] the self-organizing network was built by the elastic tape method. In the first stage the network contained the same number of neurons as the number of drilled holes to be machined by the tool. All neurons were arranged into one-dimensional neuron grid. The observation vectors and also the vectors of the synaptic weights were two-dimensional. The tool must make 16 drilled holes by covering the shortest path between the individual drilled holes. Each location of the drilled hole can be written with the two-dimensional observation vector containing the coordinates of locations. Coordinates of drilled holes were determined on a 3D model so that first the reference point, i.e., the left bottom corner of the workpiece was selected on the workpiece. Then the distance of the individual drilled hole from that point was determined and, thus, the drilled hole coordinates were obtained. Our learning group, thus, contained 16 different observation vectors x_i. The space of the input and/or observation vectors was replaced by a representative group of vectors of synaptic weights of neurons from the network. As the information about each drilled hole (observation vector) was needed, one vector of synaptic weights [10,11] was introduced for each observation vector. Thus, for 16 locations at leas 16 two-dimensional vectors of synaptic weights $_{wj}$ are needed. In that case the self-organizing neural network has at least 16 neurons. Because of the quantization stage during learning with the equivalent algorithm of the self-organizing neural network the vectors of synaptic weights in the network became similar to input vectors.

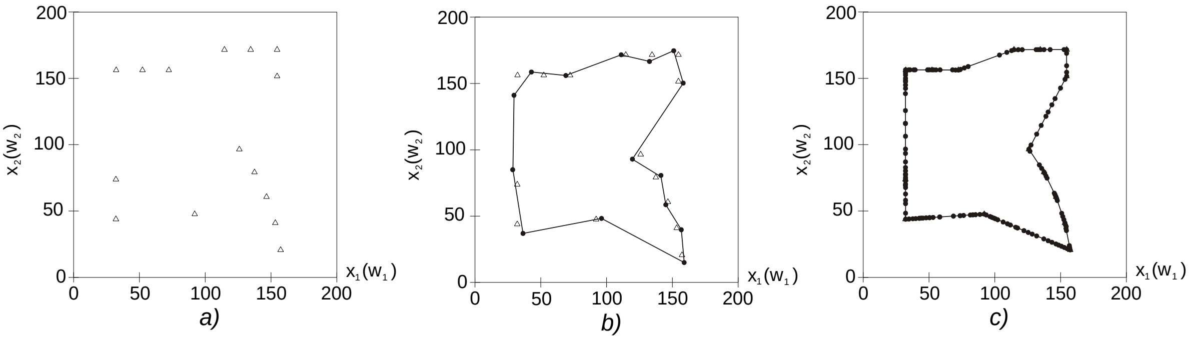

Figure 1. Architecture of neural network for the TSP

As in our case the number of input and/or observation vectors is low (16 drilled holes) the number of learning steps must be high (3500 steps). Because of the small number of inputs that group of samples (learning group) in the equivalent algorithm had to be used several times (200times). Although 16 neurons suffice for solving the problem of the salesman having to visit 16 locations, it is proper to use more neurons (100 or more in our case). Here, assurance of smooth path between locations in situations, where neighbouring locations are very distant, is in question. Redundant neurons (and weights) will interpolate the path between locations. Figure 1 a) shows 16 drilled holes to be made by the tool. The problem was solved with a self-organizing neural network. In the first solution the neural network, having the same number of neuron as the number of locations (i.e.16), was used. Those neurons were arranged into a one-dimensional grid. Figure 1b) shows the shortest path between 16 drilled holes, when the neural network with only 16 neurons was used. The shortest path was picked up so that in the neuron grid the neurons were followed up consecutively and their vector of synaptic weights recorded; then those weights were drawn on the workpiece. In the figure the synaptic weights of neurons are drawn with larger dots. The weights of two neighbouring neurons are connected with a line. It can be noticed that the obtained solution, i.e., the shortest path does not run accurately through the locations, but only approaches them (approximates them).

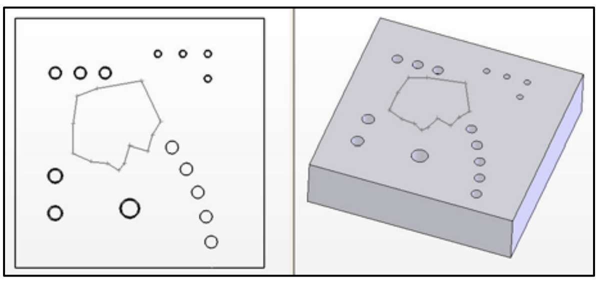

Figure 2. Ring after 50 steps

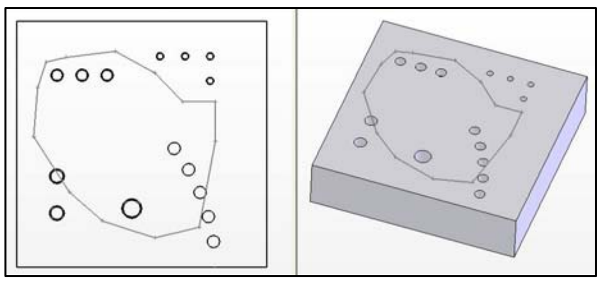

Figure 3. Ring after 1000 steps

In the second version the neural network with the group of redundant neurons was introduced. That network had in total 150 neurons arranged into one-dimensional neuron grid. The shortest path obtained is shown in Figure 1 c). It can readily be seen that the path accurately runs through 16 locations, the redundant neurons having interpolated the path between the locations. Figures 2 to 5 show the adaption of the ring to the actual position of 16 drilled holes on the workpiece. In addition, Figure 5 shows where the tool change for proper making of drilled hole is effected.

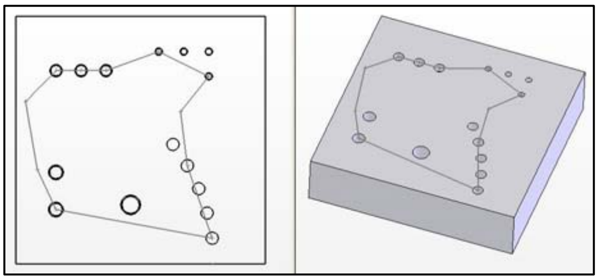

Figure 4. Ring after 2000 steps

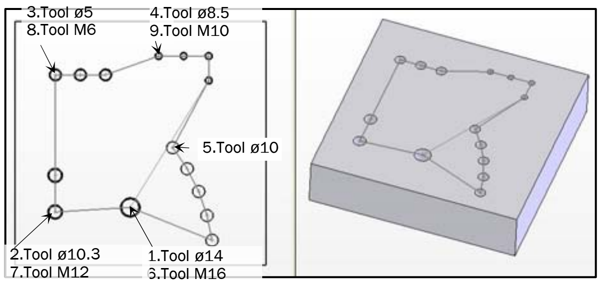

Figure 5. Ring in the end

3. CONCLUSION

The presented model of the neural network, where the principle of self-organization is considered and which served to find the solution of the salesman problem is an example indicating how the artificial intelligence method was applied to modern manufacturing system. The developed model is applicable to the determination of the optimum tool motion on the workpiece during drilling. The model allows entering of coordinates of the individual drilled holes the tool has to make; then the model finds the optimum path to be covered by the machine. This model is efficient also in other production systems, e.g., in searching for optimum path of the robot in production workshop, in assembling individual units, in optimizing the robot arm path etc. Moreover, the optimum path saves time, which is important for the modern production process.

To ensure efficient and, particularly, fast working of the model the tool NeurolSolutions was used to allow fast execution of the self-organization which is usually very slow. With the user interface the possibility of entering and changing various parameters of the self-organization and the possibility of optimization of different examples were added.

In association with the modern production system the neural network models can represent an efficient tool for optimization of processes taking place in production. Such models can be still more efficient, if they are linked with certain artificial intelligence methods (e.g. genetic algorithms). Thus, hybrid models are formed whose feature is that they are a combination of all advantages characteristic of certain artificial intelligence method. In this way, optimum solution of the problem is approached even more and still better optimization assured.

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