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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR ESTIMATION OF THE MASS OF THE WASTE POWDER DURING SELECTIVE LASER SINTERING

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ABSTRACT

The paper presents results of the efforts to improve the accuracy of cost calculation of the selective laser sintering technology using an artificial neural network as a tool for estimation of the mass of the waste powder, based on the masses of the powder that will be, and the powder that will not be, built into products during a production process.

Keywords: additive manufacturing, selective laser sintering, manufacturing costs.

INTRODUCTION

An important characteristic of the selective laser sintering (SLS) technology is the ability to re-use a part of the powder that remains after a production process. The waste powder is the part of the powder that is not built into products, but still may not be used again. There are two main sources of the waste powder during SLS, a fixed amount of the powder that remains spread over the powder bed after a production process, and a variable amount of the powder that remains attached to the products after they are removed from the product bin.

While the costs of the waste powder are not assessed in the most important studies of the additive manufacturing costs (an overview is given by Costabile et al, 2017), their importance grows with the recent technology improvements that increase the ratio between the used and fresh powder in the production powder mixture. A recent effort (Soskic et al, 2017) was aimed at development of a rough, but simple, analytic expression for estimation of the mass of a waste powder during a production job. The conclusion was that for a rather typical production job the mass of the attached powder may be very roughly estimated to be proportional to the mass of the used powder that is not built into products ("non-product mass"). This paper presents an effort to develop a more complex method, an artificial neural network (abbreviated as ANN, a computational tool inspired by biological neural systems that is often used for data pattern recognition), which would use the same input data (the product mass and the non-product mass) to estimate the mass of the attached powder with more accuracy.

METHOD

An ANN consists of artificial neurons (nodes) which are organized into multiple layers and connected to each other via synapses. The relationships between ANN input and output parameters are established in a network training process, by tuning the values of synaptic weights based on data sets with known outputs.

The structure of the developed feedforward ANN for estimation of the mass of the attached powder has one hidden layer with five nodes. The bipolar sigmoid function and the linear function are used as the transfer functions of the hidden layer and the output layer, respectively. During the neural network training process, backpropagation algorithm based on Levenberg-Marquardt optimization has been used for updating the synaptic weights and bias values.

For the presented study were used 181 data sets obtained in exploitation conditions, which were also used in the previous study (Soskic et al, 2017). 127 of the data sets were used for training of the network, while the remaining 54 data sets were used for testing.

RESULTS AND CONCLUSIONS

The results show that the correlation coefficient between the measured masses of attached powder and predicted values, as well as the distribution of the relative errors (Fig. 1 left), seem to be very close for both methods (simple analytic expression and ANN). However, the convergence of the total relative error of the subsets of production processes towards zero is much faster for the ANN, as it becomes smaller than 5% for subsets than contain more than 20 production processes, which is achieved only for subsets larger than 90 production processes (Fig. 1 right) if the simple analytic expression is used.

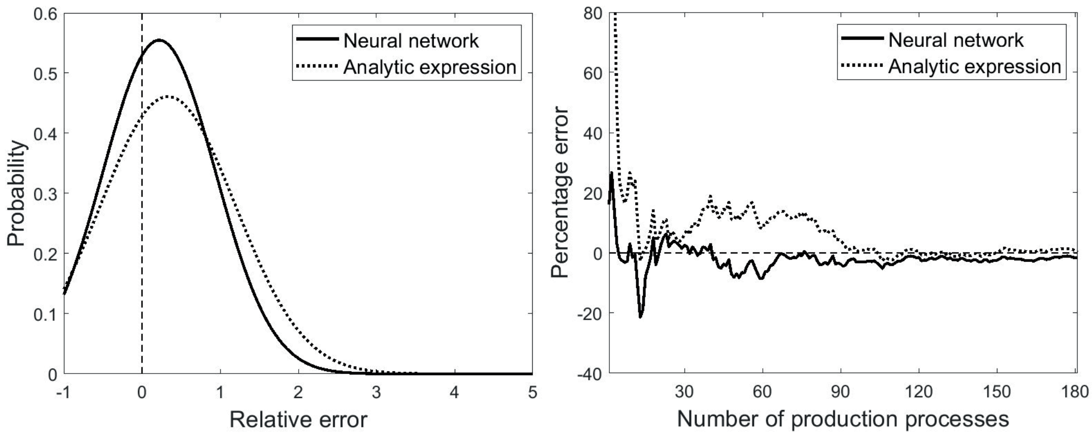

Fig. 1 – Relative errors of estimation and convergence of error of the two methods

The obtained result means that the ANN should be used by manufacturers who have less than 90 production processes within a supply cycle, i.e., those with small number of production machines that use SLS technology.

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