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Monika KULISZ*, Ireneusz ZAGÓRSKI**,
Aleksandra SEMENIUK***

ARTIFICIAL NEURAL NETWORK MODELLING OF CUTTING FORCE COMPONENTS DURING AZ91HP ALLOY MILLING

Abstract

The paper presents simulation of the cutting force components for machining of magnesium alloy AZ91HP. The simulation employs the Black Box model. The closest match to (input and output) data obtained from the machining process was determined. The simulation was performed with the use of the Statistica programme with the application of neural networks: RBF (Radial Basis Function) and MLP (Multi-Layered Perceptron).

1. INTRODUCTION

Manufacturing advanced machine and equipment elements is inextricably related to the application of new generation structural materials. Application of magnesium alloys enables reduction of weight of manufactured elements and can facilitate decreasing manufacturing and maintenance costs (Pekguleryuz et al., 2013).

* Department of Organisation of Enterprises, Faculty of Management, Lublin University of Technology, Nadbystrzycka 38, 20-618 Lublin, Poland, e-mail: m.kulisz@pollub.pl

** Department of Production Engineering, Faculty of Mechanical Engineering, Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland, e-mail: i.zagorski@pollub.pl

*** Fourth year student of Management and Production Engineering, Faculty of Management, Lublin University of Technology, Nadbystrzycka 38, 20-618 Lublin, Poland, e-mail: aleksandra.semeniuk@pollub.edu.pl

Production of different components involves effective removal of machining allowances, often through the process of milling. “Functional” machinability parameters include, inter alia, forces occurring during machining. The forces in question can contribute to deformation of a workpiece during machining. The increase of these forces can lead to the reduction of undeformed chip thickness. When the latter decreases, the cutting force increases. The rise in the shear energy per unit of volume translates to rising volume of subtracted metal and of the cutting force (Fang et al., 2005). Adhesion and build-up can also have a considerable impact on fluctuation of the cutting force components as well as result in the reduction of the surface quality and shape and dimensional accuracy (Oczóś, 2000). The demand for force in machining various materials, including magnesium alloys, is the subject of numerous studies. Compared to other materials, magnesium alloy treatment can be performed quickly and effectively, which enables machining at a large depth of cut and considerable feed (Zagórski & Kuczmaszewski, 2013; Fu et al., 2015).

Cutting speed is what directly affects the effectiveness of the milling processes. The division that is frequently adopted includes machining performed at conventional parameters and increased cutting parameters, which is the area of various HSM methods. It is possible to define the “transition” point into HSM parameters as $\partial F/\partial v_c < 0$ for HSM and $\partial F/\partial v_c > 0$ in the case of conventional machining. It is broadly accepted that what distinguishes HSM from conventional machining is that in HSM the increase in the cutting speed v_{cb} results in the decrease in the cutting forces. On the other hand, HSM machining is often defined as a high-performance cutting method which facilitates obtaining high quality of machined surface. The use of HSM helps to eliminate finishing operations which have been traditionally realised through grinding (Adamski, 2010).

In AZ91HP alloy milling with PCD cutter and in the presence of cutting fluid cutting forces assume low values and grow linearly with the increase of feed. Lower cutting forces can translate into smaller tendency for tools to overheat (smaller coefficient of friction at a tool-workpiece interface). What can be observed along with lower cutting forces, especially as far as small cross-section of a machined layer is concerned, is a significantly lower temperature in the cutting area (Oczóś, 2000, 2009).

In feed per tooth f_z (in machining with Kordell geometry tools), the F_x and F_y components and their amplitudes rise with the increase of feed. In the case of cutting with cutters of traditional tool geometry, a more significant influence on cutting forces and their amplitudes is observed when changing the feed per tooth f_z rather than cutting speed v_c ; the highest values of the cutting force components were obtained for the PCD cutting edge tool and AZ91HP alloy. Furthermore, it ought to be remarked that the cutting force components decrease with the increase of cutting speed to $v_c=1200\text{m/min}$ in traditional tool geometry (Zagórski & Kuczmaszewski, 2013). Another relevant factor is tool geometry

and its impact on the cutting force components and their amplitudes. Research studies in the field generally focus on the changes of specific technological milling parameters (v_c , f_z , a_p) with the application of carbide cutters of variable tooth geometry ($\gamma=5^\circ$ and $\gamma=30^\circ$). Lower values of cutting force components and their amplitudes indicating a greater stability of the process were observed for the tool $\gamma=30^\circ$. Increasing the depth of cut triggers a proportional increase in the cutting force components and their amplitudes. A change in the feed per tooth (in the range of $f_z=0.05\div 0.15\text{mm/tooth}$) provoked the rise of the cutting force components and subsequently their stabilisation (for $f_z=0.15\div 0.3\text{mm/tooth}$) (Gziut et al., 2014). Another factor of high importance is the impact of cutting tool coating (such as the TiB_2 and TiAlCN type) on cutting forces in milling with carbide tools. The lowest values of cutting force components (F_x , F_y) in milling Al6082 alloy were obtained for a tool with a TiB_2 coating. During the v_c change, the characteristic point of „transition” to the range of HSC (where $v_{cgr}=450\div 600\text{m/min}$) was observed (Kuczmaszewski & Pieńko, 2013). In addition, cutting force component amplitudes, which are a significant indicator of the cutting process dynamics, assume the highest values for indexable tools (which should be taken into account when selecting a tool for a particular application) (Kuczmaszewski & Pieńko, 2014).

Furthermore, excessive cutting force value can have a negative influence on the quality of machined surface. Increasing feed results in higher vibrations generated in the milling machine-milling cutter-workpiece-fixture system, which is triggered by excessive cutting force (Kim & Lee, 2010). Nowadays machining processes are increasingly frequently modelled with both mathematical modelling methods (Danis et al., 2016) and advanced artificial intelligence systems (Cus et al., 2007).

Despite multiple advantages, subtractive manufacturing of magnesium alloys involves multiple risks. Magnesium dust emerging during machining has a negative impact on both the staff operating machine tools and the machine tool itself. Moreover, magnesium is susceptible to ignition, which can occur as a result of a rapid temperature increase. Another problematic matter can be formation of build-up at the tool edge or rake face, which results from intensification of adhesion (Oczóś 2000, 2009). Thus, the analysis of the actual cutting force values and computer simulation can have a beneficial influence on the stability and effectiveness of Mg alloy machining and safety prediction. Anticipating cutting force component values seems considerably significant from the viewpoint of magnesium alloy machining due to deformations of thin-walled elements. The model enables selecting the technological parameters in a way that it is possible to obtain required force component values without producing machining errors.

2. RESEARCH SUBJECT

The simulation of cutting force components was performed for the AZ91HP magnesium alloy milling. For that purpose, experimental analysis was carried out. The applied tool was a double-bit carbide fly cutter with TiAlN coating and with a plain parallel shank, belonging to the group of cutters intended for machining Al and Mg alloys. The dimensions of the milling cutter were the following 16x25x100 mm W-Z2, $\lambda_s=30^\circ$. The scope of the technological parameters comprised $v_c=400-1200$ m/min, $f_z=0.05-0.3$ mm/tooth. Parameters such as milling depth $a_p=6$ mm and milling width $a_e=14$ mm were constant in the conducted tests. Machining was performed on a vertical machining centre Avia VMC800HS with the control system Heidenhain iTNC 530 offering maximum spindle rotation speed of $n=24000$ rpm and minimum feed of 40 m/min. In order to measure the cutting forces, piezoelectric dynamometer Kistler 9257B was applied together with the amplifier 5017B. The dynamometer allowed measuring the forces within the range of -5 kN to $+5$ kN. The sampling rate was 5kHz.

In milling, particularly at increased cutting speeds, the importance of dynamic cutting force components rises. What should be done in order to determine their value is their identification. The difficulty that arises here is the fact that the model of the phenomena emerging in the cutting area during milling is highly complex and non-linear. The outcome of force interactions is the mutual dislocation of the object and the tool in their area of cut. Non-stationarity poses yet another obstacle which results from the character of cutter feed movement. The measurement of the cutting force is impeded as it requires a dynamometer to be installed in the machine tool. Furthermore, installing any dynamometer impacts the dynamic properties of the milling machine-milling cutter-workpiece-fixture system. The adoption of such a solution is currently difficult in industrial conditions. There is, however, a remarkable correlation between the technological machining parameters such as feed, cutting speed, depth and width of cut.

Consequently, a question whether it is possible to predict the cutting force – its components should be asked. The answer to this question can be obtained by approaching the milling process as a control object. Therefore, the analysis of such an object should be carried out. Also, controllable inputs and outputs of a model occurring as a result of the identification should be determined. This can be obtained through the application of the Black Box model, *i.e.* specifying the closest match between certain (input and output) data produced by the system. This kind of a solution can be applied when it is difficult to define a mathematical equation describing the process due to its complex character (Awrejcewicz, 2007; Kuc, 2014).

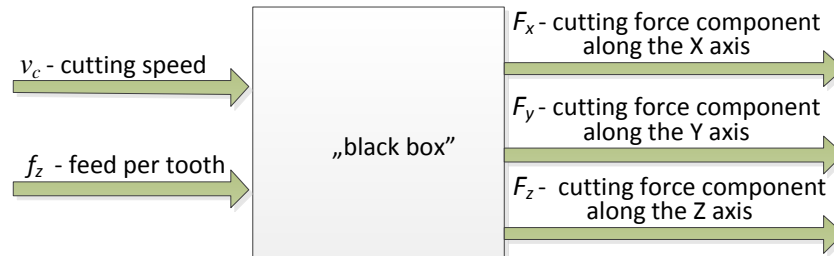


Fig. 1. The model of the milling process (own study)

Controllable parameters that a technologist has at his disposal are cutting speed v_c , feed per tooth f_z , cutting depth a_p , cutting width a_e , tool geometry (including the rake face or the inclination angle of a helix). When machining process is considered as a control object, output rates are the following cutting force components: F_x – cutting force component along the X axis (also described as feed component F_f), F_y – cutting force component along the Y axis (the normal component to the feed force F_{fm}) and F_z – cutting force component along the Z axis (reactive component F_p). In tests, cutting speed v_c and feed per tooth f_z were variable input parameters, the remaining ones were constant. The model of the process is presented in Fig. 1. Assuming that the process of machining of a specific part is repeatable, force input and cutting conditions in selected points of the tool path can be similarly considered repeatable. Several requirements should also be set regarding the accuracy of this assumption, i.e. cutting should be performed with a sharp tool and at constant cutting parameters for consecutive machining cycles.

3. NEURAL NETWORK MODELLING

The aim of the modelling is to predict the course of non-linear technological processes with the application of trained neural networks. Its analysis can contribute to the creation of a system which could support decision-making processes in an enterprise (for instance through optimization of milling process focusing on the selection of suitable technological parameters of machining).

For the purpose of cutting force components simulation, artificial neural network was used. The applied software was Statistica. During testing, two networks scrutinised: RBF (Radial Basis Function) and MLP (Multi-Layered Perceptron). Each component of the cutting force was modelled separately. Their values were calculated as the average of the maximum values from the 10 ranges separated from the stable machining area. It constituted the output value for individual models.

The networks were built with one hidden layer. The input layer consisted of two neurons whereas the output layer – one. Both the number of the training epochs (100) and the number of neurons in the hidden layer (1÷10) were selected experimentally. In order to create a simulation of all three cutting force components, 3 models of artificial neural networks were built. The input modelling parameters were cutting speed v_c and feed per tooth f_z . The outline of such a network for the cutting force component F_x is presented in Fig. 2. The outlines of the remaining components were analogical, relevant cutting force components were obtained as model outputs.

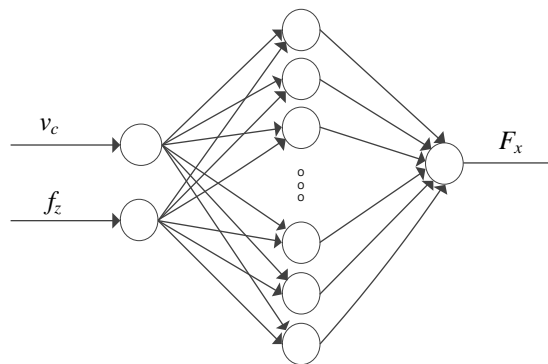


Fig. 2. Artificial neural network outline of the cutting force component along the X axis – F_x (own study)

The training of the MLP network was performed with the use of the BFGS (Broyden-Fletcher-Goldfarb-Shanno) method. It produced the best results in the reduction of functions to the required level at the shortest possible time. During the simulation, the following application functions were applied: linear, exponential, logistic and tanh. RBF network was trained with the RBFT method. The activation function for hidden neurons was Gaussian distribution, for input neurons – linear function.

The modelling was conducted focusing on 17 sets of machining parameters, 14 of which were used for training. The training group comprised 80% of the measurement results, 20% was validation. The remaining parameter sets were applied for the verification of the simulation accuracy. Due to the small amount of data sets, the test group was not created (Szaleniec, 2008).

From among obtained cutting force components simulations, on the basis of the smallest training error and the highest quality of training, the most effective MLP network models were selected. Afterwards, they were compared to the simulation based on the RBF network. The training error was determined by the method of least squares.

The parameters of the best MLP and RBF networks for specific cutting force components F_x , F_y and F_z are presented in Table 1. On the basis of the analysis of the obtained network models, it can be stated that in the case of all cutting force components the best results were achieved for the MLP networks (F_x – MLP 2-4-1 having four neurons, F_y – MLP 2-9-1 having nine neurons, F_z – MLP 2-8-1 having eight neurons). For the modelled components, the quality of the MLP and RBF networks was comparable, however for the MLP network much smaller training errors were obtained. It is therefore suggested that the recommended network should be MLP.

Tab.1. The parameters of the best MLP and RBF networks for specific cutting force components (own study)

Id.	Network name	Quality (training) [%]	Error (training)	Activation (hidden)	Activation (output)
Cutting force component F_x					
1	MLP 2-4-1	99.97	4.555	Logistic	Exponential
2	MLP 2-3-1	99.83	27.445	Tanh	Tanh
3	RBF 2-9-1	99.96	48.61	Gaussian	Linear
4	RBF 2-7-1	99.92	115.35	Gaussian	Linear
Cutting force component F_y					
1	MLP 2-3-1	99.97	4.524	Logistic	Exponential
2	MLP 2-9-1	99.98	2.818	Logistic	Linear
3	RBF 2-7-1	97.83	322.578	Gaussian	Linear
4	RBF 2-9-1	98.52	220.881	Gaussian	Linear
Cutting force component F_z					
1	MLP 2-8-1	99.96	9.726	Logistic	Exponential
2	MLP 2-3-1	99.95	9.942	Tanh	Linear
3	RBF 2-8-1	99.70	68.65	Gaussian	Linear
4	RBF 2-9-1	99.70	68.65	Gaussian	Linear

As a result of conducted neural network simulations of cutting force components emerging in AZ91HP milling, models for each component were developed on the basis of which component value could be determined. The figures below present the results of the cutting force component simulation depending on the cutting speed v_c and the feed per tooth f_z , taking into account the models of the highest quality and the most insignificant training error: F_x – a model of the neural network MLP 2-4-1 (Figure 3), F_y – MLP 2-9-1 (Figure 4) and F_z – MLP 2-8-1 (Figure 5). On their basis, it is possible to determine the value of individual force components for specific values of the cutting speed v_c and feed per tooth f_z . When the values v_c and f_z are entered into the Statistica programme, it provides the value of the adequate cutting force component.

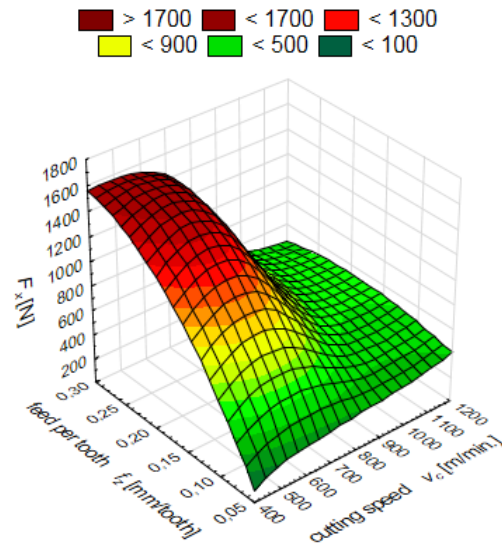


Fig. 3. The simulation results of the cutting force component F_x based on the cutting speed v_c and feed per tooth f_z for the neural network MLP 2-4-1 model (own study)

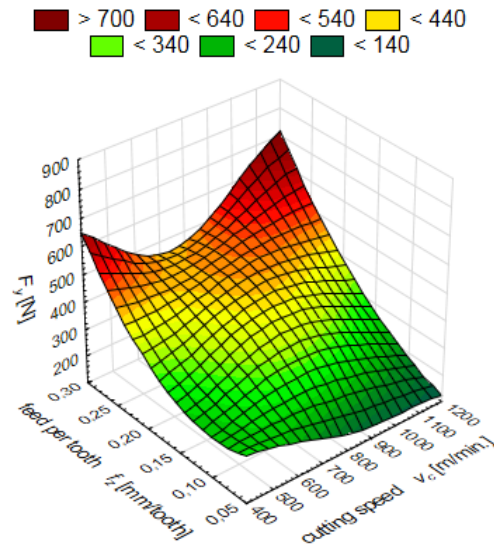


Fig. 4. The simulation results of the cutting force component F_y based on the cutting speed v_c and feed per tooth f_z for the neural network MLP 2-9-1 model (own study)

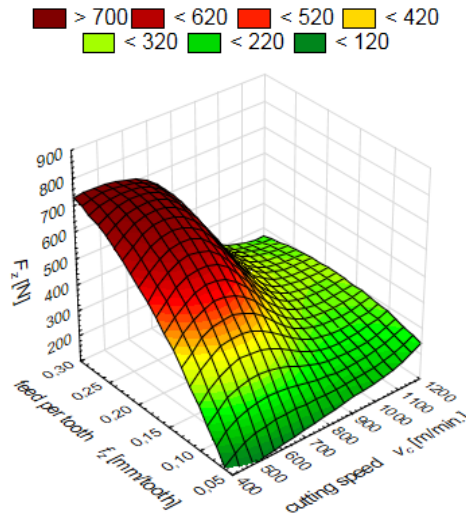


Fig. 5. The simulation results of the cutting force component F_z based on the cutting speed v_c and feed per tooth f_z for the neural network MLP 2-8-1 model (own study)

Models developed with the use of neural networks are a tool which allows specifying maximum values of the cutting force components. Modelling results can be of help to the technologists in determining technological parameters of machining. The simulation of the cutting force components can be employed for the creation of a computer system supporting technologist's decisions. In the presented study, the variable elements of the model were cutting speed v_c and feed per tooth f_z , whereas other parameters of the process such as cutting depth a_p , cutting width a_e , helix angle λ_s were constant.

4. SUMMARY AND CONCLUSIONS

It seems reasonable to conduct further research and simulations comprising solely variable parameters, which would enable application of models in a wider range of scenarios. The undertaken study will aim at increasing the number of vectors in a training sequence. In consequence, the representation of the actual functional relations presented by the model will be more accurate.

The results of the simulation create an opportunity to predict the non-linear processes. The simulations of such processes can be of considerable significance in a situation when little input data is available in relation to the need to obtain optimum results. Both the outcomes of the study and the simulations performed on their basis prove that there is a possibility to design a precise tool for modelling phenomena emerging during machining. The developed model enables testing various configurations of cutting parameters without the need to

perform machining tests, which are frequently laborious, time-consuming and requiring expensive practical testing. Initial determination of parameters and expected cutting force component values on the basis of simulation can reduce testing time for a new batch of products as well as allow economising on material, increasing the effectiveness and production capacity.

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