

POWER CONSUMPTION PREDICTIVE TOOL FOR GRINDING PROCESS BASED ON ANFIS METHOD

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INTRODUCTION

Grinding is considered nowadays as a very important manufacturing process, in terms of both industrial and experimental applications, due to its capability of producing high quality workpiece surfaces. This process is of particular interest in achieving accurate dimensions of parts, machining hard materials that are difficult to be easily processed with other machine tools and is even employed when it is required to remove a large bulk of material rapidly. The grinding wheel constitutes the cutting tool for the grinding process; numerous abrasive particles, called abrasive grains, exist on its surface of the grinding wheel and function as single-point cutting edges. Some characteristics of the grinding process are the relatively shallow depth of cut and the extremely small dimension of chip. Furthermore, another intrinsic characteristic of grinding process is the significant amount of energy per unit volume of removed material required for this machining process, as it is calculated by the grinding forces during the process.

Apart from direct measurements and monitoring through specialized systems, analytical, numerical and soft computing methods have already been developed and used as valuable tools to study various aspects of machining processes and among them, power consumption. These tools are shown to provide engineers detailed insight of the underlying mechanisms of machining processes and also allow for the determination of contribution of each machining parameter on the outcome of process, usually without considerable cost. Thus, especially soft computing methods are increasingly employed in relevant applications.

In the current paper, a soft computing model, for the prediction of energy consumption in a grinding process in relevance to process parameters such as grinding wheel type, workpiece material and depth of cut using a Sugeno-type ANFIS model is developed. The ANFIS model will be applied to a real machining process case and the results of prediction will be discussed in order to account for the efficiency of the proposed model.

STATE OF THE ART

During the past few decades, concern about energy reduction and environmental topics has been considerably increased as a part of the global problem of lack of energy reserves and more extensive use of renewable energy power is now required. Manufacturing and machining processes contribute to an important degree to the total energy consumption of the industrial sector worldwide. Dahmus and Gutowski [1] classified power demand of machine tools into three categories: idle mode, run-

time mode and production mode. Each of the first two stages require different amount of power but the power demand remains constant during these stages; on the contrary, the power demand in the production stage is variable and load-dependent. Behrendt et al. [2] stated that power measurements are dependent to various process parameters and presented a systematic three-step methodology for conducting standardized tests in different machine tools and classify them in terms of energy consumption. Bi and Wang [3] modeled the kinematics and dynamics of a machining process along with the energy demand during this process, with a view to determine the optimum setup optimization of the machine tool and reduce the energy consumption effectively. Liu et al. [4] proposed a hybrid approach for power demand calculation, based on cutting force modelling and experimental data. This hybrid model could effectively investigate the role of material removal rate and cutting parameters on power consumption. Santos et al. [5] underlined the significance of the contribution of machine-tool structure to the electricity consumption, a factor that is usually underestimated. Using suitable energy models, the energy efficiency of various press-brake machines was tested and LCI datasets were created for future reference. He et al. [6] proposed a task-oriented energy consumption model based on the analysis of task flow in machining systems. Using a discrete-event dynamic model, simulations on various scenaria were conducted in order to determine the optimum process schemes for each machining jobs, regarding their power demand. Shrouf et al. [7] introduced a mathematical model for the optimization of energy consumption cost according to changes in energy prices, during machining processes. This model was considered particularly useful to determine the best scheduling strategies for machining jobs and consequently achieve reduced energy consumption. Kant and Sangwan [8] developed a complex predictive model using grey relational analysis, principal component analysis and response surface methodology in order to address the problem of contradictory targets of minimizing both the surface roughness of a part and the energy consumption of related machine tool. This model allowed also for the determination of importance of machining parameters and finally an improvement in the power reduction was noted. Liu et al. [9] identified the main driving system of machine tool as the most crucial part of the machine related to the energy consumption and so, they studied the energy consumption of this system of machine tools and developed a detailed multi-step energy consumption calculation model, using also measured data and conducting error analysis. Böhner et al. [10] proposed a method of measuring and interpreting energy consumption data of machine tools, capable of assisting machine designers. Various energy performance measures were introduced and the method was successfully test in several cases, achieving a considerable energy consumption reduction.

Consequently, the aforementioned studies clearly indicate that the investigation on the energy consumption of machine tools is considerably increasing in interest. For the developing of a suitable and efficient energy consumption predictive tool, it is required that the computational cost is low and a simple in use but robust computational method is employed. Many modelling methods have been introduced in mechanical engineering and for various purposes [11, 12]. For this problem, soft computing methods like Artificial Neural Networks (ANN) or Fuzzy logic (FL)

models are more preferable to be employed than classical CAE-based tools. Furthermore, it could be considered more beneficial if the selected simulation method combined effectively characteristics from more than one soft computing tool, in order to create a compact and powerful predicting method. This is the case of methods like the Adaptive Neuro-Fuzzy Inference System (ANFIS) which combines ANN and FL. ANFIS method has been already employed in various cases in machining process, with considerable advantages [13-17]. Consequently, the use of these soft computing method for a large variety of actual engineering problems is nowadays beyond question. However, the predictive capabilities of these methods are challenged in cases when the correlation between input and output parameters is highly non-linear such as the case of surface roughness prediction.

METHODOLOGY

ANFIS is considered as a type of adaptive network, utilizing structures from fuzzy inference systems (FIS). Learning is achieved through a hybrid learning algorithm, which is harnessing both the capabilities of fuzzy reasoning with sets of if-then rules and the training capabilities of adaptive networks. Membership functions are employed in the same sense as in FIS and the learning ability of the neural network leads to adjustments in the membership functions, so as to represent the desired system more accurately. In fact, the ANFIS system consists of an input layer of input membership functions that convey information to a layer of output membership functions by means of a FIS with established rules, while a learning algorithm is applied to update the FIS parameters and gradually reduce the error. Fuzzy rules can be obtained through an appropriate clustering algorithm such as subtractive clustering. A schematic of the structure of ANFIS system is presented in Fig.1.

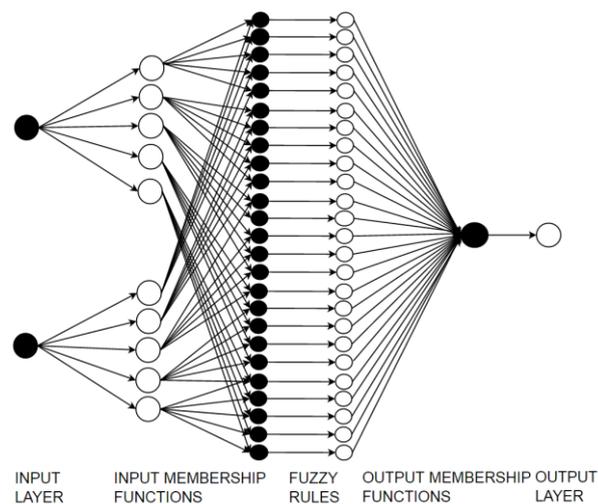


Fig.1
The structure of an ANFIS model

In this study, a dataset of 72 grinding experiments concerning various grinding wheel types, workpiece materials and depths of cut from a previous study [18] will

be employed for the development of the predictive tool. The first two parameters (wheel type, material) are denoted with a number related to their characteristics; thus they will not be interpreted as continuous variables like the depth of cut. More specifically, 6 different 250mm diameter aluminum oxide grinding wheels (with variable grain size and bonding), 3 different workpiece materials (100Cr6, C45 and X210Cr12 steels) and four depth of cut values (10, 20, 30, 50 μm) were employed in the experiments. Prior to their input in the model, the data will be normalized, in order to prevent undesired effects due to the different order of magnitude of each input quantity. From the aforementioned dataset, some data are preserved for checking purposes and some for testing purposes. The ANFIS model will be implemented in MATLABTM environment.

RESULTS AND DISCUSSION

At first, several test runs were conducted with varying numerical parameters, such as epoch number or radius parameter for clustering, in order to determine the optimum parameters that lead to minimum RMSE error. In specific, the investigation concerning cluster radius was conducted for values in a range between 0.1-1, namely 0.1, 0.25, 0.5, 0.6, 0.75, 0.9, 1, which are denoted by numbers 1-7 respectively, in Figures 2a and b.

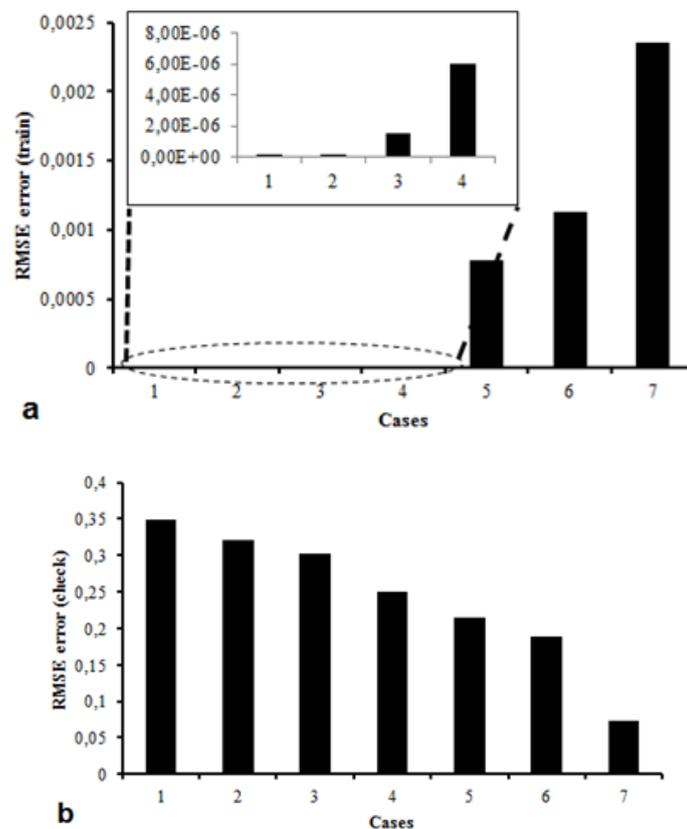


Fig.2
RMSE error during: (a) training and (b) checking stages

Cluster radius is directly related to the number of fuzzy rules employed in the network, as a smaller radius leads to more clusters and consequently larger number of fuzzy rules and more computational time. The results of the investigation are presented in Figures 2a and b. From Figures 2a and b it can be observed that as cluster radius approaches the value 1, the value of RMSE of checking data becomes lower, indicating an improvement in the generalisation capability of the network which avoids over-fitting problems. Thus, this value is selected.

Once these parameters were determined, the corresponding ANFIS model is created and the results of the model are obtained. RMSE error was found to be 2.35×10^{-3} for the training data and 0.0727 for the checking data, thus indicating that convergence of the model is achieved. In Table 1, several simulation results are compared to experimental results from [18]. It is clearly observed, that a significantly accurate prediction was performed, as the relative error between predicted and experimental results is below 1% in every case. Thus the ANFIS model has sufficiently good performance, comparable to that of the ANN models in [18].

Table 1
Comparison between various predicted and experimental values

Process parameters			Measured specific power (W/mm)		Difference (%)
Grinding wheel	Workpiece material	α (μm)	Experimental	ANFIS	
3	1	50	298.5	298.3	0.06
6	1	30	202.5	202.4	0.05
3	2	50	208.0	207.5	0.24
6	2	30	120.0	121.1	0.92

However, these results can not solely indicate a desirable performance of the model, as an over-fitting problem, related to accurate prediction of training data but irrelevant output for unknown data may occur. For this purpose, a portion of the initial dataset is preserved and the comparison between predicted and experimental results is conducted, as it can be seen in Table 2. From these results it can be more safely concluded that an over-fitting problem does not exist in the model, as the relative error between experimental and simulation results of the model is around 10%, thus confirming its generalization ability.

Table 2
Comparison between predicted and experimental results for a dataset of test data

Process parameters			Measured specific power (W/mm)		Difference (%)
Grinding wheel	Workpiece material	α (μm)	Experimental	ANFIS	
1	1	50	278.5	306.6	10.1
2	2	30	133.5	122.1	8.54
4	3	30	352.0	305.3	13.27
5	1	20	170.5	186.23	9.23

CONCLUSIONS

In this paper, a Sugeno-type ANFIS model with subtractive clustering was created for the investigation of the correlation between power consumption and process parameters in the case of grinding process. The selected inputs were grinding wheel type, workpiece material and depth of cut. From an example case, in which the proposed model was employed, several conclusions were deduced. ANFIS model was found to be significantly accurate in terms of predictive ability, as the predictions exhibited error below 1% in every case examined. ANFIS model was also shown to exhibit acceptable level of generalization ability and a relatively low computational cost.

Although the accuracy of this model was proven, further modifications to this model can be applied and the integration of this model into the framework of a more complex and complete predictive tool or a process monitoring tool will be investigated in future works.

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