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PERSPECTIVES FOR APPLICATION OF ARTIFICIAL NEURAL NET WORKS AND FUZZY LOGIC SYSTEMS FOR PREDICTION AND DIAGNOSIS OF TOOL CONDITION IN CUTTING PROCESS

В. Залога, А. Гонщик, Р. Зінченко. Перспективи застосування штучних нейронних мереж і систем нечіткої логіки для прогнозування та діагностики стану інструментів в процесі різання. Стаття представляє літературний огляд, що стосується застосування штучних нейронних мереж і систем нечіткої логіки для прогнозування і діагностики процесів механічної обробки та особливостей експлуатації різального інструменту. Запропоновані можливі шляхи подальших досліджень у сфері моніторингу та діагностування стану різального інструменту з використанням підсистеми гібридного (нейро-фаззи) ухвалення рішення безпосередньо в процесі різання.

V. Zaloha, A.Honshchyk, R.Zinchenko. Perspectives for application of artificialneural networks and fuzzy logic systems for prediction and diagnosis of tool condition in cutting process. The article presents a literature review connected with the application of artificial neural networks and fuzzy logic systems for prediction and diagnosis of machining processes and cutting tool condition particularly. The possible ways of further investigations in the field of monitoring and prediction of cutting tool condition using the hybrid (neuro-fuzzy) decision making subsystem directly in the cutting process are proposed.

Introduction. Today, the operations of metal processing with cutting are still prevalent among the shaping processes that use mechanical energy. The main goal of investigations in the field of metal cutting is to develop a method which could ensure the optimal usage of machine-tools, improve the economic effectiveness of production, reach high accuracy of machining, decrease the machine down time and cutting tool costs. The diagnosis of cutting tool condition during the working procedure has a tremendous significance for reaching the mentioned purposes, because it allows to ensure exclusion of any departures appeared during the cutting process.

The methods of artificial intelligence (AI) including artificial neural net works (ANN), fuzzy logic systems (FLS) and adaptive neural fuzzy inference systems (ANFIS) have proved their potential for cutting tool condition diagnosis.

Methods of artificial intelligence: artificial neural network and fuzzy logic. Over the past few decades there has been a great surge of interest to the expert systems (ES) based on artificial intelligence. It has shown numerousways for using AI in engineering and machining processes particularly. The problems solved via such systems are typical in many cases. They include:

- *pattern classification* – determination of a pattern which belongs to one or several classes determined previously;
- *function approximation* – assessment of the unknown dependence using the experimental data;
- *Prediction* – determination of the future process according to its past and present;
- *optimization* – finding of decisions that maximize or minimize some quality criterion according to input limits;
- *management* – transferring and maintenance of a system in required condition.

Artificial neural network – is an electronic model of neural structure of human's brain which essentially learns (trains) on its own experience. The ANN represents the system of connected processors (artificial neurons) cooperating with each other.

Generally, there are a great number of engineering problems connectedwith a big amount of computational procedures. Today, they cannot be solved using traditional computers for acceptable time, but they can be effectively solved using the ANN. The matter of the ANN method is that one or few characteristics of some process are assigned several factors via the neural network (NN) to maket his conversion reflect the simulated process. The conversion function is being formed by fitting the weights of neuron interconnection during the time of training according to the experimental data. Computation of the conversion function means consecutive and layerwise computation of neuron outputs.

The training opportunity is one of the main advantages of the NN compared with traditional techniques. The NN is able to define complex dependences between inputs and outputs as well as to carry out generalization. If the NN is trained successfully it will be able to find the correct output even when the data is absent from the training selection.

The scheme of the NN training using back-propagation (BP) algorithm is presented in Fig. 1. The BP algorithmis the formula set for calculation the required corrections of neuron weights according to the error vector. For example, there is some database with samples of certain (desired) results. Feeding the analyzeable data into the entrance of the NN, we are getting some answer, which is used for calculation the difference between the desired (in the given case) answer and the received network answer. This difference is used to get the error vector (low, big) and minimize it. The same data can be fed to the NN many times.

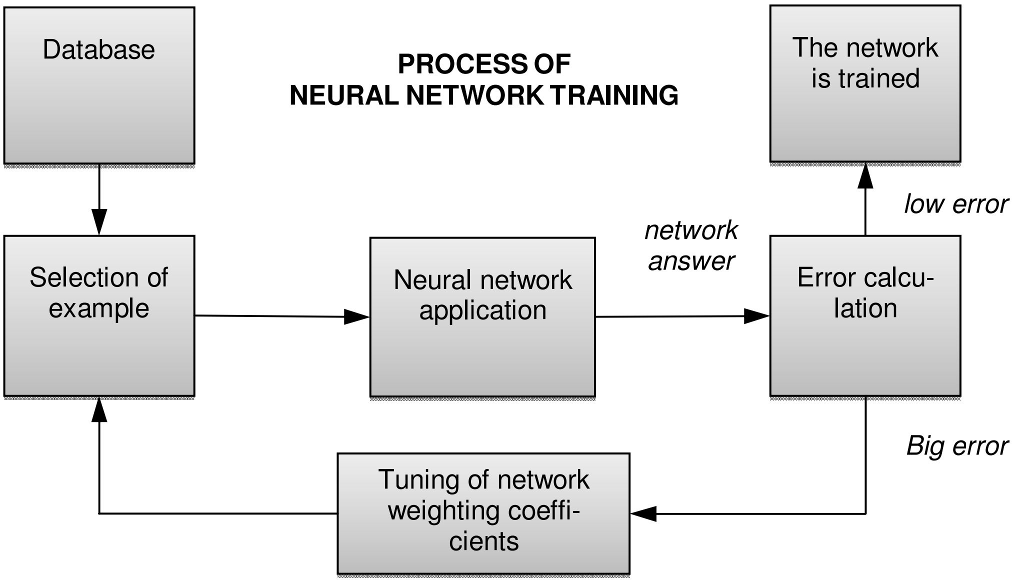

Fig. 1 – The scheme of the neural network training

After the samples from the accepted database are fed in it, its weights become stabilized.Thus, the NN starts giving relatively correct answers (with satisfactorily low (acceptable) error) for all (or almost for all) samples from this database. In this case we can tell that “neural network is trained”. The estimation of the error quantity(the sum of squared errors on all outputs), whic his gradually reducing during the training time, can be carried out by different software, for example Matlab. If the error quantity reaches the value close to zero or the low (acceptable) level, training will be stopped, and the NN will be considered ready for application using a fundamentally new database.

There are some determination and control methods that can effectivelysolve the prediction and optimization problems without an exact mathematical model of system functioning. They are used for complex non-linear systems an did entified as *fuzzy logic and fuzzy inference system.*

Fuzzy modeling is based on the idea of searching these to particular dependences of “inputs-outputs” that describe the process. It attracts the attention of researchers in and engineering; because it can express the non-linear process much easier and better than any other method.

Besides, the theory of the fuzzy set allows to use in exact and subjective expert knowledge about the subject field to make decisions. The knowledge may be nonformalized in the type of the traditional mathematical model. The fuzzy set gives anaphorunity to apply linguistic description of the complex process, to establish fuzzy relations between concepts, to predict the behavior of a system, to form the variety of alternative actions, to accomplish formal description of fuzzy decision rules etc.

The typical structure of the fuzzy inference system is shown in Fig. 2 [1]. It consists of the following component cells:

- *fuzzificator*, which converts the fixed vector of influencing factors *(X)* into the vector of the fuzzy set *X'*necessary for fuzzy inference;
- *database*, which contains information about the dependence *Y=f(X)* in the kind of linguistic rules «if – then»;
- *machine of fuzzy logic inference*, which identifies (on the basis of established rules of the database) the value of the output variable in the type of the fuzzy set *Y'*appropriate to fuzzy values of input variables *(X')*;
- *defuzzificator*, which converts the output fuzzy set *Y'* into the discrete number*Y*.

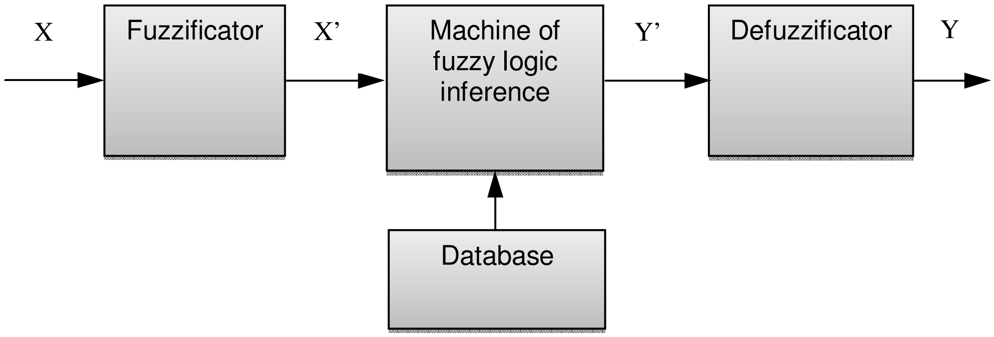

Fig. 2–Fuzzy logic inference system

Application of AI methods in systems of cutting tool condition diagnosis

The tool wear is undesirable for the efficient machining process. Nevertheless, it is inevitable. The tool wear increases the cost of the machining process as well as contributes to the undesirable and hardpredicted changes of workpiece measurements and also reduces the quality of machined surfaces. Therefore, it is very important to know the magnitude and the type of the tool wear during the cutting process as well as the time when the tool becomes worn under permissible (according to the accepted criterion) level. In order to solvethis problem for modern juxtaposition and multicolor systems an intellectual sensorsystem for machining process autoimmunization must be developed.

This system will be able to estimate the progressive toolwear during the appropriate cutting operation and permit to identify the worn tool as well as to replace it in time.

The ANN and the FLS have proved the high level of competence for solving many complex tasks in engineering including a material processing sector.

The application of the AI systems for cutting tool condition diagnosis has a special meaning of the field of metal cutting.

The NN and the FL may be effectively used as a basis for the expert system, where the corresponding output of cutting process is determinated according to the data from sensors placed in the technological system. The decisions are of ten made on the basis of the following data: the cutting force, vibration, the spectrum of the acoustic emission, motor currents and motor power etc. The aim of this article is to analyze the prior art about using the ANN and the FLS for cutting tool condition monitoring.

Artificial neural networks for diagnosis of cutting tool condition. Today there have been published a lot of studies (Table 1) devoted to monitoring of the cutting tool wear using the NN.

The Ukrainian scientiststs had worked in this field of machine building are A.G. Derevianchenko, L.V. Bovnegra, J.N. Vnukov, L.N. Devin etc.; the foreign ones are K. Patra, S.K. Pal, K. Bhattacharyya, S.S. Panda, D. Chakraborty, T. Ozel, Y. Karpat, Z. Uros, C. Franc, K. Edi, A.K. Singh and many others.

The major quantity of publications devoted to application of the NN in the systems of cutting tool condition diagnosis is focused on turning processes. A.G. Derevianchenko et al. [2] developed the system of cutter control for the process of precision turning. It includes the system of machine vision. In order to maintain the cutting tool in the functional condition the NN system was created [3].J.N. Vnukov et al. [4] investigated the problem of tool wear modeling using the sound signal. They used the multilayer NN and the neuron-fuzzy network for solving this task. The high effectiveness of the NN apparatus is occurred during the process of cutting tool condition diagnosis in precision turning [5].Here it has been proved that the NN apparatus allows to reach more accurate result than statistic methods do. The works [6–8] describe the development of the NN systems for cutter wear monitoring using the information about cutting forces during the process.

The modeling of the flank wear in drilling processes is accomplished in works [9-12]. Moreover, the results presented in each work are based on the identification of different signals. For example, C. Sanjay et al. [9] used the information about cutting forces as well as S. Garget al. do [12]. S. S. Panda and D. Chakraborty [11] used vibration and cutting forces. One of the most interesting works is drill flank wear prediction using motor currents [10]. M. Malekianet al. [13] presented the tool wear monitoring for micromilling operations. They considered the factors that influence on the tool wear and also the tool wear monitoring method utilizing different sensors (the accelerometer, the force sensor and the acoustic emission sensor). The signals were combined via neuro-fuzzy method which allowed to define the tool condition – sharp or worn. N. Ghoshet al. [14] accomplished the estimation of the tool wear during the CNC milling process using the cutting force, the spindle oscillation, the spindle currents and the level of sound pressure.

Table 1 – Application of the ANN methods in the systems of cutting tool condition diagnosis

Examined signal	Turning	Drilling	Milling
Cutting forces	S.M. Ali, N.R. Dhar [6]; A. Antic, J. Hodolic, M. Sokovic [7]; F. Basciftciи H. Seker [8]; T. Ozel, Y. Karpat [29]	C. Sanjay, M.L. Neema, C.W. Chin [9]; S.S. Panda, D. Chakraborty, S.K. Pal [11]; S. Garg, K. Patra, V. Khetrapal, S.K. Pal, D. Chakraborty [12]; S.S. Panda, A.K. Singh, D. Chakraborty, S.K. Pal [30]	—
Sound signal	J.N. Vnukov [4]		
Cutting forces, vibration	—	S. S. Panda [32]	—
Cutting forces, acoustic emission	—	—	M. Malekian, S.S. Park, Martin B.G. Jun [13]
Cuttingforces, vibration, sound pressure	—	—	N. Ghosh, Y.B. Ravi, A. Patra, S. Mukhopadhyay, S. Paul, A.R. Mohanty, A.B. Chattopadhyay [14]
Vibration	—	K. Patra, S.K. Pal, K. Bhattacharyya [31]	—
Motor current	—	K. Patra, S.K. Pal, K. Bhattacharyya [10]	—
Digital image of tool wear zone	A.G. Derevianchenko [2 , 3,5]; L.V. Bovnegra [2]		

The analysis of publications in the field of cutting tool condition diagnosis has shown that the most popular algorithm for NN training is the BP algorithm. In this case the existing data is used to correct the weights and the thres hold values to minimize the prediction error. The radial basis (RB) technique is also used for NN training. It has been proved that the BP algorithm gives more accurate result but it requires more time for training and verification. The accuracy of the RB algorithm is lower, but it is faster and more secure [11].

Fuzzy logic systems for diagnosis of cutting tool condition. The last investigations have proved the effectiveness of fuzzy logic inference systems for using it in the systems of cutting tool condition diagnosis (Table 2).

Table 2 –Application of the FLS for the cutting tool condition diagnosis

Examined signal	Turning	Drilling	Milling
Cutting forces	F. Basciftci, H. Seker [8] S. Achiche, M. Balazinski, L. Baron, K. Jemielniak [15] Q. Ren, M. Balazinski, L. Baron, K. Jemielniak [16] M. Balazinski, E. Czogala, K. Jemielniak, J. Leski [17]	A. Salimi, M. Zadshakouyan [22]	Z. Uros, C. Franc, K. Edi [25]
Motor current	—	X. Li, S.K. Tso, J. Wang [23]	—
Vibration, acoustic emission, cutting forces	A. Gajate, R.E. Haber, J.R. Alique, P.I. Vega [18]	—	T. Amin, E.M. Joo, L. Xiang, L.B. Siong, Z. Lianyin, H. Sheng, S. Linn, G.O. Peen [27]
Vibration	A. Antic, M. Zeljkovic, P.B. Petrovic [19]	—	—
Ultrasonicsignal	D. Dinakaran,S. Sampathkumar, J.S. Mary [20] D. Dinakaran, S. Sampathkumar, N. Sivashanmugam [21]	—	—
Acousticemission, cutting forces, motor current	—	—	P. Fu, A.D. Hope, G.A. King [24]
Acousticemission, vibration, cutting forces, motor power	—	—	P. Fu, A.D. Hope [26]

A big amount of research in this field is focused on the problems of turning processes. Nevertheless, the using of the different types of signals is described there. In the works [8, 15 - 17] the tool wear estimation is carried out using the cutting force data. A. Gajate et al. [18] presented the approach for tool wear prediction using acoustic emission signals, vibration and the cutting force.

A. Antic et al. [19] considered the model of the system for tool wear classification using the information about vibration. There are also some interesting works [20, 21] where tool wear prediction is implemented according to the ultrasound signal. This signal may be used for prediction both the flank and the rake tool wear. The method is based on induction of the ultrasound waves in the cutting tool. The quantity of energy reflected from worn areas (in the case of determination the flank wear) and from flank surfaces of the cutting tool (in the case of determination the rake wear) is connected with the value of cutting tool wear. The experimental investigations have shown that such system allows to define the tool wear precisely enough.

A. Salimiet al. [22] proposed the system of tool wear monitoring in the drilling process. It used the signals of the cutting force and the thrust force. X. Li et al. [23] used the FL methods for on-line tool wear monitoring on the base of motor current registration. The results show that the proposed system can securely define the tool condition in drilling with the accuracy of 90 %.

There is also information about the investigations using the FLSin milling operations. P. Fuet al. [24] accomplished tool condition monitoring for the process of face milling. The acoustic emission, the cutting force and motor currents were used as the initial signals. Z. Uroset al. [25] used the cutting force signal for tool flank wear prediction in end milling. P. Fu and A.D. Hope [26] considered mill condition monitoring using the cutting force, the power consumption, the acoustic emission and the vibration parameters, while T. Aminet al. [27] used the signals of the acoustic emission, the cutting force and vibration.

It has to be mentioned that the FLS were also used for grinding wheel condition monitoring [28], where they were used for classification of cutting abilities of the tool in external cylindrical grinding.

The publication review has shown that the perspective of FL application in the systems of cutting tool condition diagnosis is that the hybrid methods of the AI should be developed. One of them is neuro-fuzzy inference system [8, 20, 24 etc.].It can reach the accuracy of 100 %.

Conclusion.

Over the past few decades the methods of AI have been often applied for solving different tasks in machining operations. Thus, the development of the effective system for prediction and diagnosis of cutting tool condition using such methods directly in the cutting process is an urgent theoretical and practical problem.

The literature review has shown that research in the field of diagnosis of cutting tool condition and its probable breakage must be carried out in the following directions:

- development of the integrated methodology of AI application in the systems for prediction and diagnosis of cutting tool condition;
- development of methods for accuracy estimation of the systems for prediction and diagnosis of cutting tool condition;
- comparative analysis of the systems for prediction and diagnosis of cutting tool condition using different types of signals (vibration,the cutting force, the acoustic emission, motor currents and motor power, temperature, the spindle speed etc.);
- development of the hybrid (neuro-fuzzy) decision making subsystem for using it in the systems for prediction and diagnosis of cutting tool condition.

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