doi: 10.18323/2782-4039-2023-3-65-4

Control of the dynamic stability of metal-cutting systems in the process of cutting based on the fractality of roughness of the machined surface

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Received 15.06.2023 *Accepted 06.09.2023*

Abstract: The problem of increasing the efficiency of mechanical treatment within modern automated production is relevant for many branches of the processing industry. This problem requires a deep study of the physical processes occurring during cutting. The urgency of the problem increases even more with the development of digital production in our country. Today, in the presence of a wide range of products, enterprises are forced to create conditions for reducing the technological cycle when manufacturing a particular product. To carry out the study, an experiment was conducted in which the U8 carbon steel was used as the processed material, and the T15K6 alloy was used as the tool material. During the experiment, the authors observed a change in the roughness of the machined surface depending on the cutting speed. The paper considers the possibility of assessing the quality of the surface layer during cutting based on fractal and neural network modeling. It is identified that the fractal dimension shows the regularity of the reproduction of the machined surface roughness during cutting. The calculated fractal dimension of the machined surface roughness correlates well with the values of the machined surface roughness (correlation coefficient is 0.8–0.9). A neural network structure has been developed, which allows controlling the machined surface quality depending on the cutting conditions. The authors studied the possibility of using neural network models to control technological systems of cutting treatment. When creating digital twins, it is proposed to take into account factors affecting the quality of the treated surface and processing performance, which are poorly accounted for in modeling, as well as when conducting full-scale experiments during machining. Such factors are wear of the cutting tool, the process of plastic deformation, and cutting dynamics.

Keywords: cutting process; machined surface roughness; neural network; surface layer quality control.

For citation: Kabaldin Yu.G., Sablin P.A., Schetinin V.S. Control of the dynamic stability of metal-cutting systems in the process of cutting based on the fractality of roughness of the machined surface. *Frontier Materials & Technologies*, 2023, no. 3, pp. 43–51. DOI: 10.18323/2782-4039-2023-3-65-4.

INTRODUCTION

Increasing the efficiency of mechanical processing is an important scientific and technical problem that the world's leading scientists have been dealing with for many decades. The concept of "machining efficiency" implies two very important indicators: productivity and quality. In this regard, a number of scientific schools of the Russian Federation use the indicators of mechanical processing quality as the main criterion for assessing its efficiency. Surface roughness is one of the main parameters determining the quality of a machined part.

Within automated production, there is an acute problem of increasing the efficiency of machining based on a more in-depth study of physical processes accompanying cutting. This problem becomes relevant especially for digital production, the creation of which in the country is associated with the Russian Government program "Industry 4.0".

Digital transformation at all levels of machining enterprises is caused by the need both to analyse Big Data coming from equipment, systems, devices using sensors and to use this data to reduce the time for designing technological processes and launching new products increasing production flexibility, product quality and efficiency of production processes.

In the work [1], for high processing rates, a method for the formation of roughness of the machined surface is proposed, taking into account the random nature of their formation based on fractal representations. In the works, the author describes that for the formation of fractals, shock loads are necessary, which create tension–compression waves reflecting the travelling wave of the subsequent separation of the layer, the thickness of which is determined by the properties of the billet material. Such destruction is usually called spalling.

The fractal dimension (D_F) values given in the work [1], although they are fractional, have large values and require clarification. For example, finishing and precision machines have D_F=2.6–3.0, respectively. It is known that high values of D_F correspond to chaotic attractors [2], i. e., unstable regimes.

The quality of processed surfaces of various parts of machines and mechanisms is a complex operational factor that primarily affects the reliability of manufactured products. Surface quality indicators include such characteristics as roughness, waviness, shape errors, shape position errors, etc. [4–6].

Factors influencing the roughness parameter of the machined surface [7–9] can be presented in the form of three groups:

– factors depending on the geometry of the cutting process;

– factors depending on the plastic deformation of the processed material;

– factors depending on self-oscillations during processing.

In this regard, for example, the total value of the roughness height R_z during cutting can be represented in the following form:

$$R_Z = \Delta R_Z^{\text{Н}} + \Delta R_Z^{\text{ПЛ}} + \Delta R_Z^{\text{В}}, \qquad (1)$$

where $\Delta R_Z^{\text{Н}}$ is the height of uncut metal;

$\Delta R_Z^{\text{ПЛ}}$ is the roughness altitude gain due to plastic deformations;

$\Delta R_Z^{\text{В}}$ is the roughness altitude gain due to self-oscillations.

Thus, the roughness of machined surfaces is both the most important characteristic of surface quality and a reflection of the relationships between the processes occurring in the cutting system.

When factors related to the cutting process geometry arise, the process of microroughness occurrence is usually considered as copying the motion trajectory of a cutting tool of a certain shape on the machined surface. In this regard, the microroughness height and the surface shape are determined both by the cutting tool shape and by elements of the cutting modes, which can influence the change in the trajectory of the cutting blades relative to the machined surface.

Plastic deformations of the surface layer of the billet [6] during processing, as well as self-oscillatory processes, violate the reference shape of the future part and the regular distribution of surface irregularities increases by an order of magnitude. As a rule, only one of the three factors has a significant influence on the formation of surface microroughness, which ultimately determines the roughness measure. However, in some situations, all three factors influence the process of formation of the surface layer of the part, and it is very difficult to assess the degree of impact of each factor. The roughness of the machined surface in such cases becomes complex, devoid of clearly defined patterns.

There are a number of statistical relationships linking surface roughness with processing conditions. Currently, there are theoretical and empirical formulas that establish the relationship of one or another surface roughness criterion with the main technological factors. Thus, for example, in [10] the dependence of surface roughness during high-speed and fine turning on cutting conditions is given:

$$R_a = \frac{C_t C_s C_v C_r C_\varphi C_{HB} t^m s^n \varphi^x \varphi^y \alpha^\mu}{v^p r^q HB^w}, \qquad (2)$$

where R_a, t, s, r – in μm;

v – in m/min;

angles φ, φ_1, α – in degrees;

HB – processed material hardness;

m, n, p, q, etc. are exponential factors at relevant conditions, which are characterised by the constants C_t, C_s, C_v, etc.

For fine boring of steel billets with cutters made of hard T15K6 and T30K4 alloys, formula (2) has the following form:

$$R_a = \frac{t^{0,16} s^{0,45} \varphi^{0,82}}{v^{0,49} r^{0,25}}. \qquad (3)$$

As follows from equations (2) and (3), the main technological factors determining the surface roughness during cutting are speed, feed, cutting depth, properties of the material being processed, as well as the cutting edge angle φ and the radius r of the cutter tip rounding. There are other, more complex statistical dependencies. Therefore, an important point when studying the mechanism of formation of roughness during machining is also the study of the physics of processes accompanying cutting in relation to the energy transfer to the processing zone, the nonlinearity of the resulting effects and the inevitable influence of dissipative processes on the roughness height and technological system stability as a whole.

The purpose of the study is to show that the use of approaches of nonlinear dynamics and neural network modelling allows controlling the cutting process at the level of dynamic stability of metal-cutting systems.

METHODS

To carry out experimental studies, a stand was created consisting of:

– a 1K625 model screw-cutting lathe;

– an STD.201-2 model turning dynamometer;

– an NI cDAQ-9174 National Instruments interface unit;

– a PC.

To conduct the experiment, a billet made of U8 carbon steel was prepared. To obtain from the dynamometer more reliable data, this experimental assembly should be calibrated for each material being processed. The dynamometer is supplied with a standard calibration blank (including one made of U8 steel), as well as a verification procedure.

After calibration, according to the Walter calculator recommendations, cutting modes were selected, which were supplemented by others selected based on the requirements of processing efficiency: from gentle modes, but with obtaining maximum surface quality, to high-performance modes with the loss of the machined surface quality.

After processing the billets on the experimental bench, profilograms of the surfaces were taken.

To evaluate the R_a and R_z parameters characterising the roughness of the machined surface, a stand was developed [3], which included a blank fixed in the centers of the lathe, a TR200 profilometer connected via an interface to a PC. The TR200 profilometer allows both obtaining the value of any roughness parameter, in accordance with GOST R ISO 4287-2014, and observing the nature of surface irregularities.

Further, the fractal dimension D_F of the machined surface roughness was calculated using the profilogram attractors. The fractal dimension was calculated according to known techniques, but using original software.

Employees of the Department of Mechanical Engineering Technology of Komsomolsk-on-Amur State Technical University developed a DynAnalyzer computer program, which allows constructing an attractor and calculating the fractal dimension using a numerical series (according to a profilogram or using vibroacoustic emission (VAE) signals, etc.).

The final stage of implementation of the methodology was neural network modelling. In neural network modelling of surface roughness, the search for the optimal artificial neural network (ANN) structure was carried out using the version 6.5 Matlab software, which resulted in an architecture containing 7 neurons in the first hidden layer and 1 neuron in the second hidden layer. The ANN was trained based on the obtained experimental data. The neural network model was also tested on input data different from those on which it was trained.

RESULTS

Fig. 1 shows profilograms of the processed U8 steel surfaces at various cutting modes.

It is known [4] that the fractal dimension characterises the process stability and its reproduction regularity. In this case, this is the regularity of the reproduction of irregularities on the treated surface. Moreover, the smaller the fractal dimension, the more stable the reproduction of irregularities during cutting will be.

Fig. 2 shows that the attractor corresponding to the surface processed at a cutting rate of 50 m/min is the most chaotic (Fig. 2 b). It is known that at low cutting rates an intense build-up forming occurs, which affects the roughness. Based on the fractal dimension of this attractor, one can state that the processes occurring in the machine tool system are irregular, and the system itself is unstable. As a result, the surface roughness is high. The last fifth attractor (Fig. 2 e), on the contrary, indicates that the oscillations occurring in the system are regular and the system is stable.

Fig. 3 shows a model of a fractal rough surface in the form of a Cantor set [2].

This model shows the similarity of surface irregularities associated with repetitive processes during machining. Based on this model, the authors proposed a fractal approach to the formation and control of the roughness of machined surfaces during cutting for automated production conditions.

Fig. 4 shows the dependence of the roughness R_a on the cutting rate V carried out on the described stand when processing U8 steel and the results of assessing the fractal dimension of the roughness R_a profilograms after their processing. The analysis of the results shows that the greatest differences in these types of dependencies are observed in the region of low and high rates.

To assess the possibility of diagnosing the R_a parameter during the cutting process, a correlation analysis of the dependences of R_a on D_{Ra} was carried out. The values of the correlation coefficients turned out to be high (0.7–0.9).

During the development of a cutting process control system, the authors created a neural network (Fig. 5) based on diagnostics by the machined surface fractality.

DISCUSSION

As mentioned above, chip formation processes (plastic deformation), cutting tool wear, processed material properties and cutting dynamics are the main factors determining the roughness height during machining [11].

However, these factors in the literature [12] are considered independently of each other, i.e., they are studied and optimised separately. In particular, when developing methods for reducing the cutting tool wear rate, as well as the machined surface roughness, the type of chips generated and the equipment dynamic state are not taken into account. Studying the interdependence of various parameters of these factors, i.e., a system approach to machining will make it possible to create more accurately, in particular, the models of chip formation, the machined surface roughness, the cutting tool wear and the cutting process itself.

One of the promising research tools that can take into account the interrelation and interdependence of the cutting process output parameters is artificial intelligence approaches. The latter can be achieved based on the creation of digital twins (DT) [13; 14]. Digital twin is a new word in modelling equipment, technological processes and digital production planning. DT is based on a number of mathematical models reliably describing processes and relationships both at an individual facility and within the entire production equipment using the Big Data analysis. In this regard, the development of neural network models and machine learning becomes very important.

Using the existing statistical dependencies and neural network modelling [14; 15] allows both simulating it and assessing the current state of the process equipment as a whole, and, consequently, the processed surface quality.

A digital twin acts as a virtual model of a part, product, process, technology, etc. Such a model is capable, at the micro- and macro-level, of either describing an actual technology object, acting as a duplicate of a finished specific product or process, or serving as a prototype of a future technology object. At the same time, any information that can be obtained when testing a physical object must also be obtained based on testing a digital twin.

The influence of processing modes (V; s; t) and physical and mechanical properties of the processed material (σ_b) on the machined surface roughness is most covered in the literature [4; 6; 9]. The influence of the cutting process dynamics on the machined surface roughness is the least studied (equation (1)).

Currently, it is proved that self-oscillations during cutting are associated with a phase shift of cutting forces [16]. The work [16] shows the relationship r between the phase characteristic of cutting forces and chip shrinkage K_a.

Fig. 6 shows the dependences r of the phase characteristic of cutting forces on the microroughnesses R_z height [16]. It follows from Fig. 6 that self-oscillations have the greatest influence on the machined surface roughness when cutting ductile materials (steel 10). With increasing cutting rate, the influence of self-oscillations on the machined surface roughness decreases [17; 19].

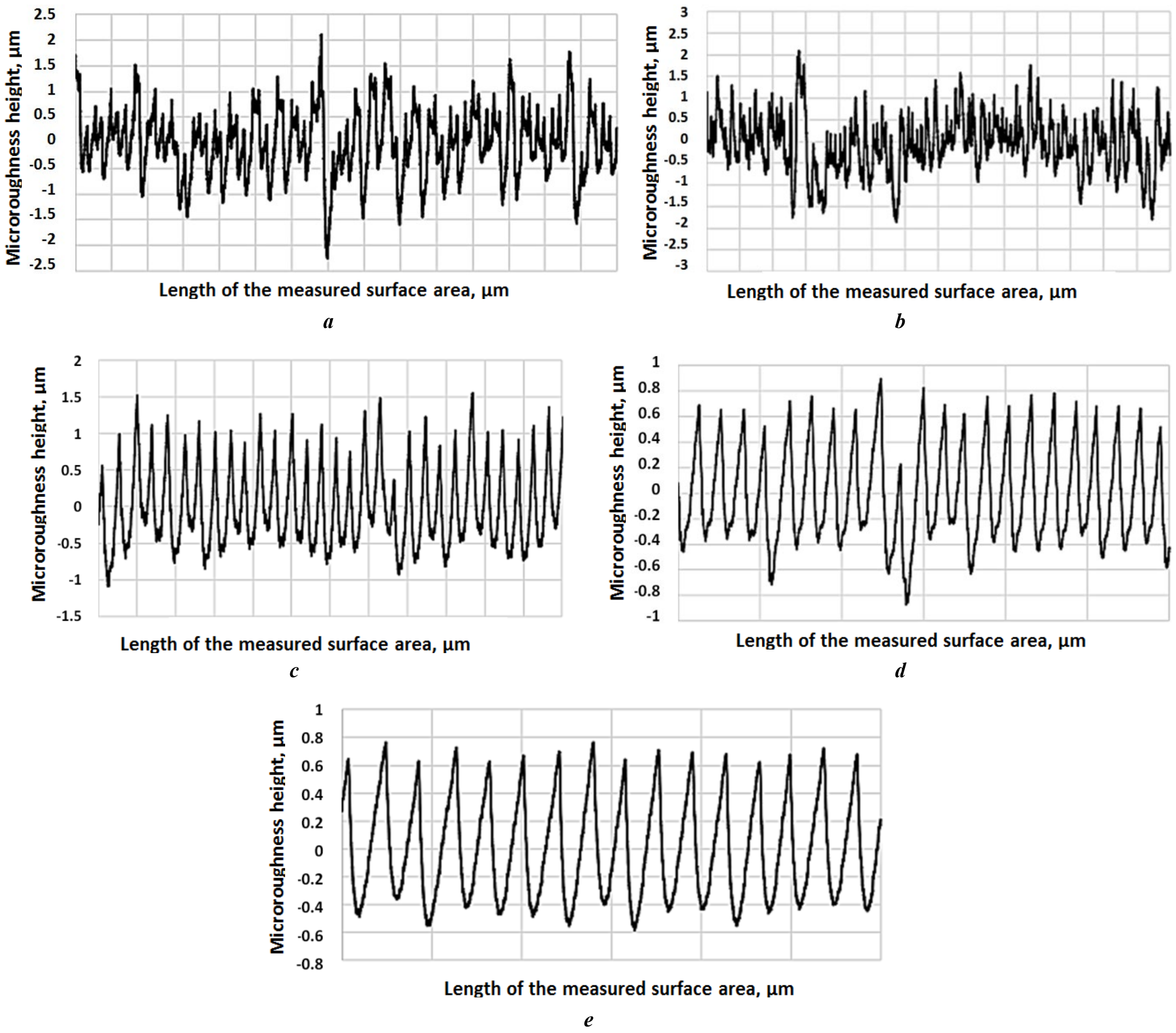

Fig. 1. *Profile records of machined surfaces (У8 steel, T15K6 cutter):*
a *– V_{cut}=20 m/min, Ra 2.32;* ***b*** *– V_{cut}=50 m/min, Ra 2.6;*
c *– V_{cut}=75 m/min, Ra 1.6;* ***d*** *– V_{cut}=105 m/min, Ra 1.25;* ***e*** *– V_{cut}=130 m/min, Ra 1.2*
Рис. 1. *Профилограммы обработанных поверхностей (сталь У8, резец Т15К6):*
a *– $V_{рез}$=20 м/мин, Ra 2,32;* ***b*** *– $V_{рез}$=50 м/мин, Ra 2,6;*
c *– $V_{рез}$=75 м/мин, Ra 1,6;* ***d*** *– $V_{рез}$=105 м/мин, Ra 1,25;* ***e*** *– $V_{рез}$=130 м/мин, Ra 1,2*

The surface roughness digital twin (Fig. 6) allows, at the stage of designing technological processes, to select machining modes providing a given roughness depending on both the dynamic state of the machine equipment and the grade of the processed material and its strength properties (σ_b).

Increasing the number of parameters at the neural network input [14; 15], changing its architecture and accumulating a database about the cutting process allows studying other factors that affect the machined surface roughness, but are difficult to study, in particular, the influence of the corner radius of the cutting blade tip, the cutting angle, etc.

Currently, modern machine tools are considered as a cyber-physical system (CPS), which uses sensors installed on the cutting tool [12; 18; 20] and on other essential controls of the machine, which collect data on the CPS state in real time, after which this information is sent to the digital twin. Constant updating of the database for the digital twin about the cutting process allows increasing the accuracy of modelling the machined surface roughness and the CPS dynamic state control during cutting.

For this purpose, the authors studied the possibility of using neural network models to control technological cutting processing systems and carried out additional experimental studies. In this regard, the authors took a time series of vibroacoustic emission signals picked up during cutting from the machine dynamic system and calculated the VAE signal fractal dimension, which, as studies have shown, correlates well with the fractal dimension of the machined surface roughness. The values of the correlation coefficients turned out to be quite high (0.8–0.9).

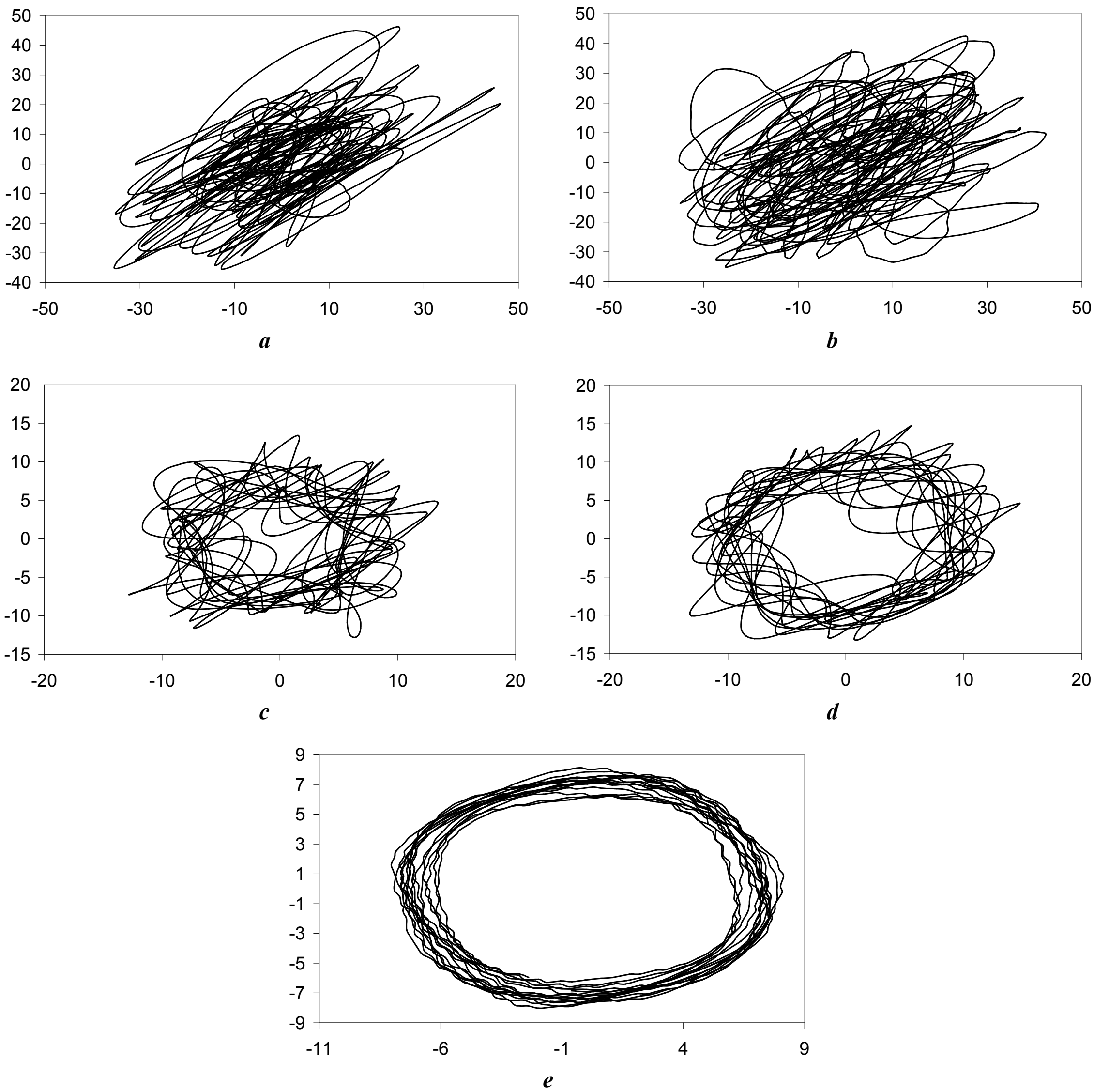

Fig. 2. *Attractors of the machined У8 steel surfaces corresponding to cutting rates:*
a *– V_{cut}=20 m/min, Ra 2.32;* ***b*** *– V_{cut}=50 m/min, Ra 2.6;*
c *– V_{cut}=75 m/min, Ra 1.6;* ***d*** *– V_{cut}=105 m/min, Ra 1.25;*
e *– V_{cut}=130 m/min, Ra 1.2*
Рис. 2. *Аттракторы обработанных поверхностей стали У8, соответствующие скоростям резания:*
a *– $V_{рез}$=20 м/мин, Ra 2,32;* ***b*** *– $V_{рез}$=50 м/мин, Ra 2,6;*
c *– $V_{рез}$=75 м/мин, Ra 1,6;* ***d*** *– $V_{рез}$=105 м/мин, Ra 1,25;*
e *– $V_{рез}$=130 м/мин, Ra 1,2*

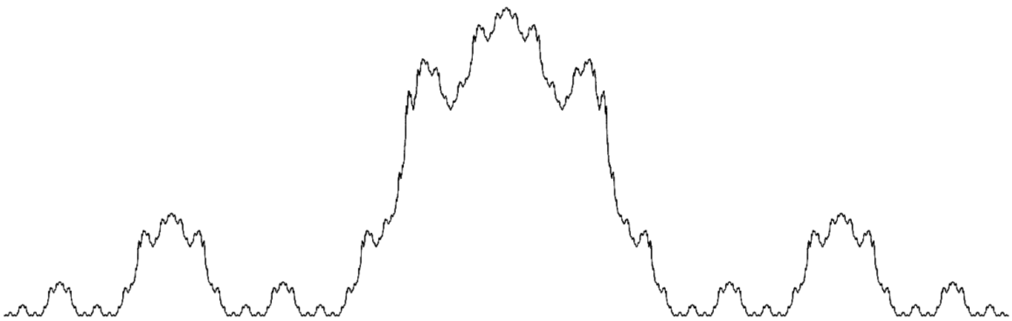

Fig. 3. *The model of Cantor profile of surface roughness*
Рис. 3. *Модель канторовского профиля шероховатости поверхности*

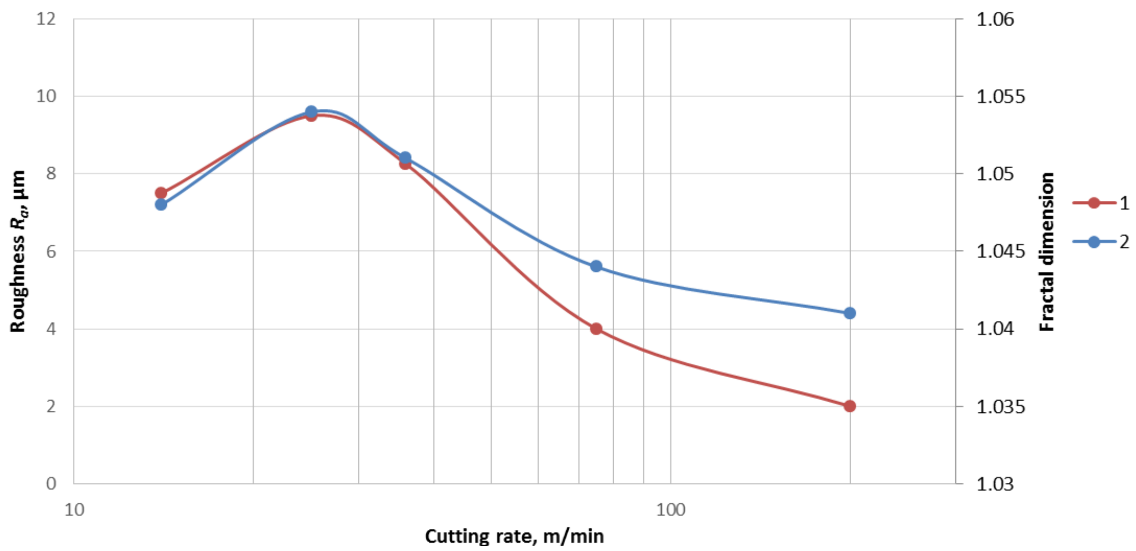

Fig. 4. *The dependence R_a of roughness (1) and D_{Ra} of fractal dimension (2) on the cutting rate (У8 steel, T15K6 cutter; S=0.11 mm/rev, t=1 mm)*
Рис. 4. *Зависимость R_a шероховатости (1) и D_{Ra} фрактальной размерности (2) от скорости резания (сталь У8, резец Т15К6; S=0,11 мм/об, t=1 мм)*

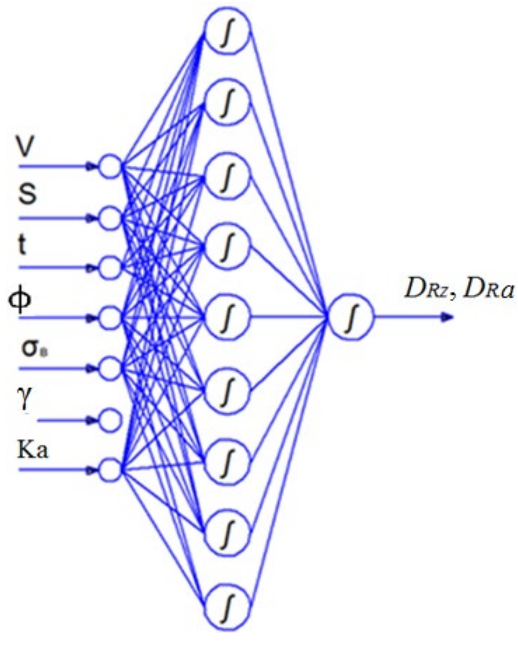

Fig. 5. *The structure of artificial neural network for assessing the fractality of the machined surface based on the cutting conditions*
Рис. 5. *Структура искусственной нейронной сети для оценки фрактальности обработанной поверхности от условий резания*

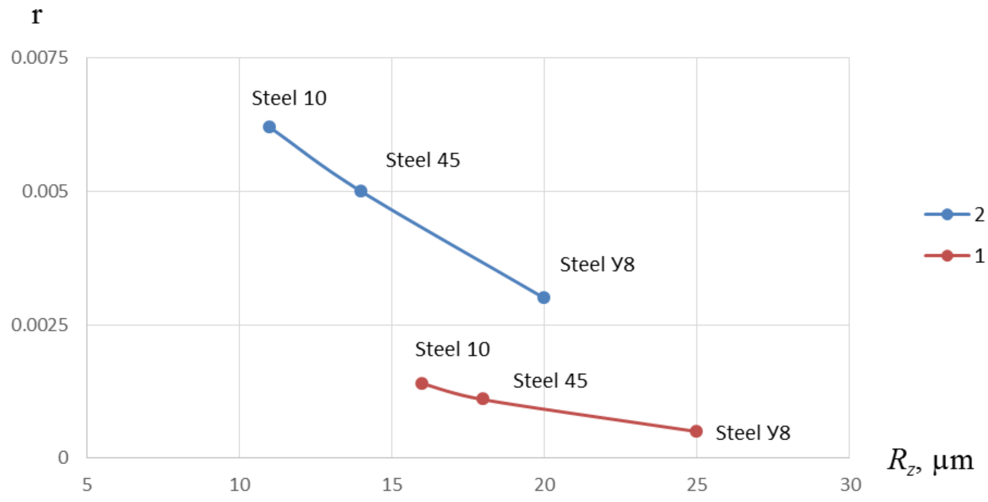

Рис. 6. *Зависимость r фазовой характеристики сил резания от шероховатости обработанной поверхности (1 – 80 м/мин; 2 – 30 м/мин) [16]*
Fig. 6. *The dependence r of phase characteristic of cutting forces on the machined surface roughness (1 – 80 m/min; 2 – 30 m/min) [16]*

CONCLUSIONS

1. A correlation was identified between the machined surface roughness and the fractal dimension D_{Ra}. The correlation coefficient was 0.8–0.9.

2. A system based on artificial intelligence is proposed that allows taking into account a wide range of input parameters affecting the machined surface roughness.

3. The proposed intelligent system is capable of self-learning, which allows increasing the number of input parameters and create a database of virtual models (digital twins).

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Управление динамической устойчивостью металлорежущих систем в процессе резания по фрактальности шероховатости обработанной поверхности

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Поступила в редакцию 15.06.2023 *Принята к публикации 06.09.2023*

Аннотация: Проблема повышения эффективности механической обработки в условиях современного автоматизированного производства является актуальной для многих отраслей перерабатывающей промышленности. Данная проблема требует глубокого изучения физических процессов, происходящих при резании. Ее актуальность еще более возрастает с развитием цифрового производства в нашей стране. Сегодня при наличии широкой номенклатуры изделий предприятия вынуждены создавать условия для сокращения технологического цикла при производстве того или иного изделия. Для проведения исследования был поставлен эксперимент, в котором в качестве обрабатываемого материала использовалась углеродистая сталь У8, а в качестве инструментального материала – Т15К6. В ходе проведения эксперимента наблюдали за изменением шероховатости обработанной поверхности в зависимости от скорости резания. В работе рассмотрена возможность оценки качества поверхностного слоя при резании на основе фрактального и нейронносетевого моделирования. Обнаружено, что фрактальная размерность показывает регулярность воспроизведения неровностей на обработанной поверхности при резании. Рассчитанная фрактальная размерность шероховатости обработанной поверхности хорошо коррелирует со значениями шероховатости обработанной поверхности (коэффициент корреляции 0,8–0,9). Разработана структура нейронной сети, позволяющая управлять качеством обработанной поверхности в зависимости от условий резания. Изучена возможность использования нейронносетевых моделей для управления технологическими системами обработки резанием. Предложено при создании цифровых двойников учитывать факторы, влияющие на качество обработанной поверхности и производительность обработки, которые слабо поддаются учету при моделировании, а также при проведении натурных экспериментов в ходе механической обработки. Такими факторами являются износ режущего инструмента, процесс пластической деформации и динамика резания.

Ключевые слова: процесс резания; шероховатость обработанной поверхности; нейронная сеть; управление качеством поверхностного слоя.

Для цитирования: Кабалдин Ю.Г., Саблин П.А., Щетинин В.С. Управление динамической устойчивостью металлорежущих систем в процессе резания по фрактальности шероховатости обработанной поверхности // Frontier Materials & Technologies. 2023. № 3. С. 43–51. DOI: 10.18323/2782-4039-2023-3-65-4.