Improvement of the Quality of Cutting Tools States Recognition Using Cloud Technologies

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Abstract. The work considers improving the quality of constructing large-scale diagnostic models in technical diagnostics systems by developing a software architecture for high-performance computing in the form of a web service using cloud-based machine learning technologies. The obtained results are brought to practical realization in the form of tools of the automated system of technical diagnostics of cutting tools with the diagnostic parameters of large dimensions. A method has been developed for building information models of cutting tool states based on indirect measurements using test pulse effects on a cutting system in the form of loads with impacts and recording system responses, based on which information models are built in the form of multidimensional transition functions. The methods of forming test pulse loads of the cutting system by successive insertion of the cutting tool into the workpiece with different cutting depths, with variable feed, and with variable cutting duration are considered. The computational experiment demonstrates the advantages of information models in the form of multidimensional transition functions for modeling nonlinear dynamic systems in problems of diagnosing the states of cutting tools. It has been established that multiclass cutting tools state recognition can be used as an effective technology of automated technical diagnostics systems.

Keywords: Tool laboratory · States recognition · Cloud ML

1 Introduction

Applied technical diagnostics (TD) problems for complex objects are becoming widespread, especially with a strong interest on the part of smart manufacturing and industry 4.0. Often, such objects are described by large-scale models, the causes of which are the object's complexity and the lack of study of the processes occurring in them, as well as increasing objects speed, the presence of many disturbing influences and environmental interferences.

Simultaneously, taking into account the maximum number of characteristics of diagnosis objects (DO), automated systems of TD (ASTD) provide the high accuracy of diagnosis, but a large amount of diagnostic information reduces the speed of setting up ASTD.

Building a reliable diagnostic model is one of the most difficult problems. There are two ways to reduce diagnostic models [1]. The first is to construct a diagnostic space

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based on orthogonal transformations to weaken the statistical relationships between model parameters and to increase the diagnostic value of these parameters [2]. These methods require a large amount of prior data, therefore, they are oriented towards the operation of ODs in certain modes of operation. Expanding the scope of application, operating in a wide range of external conditions leads to an increase in the prior uncertainty of object data, and therefore, to reduce the accuracy of diagnosis. Another way is the selection of diagnostic features using combinatorial analysis for information optimization of diagnostic models by the criterion of maximum accuracy of diagnosis at the learning stage. The main disadvantage of this approach is the need for large computing power when solving large-scale problems.

With the development of cloud technologies, the disadvantages of breeding diagnostic features have become less significant [3]. The advent of cloud managed services [4] makes the direction of diagnostic feature selection an effective tool in the construction of ASTD. These provisions determine the relevance of the development of diagnostic models of large objects in TD systems based on the selection of diagnostic features, using cloud-based machine learning (ML Cloud) technology, which provides high reliability and prompt diagnosis of objects.

Research Purpose. The purpose of this research is to create techniques for improving the quality of cutting tools states recognition in TD systems of smart manufacturing and industry 4.0 by developing a software architecture for high-performance computing using ML Cloud.

2 Literature Review

Metalworking processes in modern manufacturing are characterized by a continuous increase of cutting processes intensity. This leads to an intensification of the processes of cutting tools (CT) working surfaces wear.

Manufactures of the "Industry 4.0" level are sold on FMM (flexible manufacturing modules) with limited participation of operators. Most of the functions of monitoring, diagnosing and predicting the CT resource are transferred to the corresponding automatic intelligent systems, as an operator is not able to make decisions at the speed that is now required to cutting part (CP) states recognition and prevent sudden or gradual failure of instruments.

The main factors of the CT state's recognition quality are now the speed and accuracy of assessing the degree of cutting part operability.

Before being recommended for work on the machine tools, CT should be thoroughly studied in the laboratory – with the accumulation of relevant statistics and the formation of automatic classifiers. First of all, this applies to tools made of new materials; data sets on properties and recommended operating modes may appear in the reference literature with a delay. The need for creating a system of operational links between factories (their metalworking shops) and research instrumental laboratories (which are absent in many factories) is obvious. The authors see the solution to this problem in the use of "cloud technologies". Let us analyze the relevant literature.

In the context of the modern industrial technologies development at the “Industry 4.0” level, “cloud technologies” for data processing are widely used [5–10].

Factory operations have shifted from labor-based to semi-automatic and fully automatic and may even become unmanned in the future [5]. Indicated that factory conditions can be monitored from a distance and the machines can be remotely controlled. The attempt in their study is a step toward cloud-based manufacturing.

The factory shall allow the setup and evaluation of any preferred factory layout. One major challenge is the design of the strategy for communication between the factory modules and the identification of adequate communication technologies [6].

Learning Factories, widely using Internet technologies, have shown to be effective for developing theoretical and practical knowledge in a real production environment [7]. Communication is some of the most recurrent ones associated with a knowledge of the engineering sciences.

Industry 4.0 refers to the importance and the ruling capacity of cloud technologies in various areas [8]. Cloud computing is playing an important role in data collections, and of modern computing technology.

Cloud manufacturing as a new manufacturing paradigm has been attracted to a large amount of research interest [9, 10]. Many papers have been published, that presented the overall research status of cloud manufacturing.

The analysis of publications showed the need to use cloud technologies to ensure the diagnosis of cutting tools in modern FMM. They are complex systems that operate with limited operator involvement. That is why much attention is paid to the creation of modules for diagnosing the states of the main subsystems and machine elements and predicting the probability of their failures. A large number of FMM downtimes are caused by gradual or sudden failures of CT. Therefore, the need to create systems for CT state recognition in machine tools is obvious.

However, this is preceded by lengthy laboratory studies of the features of the wear of the CT, the assessment of the state dynamics of the cutting part, the choice of the optimal geometry of the CP and the optimal cutting conditions.

New instrumental materials are constantly improved and created, data on which are not always available in the reference literature.

Therefore, in the structure of instrumentation in the large factories, a special instrumental laboratory with appropriate test benches was always necessary.

At the same time, under the conditions of Industry 4.0, the possibilities of the modern Internet open up the prospect of creating central tool laboratories that can serve metalworking enterprises of a similar profile (with machines of the same name or similar in type, close ranges of grades of processed materials, types of CT sources, etc.). Extensive databases are formed here with a statistical generalization of test results and data processing.

A similar direction was considered in the above works [5–10] and, in particular, in the author’s publication [11]. The creation of integrated intelligent production requires the creation of intelligent systems for diagnosing the conditions of CT [12]. The following can be quickly transferred to the databases of modern CNC machine tools:

- sets of decision rules for online - diagnosing the state classes of a particular tool,
- data on the need for correction of processing modes “according to state” of CT;

– data on the need for tool presetting,
– data on the forecast of the residual resource and the CT change in a precautionary state;
– other data worked out during laboratory tests.

Machine-tool and laboratory systems for the diagnosis and forecasting of sources have become intelligent.

There is an exchange of data in both directions: factory - central laboratory and laboratory – factory. We turn to the consideration of automated systems for monitoring the CT state. They can be divided into direct [13–15] and indirect [16–21].

The advantage of direct control systems equipped with STV is that they form extensive information on the gradual shape changes of the cutting part of CT and its geometry, on the displacement of the vertex of the RS in the machine coordinate system, etc. To ensure the high quality of production processes in modern metal-cutting machines, the method of direct monitoring of the condition of the cutting tool wearing using vision systems is used [13–15].

Some results of research in machine vision, as a key technology, essential in connecting the manufacturing processes with the digital twin of the manufacturing architecture, are presented in [13]. Designing a system, that uses machine vision in combination with deep learning algorithms. The machine vision method to develop an on-machine turning tool insert condition monitoring system - for tool condition monitoring in the cutting processes of CNC machines, is discussed in [14]. The system can identify fractures, built-up edge, chipping, and flank wear of cutting tools.

The processing of images sequence of wear zones of tools coming from the system of technical vision (STV), requires a very significant expenditure of time and computational resources on preliminary data processing to increase their quality, contours and textures selection of wearing zones [15]. Based on the processed images, information models are formed and classifiers are built.

Known indirect methods of the CT control and diagnostics [16–21] are based on measurements of torque, cutting power, components of cutting forces, acoustic emission, dimensions and roughness of the machined surface of the part, etc.

Systems of direct monitoring of the state of CT sources equipped with STV cannot be used in a closed casing processing zone (especially with the active use of lubricating and cooling media). The exception is systems that provide an assessment of the CT state in a special control position of the tool magazine [11].

The specific state of cutting tools CP is recorded by both types of sensors: indirect sensors - during processing, systems with STV - immediately after its interruption. Under the conditions of finishing and precision processing (with small cutting forces, vibrations, levels of the acoustic signal), their accuracy is not high enough. Therefore, it seems appropriate to use combined systems for monitoring the CT states.

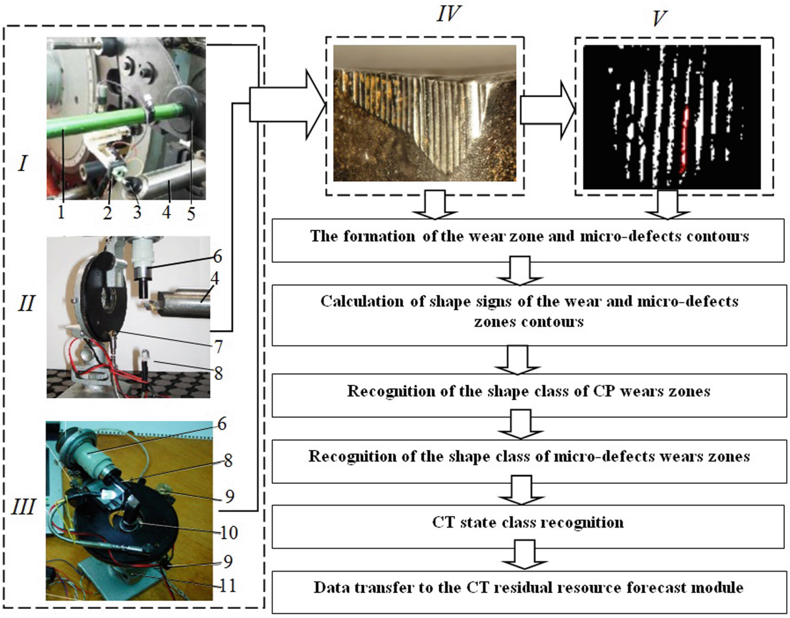

Fig. 1. Schematic representation of CT state recognition processes (according to the results of CP laboratory monitoring with the STV use). 1 - stand for mounting the device for moving the digital camera in three directions; 2 - digital camera with a backlight system; 3 - controlled boring tool; 4 - boring bar; 5 - the magnetic base of the rack 1; 6 - digital camera; 7 - remotely controlled camera rotation device; 8 - backlight system; 9 - table rotation mechanism with CT; 10 - CT; 11 - control system housing.

3 Research Methodology

The schematic representation of CT state recognition processes (according to the results of CP monitoring with the STV use) in the special instrumental laboratory is shown in Fig. 1.

Micro – defects of CP wear zones include traces of concentrated wear (Fig. 1, positions IV, V), holes along the boundaries of the cut layer, micro cracks, zones of adhesive tearing, and others. They are insignificant under the conditions of roughing and semi-finishing, but they are the causes of CT failures under the conditions of finishing and precision processing. CP’s indirect monitoring systems, as a rule, cannot detect them.

Let’s move on to the consideration of the corresponding Internet structure using modern cloud technology.

This structure must be able to transmit the results of laboratory research and testing of new tools, recommendations for the modes of their use, decision rules for recognizing their conditions and other - for the factory’s machine tools (consumers).

The main stages of the CT state classifiers formation (based on comprehensive studies in the instrumental laboratory (Fig. 1)) are shown in Fig. 2.

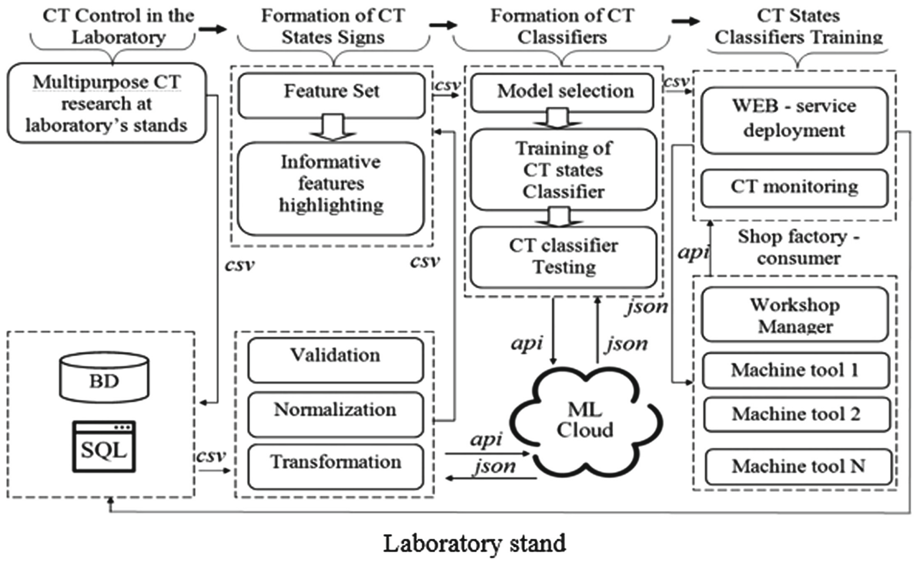

Fig. 2. The architecture of decision-making processes for CT states recognizing (and connections of the central instrumental laboratory with the workshops of the consumer plants using the WEB service) with ML Cloud technologies.

Let's clarify the contents of the operations "validation - normalization - data transformation". They analyze the obtained data, check their correction and make the necessary changes, after which informative signs of CP states are extracted.

An enlarged diagram - the structure of service processes by the central instrumental laboratory of many consumers – is shown in Fig. 3.

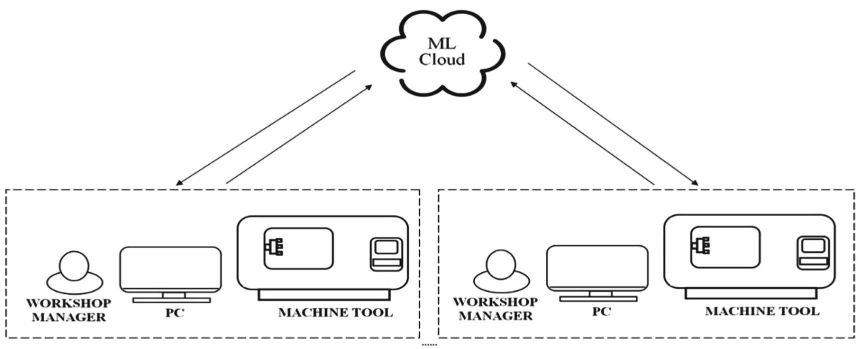

Fig. 3. The general structure of the servicing processes of the central instrumental laboratory for many consumers.

The main advantages of using the defined architecture of high-performance computing in the tasks of diagnosis are to increase the reliability and timeliness of diagnosing objects of large size in the absence of powerful hardware resources and mathematical support.

4 Results

The application of the developed principles of diagnosis is limited by the lack of effective tools for the functioning of the ASTD. The development of problem-oriented software in the field of control and diagnostics of various cutting tools in modern manufacturing is an urgent problem.

ASTD design tasks based on multidimensional training samples require large time resources and cloud machine learning technologies must be used to accelerate the design process.

Well-known ML Cloud platforms offer similar training and forecasting services. These platforms have similar structural solutions, thus offering a software architecture for high-performance computing using ML Cloud as a basic part of large-scale ASTD objects.

Next, the problem of diagnosing 4 states of a cutting tool in a training sample of 247 measurements of the contours of the cutting tool wear on 8 features is considered:

A fragment of the training sample of 247 measurements on 8 grounds loaded into the Microsoft Azure ML Cloud is presented in Fig. 4.

rows 247 columns 8

view as

y1	y2	y3	y4	y5	y6	y7	y8
124.7393	21.1316	58.3057	1.5717e+03	13.1065	44.4233	18.4452	30.4305
94.6363	31.7375	61.3622	780.3752	13.5868	103.0198	13.4453	36.5058
144.2986	42.9744	38.5291	822.1242	20.9682	119.8435	7.1965	35.2785
163.9857	52.8952	43.6593	674.8609	14.9366	116.4613	7.0698	38.9528
108.9410	44.5891	51.1346	707.8066	16.5286	52.2486	9.3272	26.6709
133.1984	45.0401	48.5951	1.8875e+03	8.0673	124.1537	12.1231	27.7948
100.7186	45.4383	47.5310	1.4230e+03	16.2282	79.9175	17.0549	23.0083
121.0189	49.3936	39.7878	1.9125e+03	18.8845	117.3154	9.2319	26.6741
168.2321	44.1030	59.3174	2.3820e+03	17.2006	116.3858	10.9028	31.0736
144.1591	38.7576	49.2745	2.1817e+03	15.3964	72.5429	16.0291	31.0059
167.1381	31.6060	56.8801	2.6396e+03	19.5608	96.2786	11.0209	23.2084

Fig. 4. Training sample fragment for multiclass cutting tools states recognition in ML Cloud platform Microsoft Azure.

The common model of multiclass cutting tools states recognition based on ML Cloud platform Microsoft Azure is presented in Fig. 5.

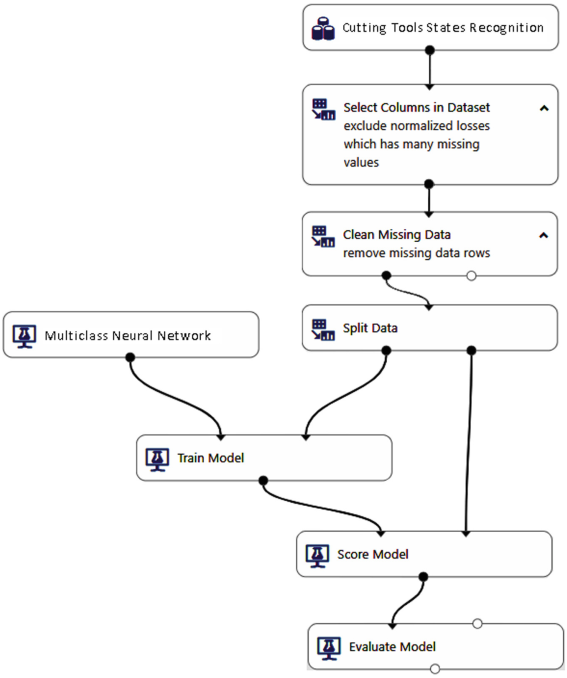

Fig. 5. The common model of multiclass cutting tools states recognition based on ML Cloud platform Microsoft Azure.

Results of multiclass cutting tools model machine learning based on ML Cloud platform Microsoft Azure is presented in Fig. 6.

Metrics

Mean Absolute Error	0.240062
Root Mean Squared Error	0.284372
Relative Absolute Error	0.354608
Relative Squared Error	0.12545
Coefficient of Determination	0.87455

Fig. 6. Results of multiclass cutting tools model machine learning based on ML Cloud platform Microsoft Azure.

{"datetime": "2019-10-15 11:08:52",¶
"title": "UNIVERSAL MILLING GRADE",¶
"partnumber": "ACU2500",¶
"tool": {¶
"y1": "113", "y2": "31",¶
"y3": "39", "y4": "951",¶
"y5": "14", "y6": "79",¶
"y7": "13", "y8": "23"},¶
}¤

Fig. 7. A message example with the parameters of the diagnosed tool sent to the webserver is given below.

{"datetime": "2019-10-15 11:08:53",¶
"title": "UNIVERSAL MILLING GRADE",¶
"partnumber": "ACU2500",¶
"tool": {¶
"class": "3",¶
"probability": "0.89382"},¶
}¤

Fig. 8. An example response message from a web server is given below.

The interaction of the client and the web server in the REST API architecture is required for the HTTP protocol. Additional information (models, parameters, control values) will be transferred in JSON format. A message example with the parameters of the diagnosed tool sent to the webserver is given in Fig. 7. An example response message from a web server is given in Fig. 8.

5 Conclusions

The presented results allow creating techniques for improving the quality of cutting tools states recognition in TD systems of smart manufacturing and Industry 4.0 by developing a software architecture for high-performance computing using ML Cloud.

The proposed approach provides indicators of the quality of RI states recognition that are 1.2–3% higher than the results obtained by the authors earlier on the same machine in laboratory conditions (using maximum likelihood methods, stochastic approximation, neural networks, and hybrid methods [12]).

At the same time, the obvious advantage of using "cloud technology" is the possibility of using a central tool laboratory to solve the problems of diagnosing CT states on various machines of many factories.

This provides the following benefits when working with distributed data. There are sets of decision rules building for online - diagnosing the state classes of a particular tool; data on the need for correction of processing modes "according to state" of CT; data on the need for tool adjustment; data on the forecast of the residual resource and the moment of the CT change in a precautionary state; other data, worked out during laboratory tests.

Due to this, significant savings are achieved in the corresponding production resources, and, first of all, time and financial.

A computational experiment confirms the advantages of using cloud technologies for cutting tools states recognition in modern manufacturing.

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