Development of intelligent algorithms for the continuous diagnostics and condition monitoring subsystem of the equipment as part of the process control system of a stainless steel pipe production enterprise

E S Grishin

Immanuel Kant Baltic Federal University, ul. A Nevskogo, 14 236041 Kaliningrad, Russia

E-mail: negrshn@mail.ru

Abstract. This article describes the process of development and implementation of an integrated APCS and continuous diagnostics and equipment condition monitoring subsystems using intelligent machine-learning-based algorithms for a stainless steel pipe manufacturing enterprise with combining local automatic control systems into a single information technology system. Briefly, the author describes the technological equipment and the production cycle, its features, as well as its change as a result of the implementation of APCS. The software tools and their structure, the interaction of elements in the system, the main tasks solved with APCS and their impact on the quality of finished products are described. A feasibility study and justification of the application of PCS for this production are carried out.

1. Introduction

The LLC Techno Tube enterprise specializes in the production of welded stainless pipes for a wide range of consumers. The production of stainless welded pipes includes the use of welding equipment. Regardless of which welding method is used (electric welding, laser welding, plasma welding, and electron beam welding), the essence of the process is the same: a stainless steel sheet (strip is a flat billet in the form of a roll) is rolled using rolls of a rolling mill, and its edges are connected using a weld. After this, the seam is cleaned, sanded and passes all the necessary tests proving its strength. At the last stage, the pipe is calibrated and is cut into pieces of the desired length. According to GOST 11068–81, (Electric-welded pipes from corrosion-resistant steel. Technical conditions) [1] the permissible diameter of welded stainless steel pipes is from 8 to 102 mm and the permissible thickness of their walls is from 0.8 to 4 mm. In order to control the quality of products, to control the compliance of the actual production process with flow charts and schemes for various types of materials and to confirm product parameters to consumers, the company plans to create a process control system with a subsystem of intelligent continuous diagnostics and equipment condition monitoring.

2. Development of APCS enterprise

The company has five rolling mills and a stainless steel strip (flat billet) preparation section (cutting machine from material rolls), and it is also planned to install a mill for the production of pipes with
increased requirements for the chemical and nuclear industries. It is planned to include mills with a laser welding process and a mounted mill in APCS. In total there are up to five rolling mills and a preparation section for billets.

2.1. Organization of the technological process before the implementation of the developed APCS
At present, pipe production lines are a system of local automated control systems on microcontrollers of various manufacturers (Siemens [2], Omron [3]), synchronized with a moveable work piece. The Italian-made equipment is used.

The disadvantages of the existing production system include the following:
1) The parameters of the technological process are not recorded, it is impossible to establish the relation between the batch number of the manufactured products and the parameters of its production life cycle.
2) It is impossible to control the compliance of the parameters of the technological process of production with the technological map from the database for various types and grades of steel.
3) Maintenance of the equipment and polishing of the rolls, elimination of the defects that occur, are performed on the basis of operating time.

2.2. Organization of the technological process after the implementation of the developed APCS
After the implementation of APCS, the following tasks will be solved and the organization and control of the production process will change:
1) For various grades of steel, significant parameters of the technological process will be controlled in accordance with the database [4] containing the required parameters of the technological process depending on the grade of raw material and its geometric steam meters.
2) All significant process parameters will be recorded in the database, the batch number will be associated with a set of technological parameters.
3) Product quality will be continuously monitored with nondestructive testing methods.
4) Production process will be visualized, equipment operation control will be carried out continuously with access for persons controlling the production process.
5) Continuous monitoring of the state of the equipment will be carried out on the basis of the analysis of trends in the change (departure) of technological parameters from operating characteristics. Accordingly, a logical conclusion will be formed about the need for technical maintenance or the acquisition of spare parts for equipment items that may fail [5]. Knowledge will be accumulated on troubleshooting equipment in the database, which will reduce equipment downtime due to failures. A model will be trained that will significantly accelerate the analysis of trends in technological parameters from operating characteristics (analysis of the dynamics of the time series).

This will allow service personnel to carry out maintenance and equipment repairs according to its actual condition. Studies [6] showed that the effectiveness of the service strategy as estimated at 30% of the cost of the total machines and can reduce by 10–15% the output of substandard products that are detected with non-destructive testing methods for quality control.

The scientific novelty in this work is the machine learning algorithm and additional model training “using examples” using classical methods of mathematical statistics to determine the dynamics of a time series and methods of logical predictive inference in the process of continuous equipment diagnostics.

3. Development of a subsystem of intelligent continuous diagnostics and monitoring of equipment status
The subsystem of intelligent continuous diagnostics and monitoring of equipment status is based on the production model of knowledge representation of expert intelligent systems with direct logical inference [7]. In this model, knowledge is represented in the form of rules: “If (condition [and condition ... and condition]), then (conclusion)”. A system with direct inference performs processing from conditions to conclusion. To adapt to the diagnostic tasks and ease of use of the diagnostic
subsystem by operators of production lines, the rules have been expanded to the form: “If (condition [and condition ... and condition]), then (defect). Recommended: (action). ” The rules are formed in advance by a specialist when implementing APCS with analyzing technical documentation, statistical information on the maintenance and repair of diagnosed equipment, as well as formalizing the knowledge of service personnel. When rules are entered into the system, the rules are automatically checked for consistency. General view of the production model is:

$$N =< S; L; A \rightarrow B; Q; R >,$$

(1)

where N – product model name;
S – description of the class of situations;
L – product activation condition;
A – core products;
Q – inference of the production rule;
R – recommendations to the operator.

The development of equipment defects during the operation phase is mainly associated with the physical aging of the equipment, which is caused with the processes of wear and corrosion and mechanical damage under various conditions, and occurs smoothly. The development of each defect is accompanied with some changes in the characteristics of the part or unit of equipment (temperature, vibration, and others). Analyzing the dynamics of changes in characteristics, grouping changes in characteristics corresponding to certain defects, a diagnostic model of the equipment fleet of this enterprise was built into the diagnostic rules.

An analysis of the trend in the movement of the value (dynamics) of the observed characteristics is based on the analysis of the absolute and average absolute increase in the series of dynamics, as well as the sum of the absolute chain increments of levels. Absolute growth shows the rate of change of the series and is defined as the difference between the current and base levels. For the base level, the level of the previous period is taken.

In view of the large number of measurements and the corresponding increase in the complexity of the calculations, the author proposed to reduce the data with quantizing the analyzed time interval into equal segments according to formula (2).

$$n = \frac{q}{k},$$  

(2)

where n – quantization step;
q – sampling depth;
k – regulatory coefficient.

The quantization step is essentially a sampling step of depth q. The control coefficient allows you to adjust the overall complexity of the algorithm and the calculation error in particular. To obtain an error in the calculation of the algorithm of less than 1%, the coefficient k = 26280 was selected empirically.

Comparisons of the analysis of the complete set of technological data and the reduced set showed that the reduction of the data did not significantly affect the result of the analysis of the dynamics of the observed characteristics. In figure 1, blue is the average absolute increase in the initial series, red is the average relative increase in the reduced series, for example, 30 different series are shown levels.

The computational complexity of the algorithm for determining the dynamics of the initial series is directly proportional to the number of observed characteristics (A) and sample depth (B), and is determined by formula 3, the same is true for the reduced sequence, but inversely proportional to the value n of formula (2) and is determined by formula 4 .

$$T = A \times B + C,$$

(3)

$$T = \frac{A \times B}{n} + C,$$

(4)

where C – some constant.
Thus, the theoretical computational complexity of the algorithm for $10^3$ pieces of equipment with $10^2$ observed characteristics for each with a maximum sampling depth will be approximately $10^{13}$ for the initial series, for the reduced series it is approximately $10^9$. This method of data reduction allows you to comfortably use the diagnostic system; however, the complexity of the algorithm is still linear.

The task of determining the dynamics of a series is highly specialized, and to accelerate its solution, you can use the machine-learning model. In this situation, the “learning by examples” model of the ML.NET development tool was used. The training examples for this model are generated during the first six months of diagnosis. From the moment the diagnostic subsystem is introduced into production, the model begins to learn the data from the analysis of the dynamics of the observed characteristics obtained with the method described above. The training data consists of time series, which, in turn, are divided into three types: those with a tendency to increase, with a tendency to decline, and static (taking into account possible fluctuations in the measurement values). The ML.NET development tool machine learning model contains implementations of various algorithms: linear (average perceptron, stochastic double coordinate wise lift, Broyden - Fletcher - Goldfarb - Shanno algorithm, character-by-symbol stochastic gradient descent), decision trees (gradient boosting, fast tree, fast forest, generalized additive model), metaalgorithms and others [8]. Empirically, while training the model on various input data, the algorithm of averaged perceptron was chosen, because it reaches the established or absolute accuracy faster than the others do. This is a linear classification algorithm based on an artificial neural network (a classification problem with more than two linearly separable classes is solved with including several neurons in the output (computational) layer of the perceptron, which makes its predictions with finding a separating hyperplane [9]. The algorithm was built on the basis of the perceptron model proposed by Frank Rosenblatt [10], who, together with his colleagues, proved its convergence [11].

Data for primary education is formed by a package containing tuples, of the form: “row, type of dynamics”. The number of tuples for each type of row dynamics is balanced. A package is considered formed if one of the following conditions is met: its size has reached 10 megabytes; a month has passed of the continuous formation of the package. Upon completion of the formation of the data package for primary training, it is transferred to the machine-learning model and the process of its training is launched. The duration of model training for a given volume of training data is up to 60 minutes, it depends on the computational performance and the performance of the computer memory subsystem.
After the training process is completed, an arbitrary sample is formed from the previously obtained data, with a volume of 1000 tuples for each type of dynamics of the series, and an analysis of the error in the calculation of the model for each type of dynamics is performed. If the error for any type of dynamics exceeds 1%, then the process of additional training of the model for this type of dynamics is performed. Training data is grouped in a package of up to 5 megabytes, additional model training takes up to 20 minutes. After that, a second analysis of the error is performed and, if necessary, the process is repeated. A generalized scheme of the model-learning algorithm is presented in figure 2.

![Generalized algorithm diagram.](image)

After training the model to the established accuracy, the statistical algorithm for analyzing the trend of value movement is replaced with a machine learning model, but it is not completely withdrawn from work and continues to be used in the training data preparation module, preparing data tuples of the form: “row, type of dynamics”. To reduce the computational load, the time series analysis interval is reduced. Every day, to verify the model in an automated mode with a certain time interval, a repeated analysis of accuracy is performed. If for some type of dynamics the machine-learning model ceases to fit into the established error, then the additional training procedure described above is carried out for this type.

The average speed of the model was analyzed on $10^2$ samples of time series of $18 \cdot 10^3$ levels in each and it is less than 250 milliseconds (figure 3).
In addition, when diagnosing equipment, its residual life at a given time is taken into account according to the formula (5)

\[ t = \frac{n-k}{T}, \]  

where \( t \) – the residual life, hours;
\( n \) – the threshold value of the characteristic;
\( k \) – the current value of the characteristic;
\( T \) – the average absolute increase in the characteristic value per hour.

Taking into account the above factors, equipment is clustered into states according to the highest degree of wear of its component parts and residual resource. There are three levels:

- **Initial** – if the value of the observed characteristic is between the lower and upper warning settings and the residual resource of each node is more than 6 months, it is necessary to consider the condition of the equipment as stated or normal.
- **Medium** – if the value of the observed characteristic is between the lower and upper warning settings and the residual resource of each node is more than 3 months, it is necessary to consider the condition of the equipment as transient;
- **Pre-emergency** – if the value of the observed characteristic is between the lower and upper warning settings and the residual resource of each node is more than 1 month, it is necessary to the condition of the equipment pre-emergency.

For the convenience of using the diagnostic subsystem by the operator, the author suggested dividing the equipment nodes according to the degree of criticality into five levels:

1) Low;
2) Below average;
3) Medium;
4) Above average;
5) High.

For each criticality level, a time interval is established that determines the sampling depth obtained with a statistical study of the service intervals of various equipment and their components:

- 60 months;
- 36 months;
- 12 months;
• 6 months;
• 3 months.

4. Results
Sample reduction allows the use of a statistical algorithm for analyzing the trend of the observed characteristics with linear complexity quite long and efficiently until the time when the processed data becomes enough to train the machine-learning model. In turn, constant monitoring of the model error does not allow errors in the diagnosis. In the presented work, it was obtained an intelligent algorithm that functions at a constant speed and fits within one second. This allows doing continuous diagnostics of equipment and promptly notifying maintenance personnel of the occurrence of defects.

5. Conclusion
The introduction of intelligent algorithms of the continuous diagnostics subsystem and monitoring the status of equipment as part of APCS at the automation facility will give the following positive results:

1) It will allow doing continuous quality control of products based on the analysis of the measured technological parameters and the actual condition of the equipment.

2) It will allow monitoring the state of the fleet of industrial equipment used and optimizing the costs of its maintenance.

3) It will allow the management staff of the enterprise to control the progress of the process and its significant parameters.

4) It will allow management of technical maintenance and regulation of industrial equipment in actual condition.

5) It will allow management of spare parts, tools and accessories based on knowledge of the actual condition of the equipment.

Acknowledgments
The research was supported by the Ministry of Science and Higher Education of the Russian Federation, unique identification number RFMEFI57817X0252.

References
[1] GOST 11068–81 Electric-welded pipes from corrosion-resistant steel. Technical conditions
[2] Siemens LTD (Official website: https://www.siemens-pro.ru/components/s7-1500.htm)
[3] Guzzetti SPA (Official site: http://www.guzzetti.com/en/azienda/) retrieved May 11, 2020
[4] A typical industry-specific technological database for the automated generation of sets of technological documentation for all types of technological conversions using licensed software products from Intermech 2019 URL: http://lab18.ipu.ru/projects/conf2006/2/22.htm (Retrieved December 13, 2019)
[5] GOST 34. 601. 90. Automated systems. The stages of creation
[6] Stephan H and Karl F 2000 Knowing plant – Decision supporting and planning for engineering design Intelligent Systems in Design and Manufacturing III. Proc. SPIE pp 376–384
[7] Popov E V 1987 Expert systems (Moscow: Nauka)
[8] Guide to ML.NET URL: https://docs.microsoft.com/ru-ru/dotnet/machine-learning/how-to-choose-an-ml-net-algorithm (Retrieved May 11, 2020)
[9] Description of the averaged perceptron algorithm URL: https://docs.microsoft.com/en-us/dotnet/api/microsoft.ml.trainers.averagedperceptrontrainer?view=ml-dotnet (Retrieved May 11, 2020)
[10] Frank Rosenblatt URL: https://ru.wikipedia.org/wiki/Rosenblatt,Frank (Retrieved May 11, 2020)
[11] Perceptron URL: https://ru.wikipedia.org/wiki/Perceptron