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INTELLIGENT PROCESS CONTROL FORECASTING SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK

Abstract. The research is aimed at developing a neural network model for network data processing, which can be used to control technological processes in modern metallurgical production at various stages of metal processing. The proposed system is characterized by high speed, accuracy, reliability and efficiency, which contributes to improving product quality. The system includes a cluster of network sensors that can be reconfigured and connected to a high-performance distributed system. It also provides a mechanism for redundancy of key components and is aimed at increasing the efficiency of the technological process at each stage.
Keywords: distributed computer system, reconfigurable network, neural network, computing nodes, sensor cluster, laser scanners, learning algorithms.

Problem statement. The need for modern systems for controlling process parameters is the basis of the strategic potential for the development of the industry and has important scientific, technological and economic significance. In metallurgical production, a number of problems arise related to the control of process parameters and their control systems. The main ones include:

Inaccuracy of the geometric parameters of rolled products, which is expressed in the deviation of its thickness and width. At the same time, unevenness of the thickness and width of the rolled products can lead to non-compliance of the product with quality standards due to roll wear, temperature fluctuations or other factors.

Problems with flatness, in this case, waviness or curvature of the rolled surface complicates its further processing and reduces the aesthetic characteristics of the product.

Surface defects are associated with various mechanical damage. Scratches, dents and other defects can occur due to contact with equipment or foreign particles during the process.

Metallurgical defects such as cracks, porosity, or inclusions of unwanted elements can occur due to imperfections in the starting material or process disruptions.

Uneven temperature distribution leads to internal stresses. In this case, uneven heating or cooling of the metal can lead to internal stresses that negatively affect the mechanical properties and durability of the product.

Thermal deformations, which are expressed as a difference in temperatures across the cross-section of the rolled product, can cause it to warp or other undesirable deformations.

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Equipment wear due to roll deformation. Constant contact with hot metal leads to roll wear, which can affect the quality of the rolled product and require frequent replacement or repair work.

Breakdowns of auxiliary equipment. Malfunctions in the feed, cooling, or other auxiliary mechanisms can lead to downtime and reduced productivity.

Modern methods for solving these problems include the use of distributed systems with clusters of network sensors for data pre-processing. The use of neural networks in combination with infrared sensors and laser scanners opens up new horizons for improving the processes of rolling and rolling of metals, reducing costs and increasing product quality.

Monitoring and control of temperature regimes of rolled products in this case leads to the improvement of technological processes and increasing the efficiency of its functioning. At the same time:

– the use of non-contact infrared sensors allows for accurate monitoring of the metal temperature in real time, ensuring prompt response to deviations in temperature regimes.

– the use of neural networks for the purpose of analyzing data from infrared sensors allows for the prediction of possible deviations in temperature regimes and the suggestion of corrective actions for uniform heating and cooling of rolled products.

High-precision control of geometric parameters can be carried out on the basis of laser scanners and neural networks. Thus, the use of laser scanners allows you to obtain detailed three-dimensional models of rolled products in real time, detecting the slightest deviations from the specified parameters. At the same time, processing data from laser scanners, neural networks can detect patterns and predict possible deviations, which allows you to quickly adjust the process parameters.

Automated detection and classification of metal surface defects is implemented based on the use of convolutional neural networks (CNN). In this case, thanks to the ability to recognize complex visual patterns, CNN networks can effectively detect and classify defects on the surface of rolled products. Images of the metal surface obtained using laser scanners can be analyzed by the CNN network for quick detection of defects.

Forecasting and management of equipment wear can be controlled based on equipment condition sensors. Installing such sensors to track vibrations, temperature and other parameters of equipment operation allows you to obtain data on its condition in real time. By analyzing data from sensors, neural networks can predict the time until a possible failure of equipment components, which allows you to plan maintenance and prevent unexpected breakdowns.

This approach helps solve a number of problems, increasing product quality and overall production efficiency.

Analysis of recent research and publications. Modern cluster network interfaces are a key component of industrial distributed systems. They include high-speed data transmission technologies. Among them are: InfiniBand - provides low latency and high bandwidth, which makes it ideal for high-performance computing; Ethernet (10/25/40/100GbE) - widely used in industrial systems due to its compatibility and flexibility, as well as support for software-defined networks (SDN); Fiber Channel - used for high-performance data storage, providing fast access to large amounts of information; PCIe over Fabric - allows for the effective combination of computing resources in distributed systems, improving scalability and efficiency of equipment use.

Consider the problem of rolling based on the use of infrared sensors in a cluster. Thus, in the process of rolling metals, especially when using high temperatures and high processing speeds, it is extremely important to constantly monitor technological parameters to ensure accuracy, quality and safety of the process. Infrared sensors are effective for this purpose, as they allow non-contact monitoring of temperature, movement and deformation of the material. The role of infrared sensors in the rolling process is as follows:

– Temperature control. Infrared sensors are used for non-contact measurement of the temperature of the metal passing through the rolls. This is critically important, since temperature determines the plasticity of the material and its ability to deform. The correct temperature regime ensures the efficiency of material processing and prevents its overheating or insufficient heating.

– Roll speed control. Infrared sensors can measure the speed of material movement through the rolls. This is important for adjusting the operating parameters of the rolls and achieving accuracy in processing, especially in cold rolling, where changes in the speed of rotation of the rolls can affect the properties of the finished product.

– Material condition monitoring. Infrared sensors located at several points in the rolling line allow monitoring of the condition of the metal at different stages of processing. This can include measuring material thickness, detecting defects or irregularities on the metal surface.

– Creating clusters of infrared sensors for rolling. To increase efficiency and reliability in the rolling process, several infrared sensors can be combined into a cluster. This allows for uniform monitoring of a large area or several parameters simultaneously.

– Temperature monitoring over the entire processing area. A cluster of sensors can create a network for measuring temperatures at all stages of rolling, from preheating to the final forming stage. This allows for real-time process adjustments, avoiding overheating or underheating of the metal.

– Surface defect analysis. Thanks to several sensors scanning the metal surface, defects, cracks or other problems can be effectively detected at the rolling stages. This allows for timely action to be taken to eliminate them and prevent product defects.

– Redundancy and safety. In the event of a sensor failure, the other sensors in the cluster can compensate for its functions, ensuring system continuity and reliability. This is important for ensuring smooth operation in the rolling process, where even minor failures can lead to significant losses.

The integration of infrared sensors into a cluster in the rolling process allows for high-precision monitoring and control, ensuring control of temperature, speed and material condition at all stages of processing. This allows not only to increase process efficiency, but also to improve product quality and ensure safety. The choice of an appropriate network interface significantly affects the efficiency of industrial distributed systems. At the same time, high-speed networks provide minimal delays in data exchange between cluster nodes,

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which is especially important for real-time [1]. High throughput allows for simultaneous processing of large amounts of data without the formation of “bottlenecks”. Flexibility of configuration allows for adapting the system to specific production requirements, including dynamic load distribution. The reduction in energy consumption is explained by the fact that the latest interfaces use less energy-consuming data transmission mechanisms, which reduces the overall cost of system maintenance [1].

The advantages of using neural networks in controlling metallurgical production parameters can be considered as follows:

– Improved accuracy of ANN measurements provide higher accuracy of parameter analysis compared to traditional methods. This is achieved through the use of deep learning algorithms for recognizing complex patterns, automatic error correction through self-learning [4].

Optimization of technological processes ANN allows you to automatically adjust process parameters to increase efficiency. At the same time, the following tasks are solved:

– Optimization of temperature regimes in metallurgy [5].
– Control of material dosing in chemical production [6].
– Control of engine rotation speed in robotics [7].
– Automation of control and reduction of the human factor.

The use of neural network systems reduces the likelihood of human errors: reduced dependence on operators, automatic detection of deviations and quick decision-making [8], prediction of malfunctions. Fault prediction algorithms can prevent accidents and reduce repair costs: predicting equipment wear, determining the risk of engine overheating, analyzing product quality, and predicting defects [9].

It is worth noting the challenges and limitations that arise in this context. One of the key aspects is the high computational complexity, since the effective operation of neural networks requires significant computing resources, in particular, the use of GPUs and TPUs for training models. In addition, such systems are characterized by high energy consumption requirements [10].

Another important factor is the need for large volumes of training data, since the quality of neural networks directly depends on their quantity and reliability. At the same time, there may be difficulties with access to real production data, as well as the risk of retraining on incomplete or incorrect data sets [11].

Special attention should be paid to the requirements for explainability of decisions, which is especially relevant for critical industries such as aviation, medicine, and energy. In these areas, it is important to understand the logic of the ANN decisions made, which necessitates the development of algorithms to explain the results obtained [12].

Unsolved part of the problem. Modern systems do not provide a comprehensive approach to the implementation of the technological process, combining product quality optimization and parameter matching to accelerate data processing. In addition, such systems lack mechanisms for system parameter prediction, which limits their effectiveness.

To date, the impact of the type of network interface and the performance of a distributed system on the overall efficiency of operation has also not been sufficiently studied. Most existing solutions are either too simplified at the controller level or excessively complex due to the complex architecture of the equipment and the high need for additional computing resources. This significantly complicates the universalization and scaling of such systems, making them unsuitable for widespread implementation.

The purpose. The purpose of the research is to develop a neural network for analyzing data from a cluster of sensors, which will ensure maximum versatility, efficiency and productivity in metal pressure processing systems. In addition, the system must be highly reliable and energy-efficient. The device units must be equipped with mass-production computing equipment.

The research also aims to:

– Development of methods for optimizing the rolling and rolling process by integrating the obtained data into the production control system.

– Automation of detection and classification of metal surface defects to improve product quality.

– Forecasting and prevention of technical equipment malfunctions based on analysis of wear and condition of rolls and auxiliary mechanisms.

– Development of algorithms for adaptive control of rolling parameters to ensure process stability under variable conditions.

– Reduction of production costs and increased energy efficiency through precise temperature control and optimization of rolling parameters.

These goals will allow us to create an intelligent process control system that will ensure high product quality, minimize defects, and increase productivity.

Main research material presentation. Let us define the design features of the neural network construction (fig. 1). The graphical model of the constructed neural network includes:

Input layer:

Input data: 6 values from infrared temperature sensors and 3 values from laser scanners. Total: 9 input neurons.

Hidden layers:

One or more hidden layers for detecting complex patterns in the data. The number of neurons depends on the complexity of the task. Two hidden layers: the first hidden layer: 64 neurons, the second hidden layer: 32 neurons.

Output layer:

The output layer depends on the purpose of the analysis. If the classification task is considered, then there will be one or more neurons for each class. If the regression task is, then the output can be one neuron for predicting a certain value. For simplicity, let's assume that the task is regression, then one neuron at the output for predicting the value.

Activation functions:

ReLU (Rectified Linear Unit) is usually used for hidden layers, as it works well for tasks where nonlinearities need to be modeled. For the output layer, depending on the task, Linear can be used for regression or Softmax for classification.

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Training algorithm:

To train the network, you can use the Backpropagation algorithm with an optimizer, such as Adam or SGD.

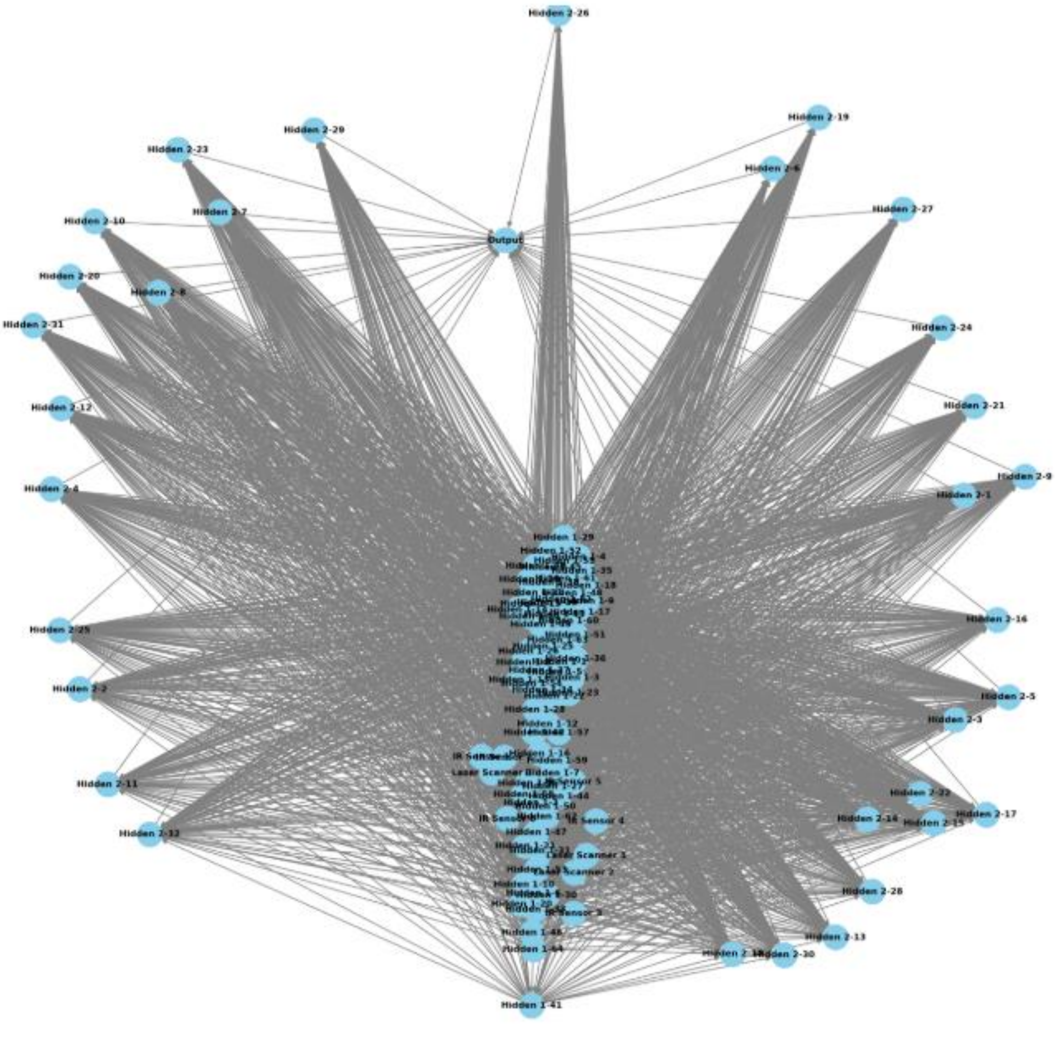
Algorithm and data processing. To build a graphical model of a neural network that analyzes data from six infrared sensors and three laser scanners, the following structure was proposed:

Infrared sensors (6 pieces): Used to measure temperature, distance, or object detection. Data from these sensors is represented as a vector of six elements, where each element corresponds to a measurement from a specific sensor.

Laser scanners (3 pieces): Generate high-precision data on the distance to objects in space. Data can be represented as a vector or matrix that describes the spatial geometry taking into account several measurements from each scanner.

The received input data is pre-processed, normalized, and transmitted to the neural network for further analysis, pattern recognition, and prediction of key parameters of the production process.

Let's consider the data processing algorithm in a neural network.



Fiure 1 - Structural diagram of a neural network

Neural network architecture. For the combined analysis of data from infrared sensors and laser scanners (fig.2), a multilayer neural network with the following structure is used:

Input layers:

Layer 1: Input data from 6 infrared sensors (vector of 6 values).

Layer 2: Input data from 3 laser scanners. If each scanner transmits several measurement points, the data can be represented as a vector or matrix.

Data processing:

Layers for infrared sensors: Processing can be carried out through several fully connected or convolutional layers, allowing to highlight key features.

Layers for laser scanners: Data is processed using convolutional layers or even recurrent neurons, if it is important to take into account spatio-temporal variability.

Data fusion and further processing:

After separate processing, the data from both groups of sensors is combined through a concatenation layer, which allows taking into account all available characteristics.

Then, it is possible to use several fully connected layers, the number of which depends on the complexity of the task.

The output layer depends on the purpose of the network:

If a classification problem is solved, then a layer with several neurons is used (according to the number of classes).

If a regression problem is investigated, then the output layer contains one neuron for predicting a numerical value.

Functionality of infrared sensors:

Infrared sensors are used to measure temperature and distance, which helps to determine the position of objects, their proximity and temperature state in the production process.

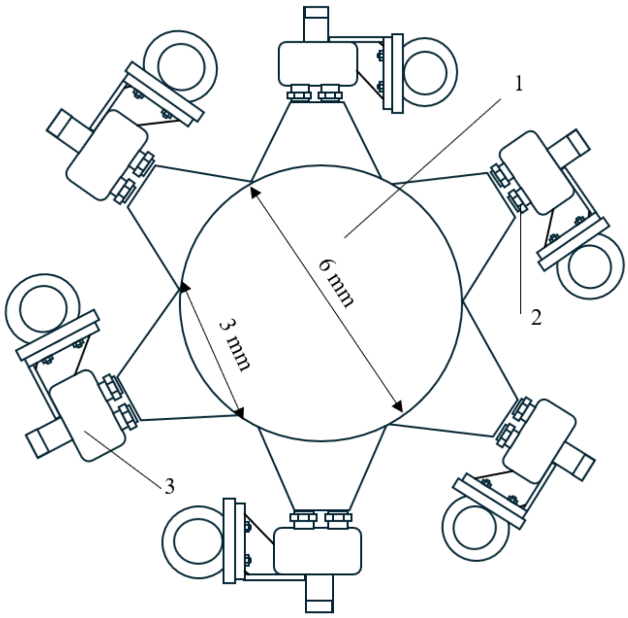


Figure 2 - Layout of infrared sensors: 1 – sample (rod of the required diameter), 2 – measurement zone (segment), 3 – infrared sensor in the cluster

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Let us consider the features of using laser scanners. It should be noted that laser scanners provide more accurate and detailed data on spatial geometry. They can also be used to create 3D models of objects or map the environment, which is important for analyzing the shape, location and movement of objects.

The analysis also allowed us to identify the types of neural networks for solving the problems set in this study. These are:

– *Convolutional Neural Network (CNN):* most suitable for analyzing spatial data, such as images or 3D objects, so it can be used to process information from laser scanners.

– *Fully Connected Neural Network:* best suited for working with tabular data, in particular information obtained from infrared sensors.

Data preparation and effective training of a neural network consists of the following:

– *Cleaning and normalizing data*, since different types of sensors can operate in different ranges of values.

– *Selection of the appropriate loss function:*

For regression tasks – mean square error (MSE).

For classification tasks – cross-entropy.

To implement individual neural networks that analyze data from six infrared sensors and three laser scanners, the Keras library with TensorFlow in the Python programming language environment was used.

Conclusions. The conducted research has shown that the use of neural networks, clusters of infrared sensors and laser scanners opens up significant opportunities for improving product quality, optimizing production processes and reducing costs. The integration of modern technologies not only automates parameter control, but also allows you to predict deviations, ensuring stability and efficiency of production.

The key benefits of implementing the proposed intelligent technology are as follows.

Increasing the accuracy of the geometric parameters of rolled products.

Laser scanners provide continuous measurement of the thickness, width and flatness of rolled products, which helps to minimize deviations from standards. Neural networks analyze the data received and automatically adjust the operating modes of the rolling mill, ensuring stable quality of the final product.

Reducing surface defects.

The use of deep neural networks (CNN) in combination with laser scanners allows you to detect even the smallest defects on the metal surface in real time. This allows you to quickly eliminate problems, reducing the need for reprocessing or product scrapping.

Optimization of temperature regimes.

Infrared sensors provide precise control of metal temperature at all stages of processing, which allows to avoid non-uniform heating or cooling. Neural networks predict temperature fluctuations and automatically adjust heating and rolling regimes, which helps to reduce internal stresses and thermal deformations.

Forecasting and reducing equipment wear.

Intelligent analysis of the condition of rolls and auxiliary equipment allows to predict their wear and prevent emergency situations. This significantly reduces repair costs and extends the service life of the equipment.

Automation of control and increasing energy efficiency.

Intelligent algorithms provide adaptive control of the rolling process, which allows to reduce energy costs and optimize the use of materials. This not only improves the economic performance of production, but also reduces the environmental load.

In addition, the implementation of modern technologies allows: to ensure stable product quality without the need for frequent manual checks, to reduce waste and minimize costs for additional processing, to speed up production processes through real-time parameter control, to reduce equipment failure rates and ensure continuous production.

The implementation of the technologies presented in this study is a key stage in the modernization of production, which contributes to the creation of intelligent metallurgical enterprises.

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Інтелектуальна система прогнозування управління технологічним процесом на основі штучної нейронної мережі

Дослідження спрямовані на розробку моделі нейронної мережі для обробки мережевих даних, яка може бути використана для управління технологічними процесами в сучасному металургійному виробництві на різних етапах обробки металу. Запропонована система відзначається високою швидкодією, точністю, надійністю та ефективністю, що сприяє покращенню якості продукції. Система включає кластер мережевих датчиків, які можна реконфігурувати та підключити до високопродуктивної розподіленої системи. Вона також забезпечує механізм резервування ключових компонентів і спрямована на підвищення ефективності технологічного процесу на на кожному його етапі.

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