PREDICTIVE ANALYTICS FOR INDUSTRY 4.0

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Abstract: *The Industrial Predictive Analytics for Industry 4.0 is a system that predict and prevent machine failures and breakdown by analyzing time-series data (temperature, pressure, vibration etc.) received from sensors embedded in machines and equipment. The system can analyze machine parameters to identify patterns and predict breakdowns before they happen. The core of the proposed system is based on Artificial Neural Network approach (both Deep and Shallow Neural Networks). Artificial Intelligence and Artificial Neural Networks allow analyses the huge amounts of data collected from the manufacturing process and predict what will go wrong, and when. The proposed system works in the paradigm of Industry 4.0 and provides the abilities in the area of predictive maintenance. The Industrial Predictive Analytics for Industry 4.0 also contains a decision-making system and support system that significantly increases the level of maintenance.*

Keywords: INDUSTRY 4.0, SMART FACTORY, PREDICTIVE MAINTENANCE, ARTIFICIAL INTELLIGENCE

1. Introduction

The progress within the framework of the fourth industrial revolution "Industry 4.0" combined such elements as automation, exchange and analysis of industrial data, cyber physical systems, the industrial Internet of things, cloud computing etc. and lead production processes to a new level.

The evolution of information technologies offers great opportunities in the area of industrial data analysis - collection, processing, analysis and visualization of large amount of heterogeneous data that to improve existing industrial information processing systems. Thus, embedded devices, such as different sensors, allows receive a valuable information about the usage of industrial equipment during the whole production cycle. This information play important role in the building of new business models and provide additional income from the new services such as for example, a life cycle contract for industrial equipment, contract manufacturing as a service, transportation as a service, safety as a service, and others.

For the analysis of constantly increasing industrial data flows, new powerful data processing methods are needed. The evolution of Artificial Intelligence in general, and in particular, Artificial Neural Networks, makes it possible to design, develop and implement such systems that can successfully analyze huge data flows, provides extreme automation and, as a result, allows develop high quality industrial support approaches.

The present-day industry involves the interconnection of a large number of various equipment, which require constant monitoring, maintenance and repairing. The concept of Industry 4.0 allows analyze data received from sensors installed in industrial equipment in order to detect a hardware and functional failure even before something serious has happened. Now there is an urgent need to switch from reactive maintenance (breakdown service while a machine can no longer function normally) or scheduled maintenance (that ignore an actual load specific machines and assemblies) to proactive and predictive maintenances.

Artificial intelligence methods allow detect potential equipment problems at an early stage of a breakdown and eliminate them before minor defects lead to big problems - expensive equipment breakdown and stop the production process. In this way, the predictive analytics can provide answers not only to the questions such as "What happened?" or "Why did this happen?", but also "What is likely to happen?" and "What can we do, to prevent this?".

Within the framework of the discussed problems, we developed the system "Predictive analytics for Industry 4.0" which based on the Artificial Neural Networks and monitors equipment condition and production processes in real time.

The rest of the paper is structured as follows. Section 2 gives the theoretical aspects of Artificial Neural Networks implementations in the Industry 4.0 paradigm. Section 3 provides the experiment description and results. The final section concludes this paper.

2. Artificial Intelligence for Industry 4.0

2.1. Theory of Artificial Intelligence

An Artificial Neural Network is a model built on the principle of the organization and functioning of biological neural networks (brain) and consists of several layers of computational elements - neurons. The main feature of artificial neural networks is their learning ability. ANNs are not programmed in the classical programming paradigm, but are learned. Learning ability is one of the main advantages of neural networks over traditional algorithms. Technically, training consists in finding the coefficients (called weights) of connections between neurons in different layers. In the learning process, a neural network is able to identify complex hidden relationships between input and output data. After the training phase, neural networks are capable of working with data, even if they are incomplete or noisy data.

Today, there are many architectures of artificial neural networks. The wide variety of neural networks can be divided into two large groups – Shallow and Deep Neural Networks.

Shallow neural network is a term used to describe artificial neural networks that usually have only one hidden (computational) layer as opposed to deep neural networks that have several hidden layers, often of various types. The classical example of shallow neural network is a Multilayer Perceptron (MLP) [1]. A MLP is a feedforward artificial neural network that consists of three layers (Fig.1) – input layer, hidden layer and output layer - and can solve accurately complex tasks.

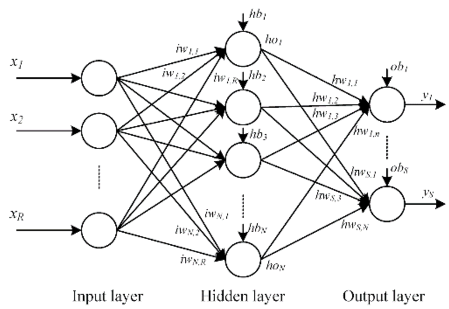

Fig. 1 *Structure of a Shallow Neural Network*

Input layer send data to all the neurons in the Hidden (processing) layer. The number of neurons in the Input layer depends on the size of the input vector x_1-x_R. Hidden layer is a second layer of a neural network. It is the main layer that process the inputted data. The optimal number of neurons in the Hidden layer is usually determined experimentally. Output layer is a final layer of neural network. It reflects the calculation results y_1-y_S. The weights $iw_{N,R}$ between input and hidden layers and $hw_{S,N}$ between hidden and output layers are configured at the training stage.

The described architecture of ANN can be successfully used for solving such problem as pattern recognition, time-series forecasting, approximation, classification and many others.

However, to solve modern technical problems the implementation of classical architecture of neural networks is no longer enough. They were replaced by Deep Neural Networks - are a class of neural networks that consists of large and complex hidden component between the input and output layers, giving them a greater ability to recognize patterns and process complex information than Shallow Neural Networks. Fig.2 demonstrates a classical structure of deep neural networks.

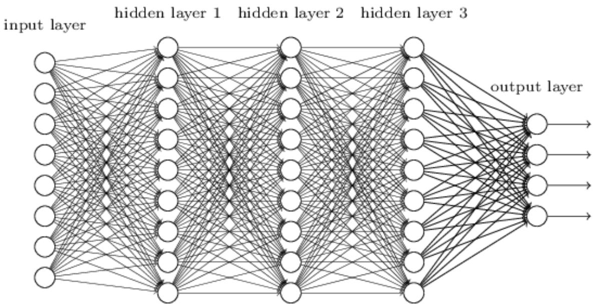

Fig. 2 *Structure of a Deep Neural Network*

To be considered a deep neural network, the structure must contain at least two hidden layers. The area of application of Deep Neural Networks includes (but not limited) image and video recognition, time-series analysis, forecasting and prediction, control etc.

2.2. Predictive Analytics

In our research, we used both Shallow and Deep Artificial Neural Networks for the forecasting of the industrial equipment parameters, such as temperature, vibration, pressure etc. Fig.3 demonstrates the neural network training process.

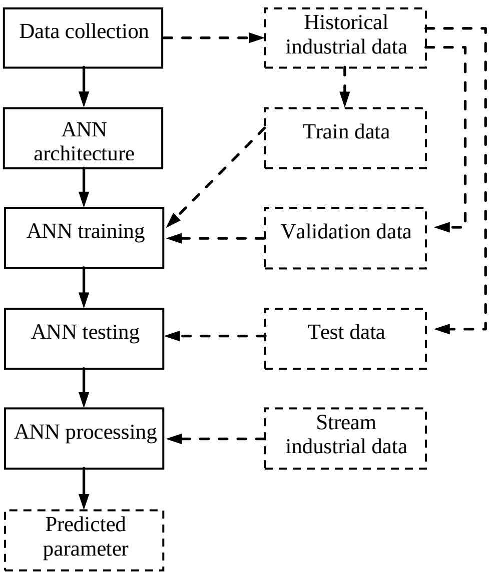

Fig. 3 *Stages of a neural network creation*

Data collection. Machine data (such parameters of equipment as vibration, temperature, pressure etc.) is streamed from the sensors to a central repository using communication protocols and gateways - this is the typical task for SCADA (Supervisory Control and Data Acquisition - is a control system architecture that uses computers, networked data communications and graphical user interfaces for high-level process supervisory management). However, SCADA only can show the current machine conditions. Fig.4 demonstrate the example of data from the turbine of JSC ”Lakokraska” [2].

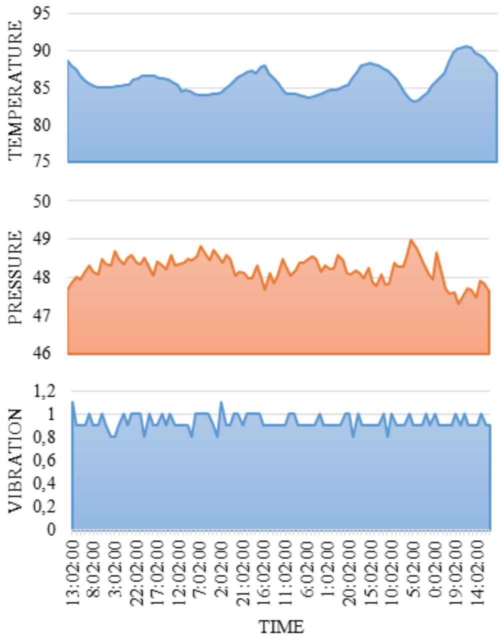

Fig. 4 *Example of industrial data: temperature, pressure and vibration*

Neural network creation. Data structure defines the architecture of an artificial neural network that will be used to predict of machine parameters because received data can be incomplete, noisy, non-regular and multidimensional.

Neural network training and testing. For the training of an ANN with the chosen architecture, we use historical data of the equipment that will be controlled. Of course, the quality, as well as the completeness of the data determines the quality of the training of neural network and the further forecasting of equipment parameters.

For the training of an artificial neural network all available historical data is divided into three subsets. The first subset is the training set, which is used for training and updating the network weights. To avoid the problem of overfitting the neural network and to early stop the learning process, a validation sample (the second subset) is used. The error on the validation set is monitored during the training process. When the network begins to overfit the data, the error on the validation set typically begins to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights of an ANN at the minimum of the validation error are returned. The test set (the third subset) is not used during training, but it is used to better estimation the correct functioning of a trained neural network and to compare different models. In the classical scheme for division data into training, validation, and test sets, the relation 70%-10%-20% of the whole data amount is used correspondingly. Figure 5 shows the changing of neural network’s error value during the training process.

Preprocessing data is another important step in the working of artificial neural networks. The goal of this stage is prepare raw industrial data in a format that the network can accept and analyze. For example, you can preprocess data to enhance desired features or reduce artifacts that can bias the network, as well as you can normalize or remove noise from input data.

ANN working. After the training an artificial neural network can be used for the analyzing of the industrial data. In our study we learn neural network to predict the values of parameters to the given time horizon – (1 minutes, 5 minutes, 1 hour, etc.). The predicted condition of the equipment will allow the technical staff to receive forecasted objective and precise data about the current and near future state of the production process and machine condition, which will allow quickly react to probably breakdown and schedule maintenance and servicing procedures.

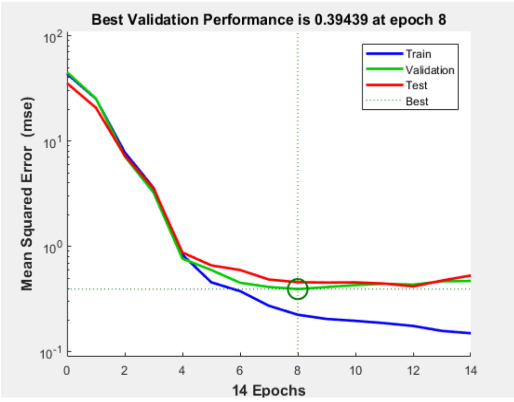

Fig. 5 *Example of industrial data: temperature, pressure and vibration*

3. Experimental results

The developed Predicted Analytics system for Industry 4.0 was tested on several real industrial environments and real data. The first implementation and was JSC "Lakokraska" [2]. The pilot project for the forecasting of parameters for turbine was developed and tested. The proposed system of Predictive Analytics received such data in real time as pressure, vibration and temperature, analyzed them and gave a forecast of the values of the observed parameters for 1, 5, 10 and 24 hours.

Figure 6 shows historical data that was used for the training of feedforward shallow neural network [3].

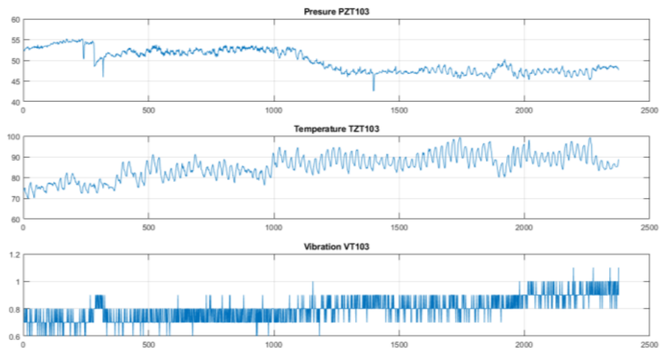

Fig. 5 *Industrial data JSC "Lakokraska"*

We used the feedforward neural network (Fig.1) with the following structure: 25 neurons in an input layer (it means that each time we input to an ANN the current value of the controlled parameter + 24 historical values); 50 neurons in a hidden layer; and 4 neurons in an output layer (where the first neuron reflects the forecast results for 1 hour, the second neuron reflects the forecast for 5 hours, the third and fourth neurons reflect forecasts for 10 and 14 hors correspondingly).

After the training, we implemented this neural network for data analyzing and forecasting in real time. Figure 6 demonstrates some results of the quality for 1-hour forecast and Table 1 presents the results for all forecasting horizons.

As can be seen, the Mean Absolute Percentage Error (MAPE) for 1-hour prediction is 0.27% for pressure, 0.25% for temperature, and 5.4% for vibration. MAPE - is a measure of prediction accuracy of a forecasting method and usually expresses accuracy as a percentage [4]. It defined by the formula (1):

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \qquad (1)$$

where A_t is the actual value and F_t is the forecasted value.

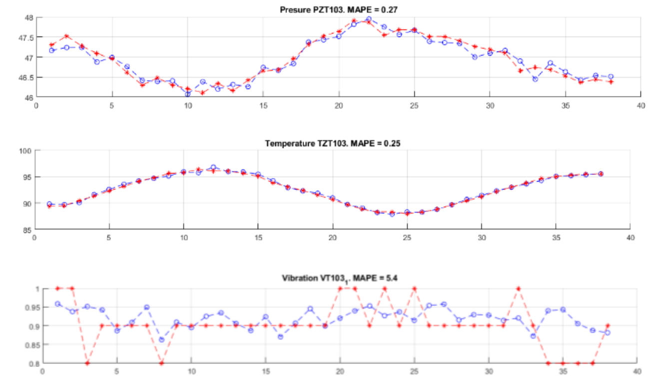

Fig. 6 *Prediction results. The red line is real data, blue line – predicted values*

Table 1: *Prediction error values for all time horizons.*

	MAPE for each horizon, %		Average MAPE, %
Temperature (TZT103)	1H:	0.48	1.41
	5H:	1.29	
	10H:	1.80	
	24H:	2.06	
Pressure (PZT103)	1H:	0.35	0.72
	5H:	0.69	
	10H:	0.88	
	24H:	0.95	
Vibration (VT103)	1H:	5.50	5.82
	5H:	5.16	
	10H:	6.55	
	24H:	6.08	

We can see that proposed feedforward shallow neural network predict the controlled parameters for each time horizon very well, that confirmed by the values of MAPE. But, the prediction values of vibration are not so good compared to temperature and vibration. In our opinion, it occurs due to a sufficiently large time interval for the arrival of new portion of data (new value for one hour). All this leads to a "sawtooth" shape behavior of the vibration parameter, which is rather poorly predicted. Increasing the frequency of measurements will increase the quality of the forecast of the proposed feedforward shallow neural network. If this is not possible, it will achieved by selection a more complex architecture of neural network.

The next example demonstrates the increasing of the quality prediction by the implementation of deep artificial neural networks. Both shallow neural network (in our case it is MLP) and deep neural network (Deep LSTM) was used to predict the bearing quota parameter for STS Machines (data was provided by Opera MES company [5]). Figure 7 demonstrates the prediction results from MLP and Figure 8 demonstrates the predictions form Deep LSTM [6, 7].

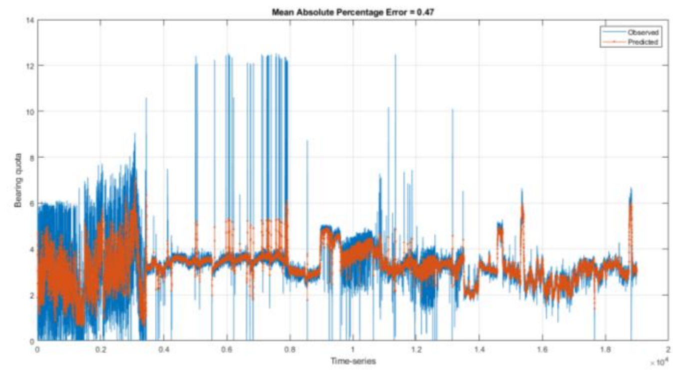

Fig. 7 *Bearing parameter prediction results by MLP neural network*

Long Short-Term Memory Neural Network (LSTM) is a unique type of Recurrent Neural Network capable of learning long-term dependencies. With comparison of feedforward neural networks, where signals go only in one direction – forward, LSTM has feedback connections. This ability allows LSTM networks show outstanding results in classification and prediction time series data.

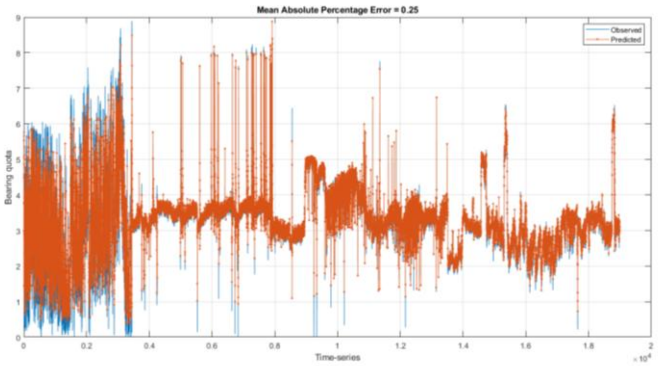

Fig. 8 Bearing parameter prediction results by Deep LSTM neural network

As can be seen from presented results, the implementation of more difficult structure of ANN like a Deep LSTM allow to increase the quality and accuracy of predictions by 50%.

4. Conclusions

Industry 4.0 is the phase of the industrial revolution, involving advanced manufacturing techniques and the Internet of Things coming together to create a “smart factory.” The smart factory is where cyber-physical systems collaborate with each other and monitor physical processes of a factory to make decentralized decisions. It has led to significant reduction of downtime and wastage bringing in quality and efficiency in factory production. The Predictive Analytics is a big important part of Industry 4.0 concept.

In this paper we presented artificial neural network approach for forecasting the equipment parameters and control the conditions of industrial machines in the Industry 4.0 paradigm. The proposed Predictive Analytics system performs a real-time analysis of large data streams, built in the Industrial Internet of Things (IIoT) standard, allows industrial to be more proactive, make preemptive actions in the maintenance of industrial equipment and the optimize industrial processes. Implementation of this system will allow enterprises from different sectors of the economy and industry to obtain significant advantages, namely:

- automate the process of monitoring and managing the equipment life cycle;
- modeling of technological processes;
- increase the efficiency of the use of production assets by reducing the number of unplanned downtime;
- reduce maintenance costs by improving forecasting and preventing catastrophic equipment failures and identifying inefficient operations;
- increase productivity;
- increase energy efficiency and reduce operating costs.

We demonstrated that the changing the architecture of artificial neural network from MLP to LSTM significantly increase the prediction accuracy.

We implemented and tested our systems in real factories JSC “Lakokraska” and Opera MES. The developed system makes predictions on several time horizons, up to 24 hours, of important parameters of industrial equipment with great accuracy.

Acknowledgments

We would like to thank Mr. Maxim Khakhalov, a founder of Qnitel Ltd., who kindly support this research.

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