Possibilities of using an autoencoder network in the failure state recognition

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Abstract: *Approaches to machine and equipment maintenance based on data analytics and artificial intelligence are trending in modern manufacturing. These methods are used to predict the remaining useful life (RUL) of equipment and thus enable forward maintenance planning. However, for predictive maintenance systems, it is also necessary to detect anomalies in operation and classify the occurring errors. Classical approaches of supervised machine learning are often in this case unusable because those methods require a large amount of run-to-failure data (R2F), which is often not possible to collect due to the undesirable character of failure states in the manufacturing process. The paper presents and tests several methods of detecting device fault states using an autoencoder network, which offers a beneficial solution in the case of the unavailability of R2F data in the system.*
Keywords*: PREDICTIVE MAINTENENCE, AUTOENCODER NETWORK, FAULT DETECTION, DATA RECONSTRUCTION*

1. Introduction

In modern production, with the increase in production capacity, the requirements for manufacturing process productivity are also increasing. However, maintaining the productivity of the production process is only possible with a fault-free operation process of all machines and equipment that are included in the observed production process.

Keeping the operability and the fault-free state of the equipment is the task of maintenance. There are many maintenance strategies, which are divided according to the time of performing (pre-failure or post-failure maintenance), the level of intervention (full repair or partial repair), or also based on the time intervals of execution (systematic, conditional, or planned) [3]. This research is focused on predictive maintenance (PdM) as a modern maintenance trend. The goal of this approach is to increase uptime, reduce maintenance costs, and improve safety by identifying and correcting potential problems before they cause a breakdown or accident.

Using sensors, data analysis, and machine learning algorithms, PdM can provide real-time information about the performance of various components of systems. By collecting and analyzing data on factors such as temperature, vibration, and noise levels, predictive maintenance algorithms can detect early warning signs of equipment failure and alert responsible persons. Also, an important task of PdM is the detection and subsequent classification of abnormal device states and the definition of condition indicators (CIs).

Commonly used machine learning algorithms include NAR and NARX neural networks [4,9], convolutional neural networks [6,7], LSTM networks [1], and hybrid approaches [2]. However, these algorithms belong to the group of supervised learning algorithms, for the training of which a large amount of labeled data, which contains possible faults and errors in the operation of the observed device is required. That could be a problem if the observed system starts to become more complex and contains many possible fault scenarios.

Based on the analysis of existing research for the solution to the given problem, it was investigated the possibility of using an autoencoder for anomaly detection in the operation of the test equipment.

2. Training and experimental data

Training and experimental data were collected using equipment developed for testing prediction models. The scheme of the testing device is shown in Fig. 1 The device essentially consists of a hydraulic circuit with the ability to heat and pump the working fluid. A set of sensors placed on the device allows sensing of the fluid temperature at three points in the hydraulic circuit, the temperature of the heat exchanger, the flow rate and pressure in the system, and the electrical current and voltage in the electrical circuit. The device is also equipped with an ambient temperature and air humidity sensor for the possibility of investigating the influence of external factors on the operating characteristics of the device.

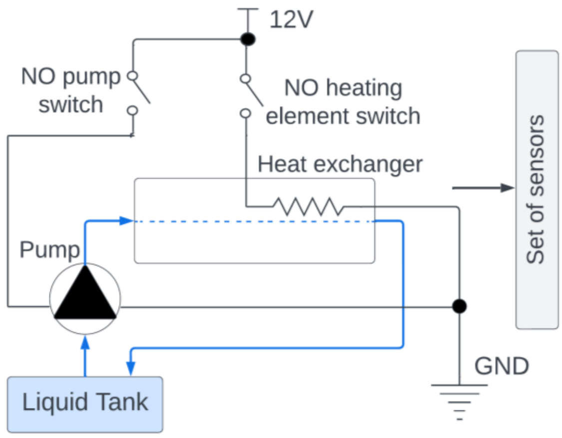

Fig. 1 *Scheme of the testing device*

The control of the working cycle is realized by the Arduino UNO microcontroller. Data acquisition is realized by Arduino MEGA microcontroller with a frequency of 1 measurement every 5 seconds.

Since the proposed neural network should act as an anomalous condition detector in the device operation, the training dataset contains only error-free data. In the context of the present work, error-free data means data while sensing of which there was no abrupt change in the behavior of any of the 10 sensed parameters.

To test the proposed model, it were used two test datasets. Firs dataset contains error-free data and would be applied for testing the ability of the autoencoder to reconstruct the correct waveform of value changes for the new data. The second dataset contains data that are affected by a change in the climatic conditions of the room where the equipment is located. This dataset would be used for evaluating the ability to detect anomalies.

The slight temperature differences at the beginning of the data collection are explained by the 1-2°C differences in ambient temperature at the beginning of the equipment run on each day that the data collection took place.

3. An autoencoder model

Autoencoders (AEs) are the unsupervised learned type of neural network whose primary applications are data compression and dimensionality reduction. However, some studies [5,8] show that AEs can be also implemented as anomaly or fault detectors in machinery.

Autoencoders are trained to learn a compressed representation of input data and then can reconstruct outputs based on only a compressed representation of data. The input to the autoencoder is a fault-free sequence of one or multiple sensor data, and the output is the same sequence but reconstructed by the decoder. This way during the training process, the autoencoder learns to reconstruct the normal operating conditions of the machinery. During training, the autoencoder learns to reconstruct the normal operating conditions of the machinery.

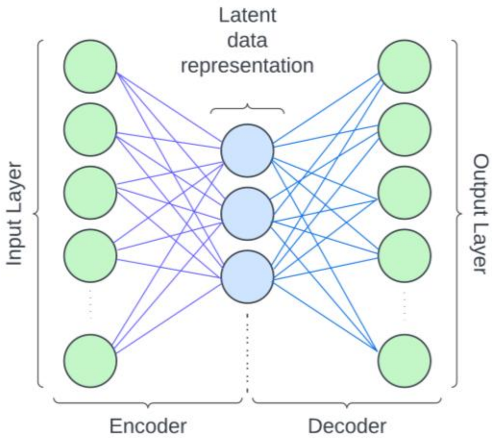

Fig. 2 Basic autoencoder architecture

As it is shown in Fig. 2, schematic autoencoder architecture consists of 3 main parts: encoder, decoder, and compressed latent representation. The latent representation or bottleneck forces a neural network not only to copy the input but to learn only the specific features of data which are useful for the next data reconstruction. Once the autoencoder is trained, it can be used to detect anomalies in the sensor data. When new sensor data is fed into the autoencoder, the output of the decoder will be different from the input if the data contains an anomaly.

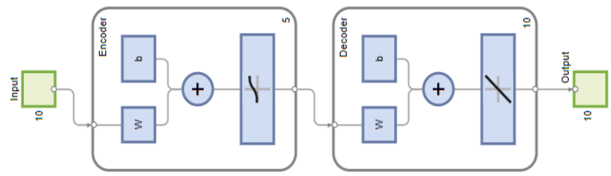

Fig. 3 Proposed network architecture

In this paper, we proposed an autoencoder model in MATLAB software. The model is shown in Fig. 3. It consists of 3 layers: 5 neurons bottleneck layer, 10 neurons input layer with a logistic sigmoid transfer function, and 10 neurons output layer with a linear transfer function. The neural network was trained on the fault-free dataset with 10 input features and 5633 samples corresponding to 7,5 hours of real-time measurement.

4. Evaluation of the purposed autoencoder network

After training the neural network, the ability of the autoencoder to reconstruct already-known data was first tested. Some reconstructed features compared to the original data are shown in Fig. 4.

As it can be seen in Fig. 4 (a-c) the neural network can reconstruct the known data with the repeating character of the pattern with good accuracy. For data with a more complex nature of change over time (ambient temperature, Fig. 4d) the reconstruction is a more difficult task since it is difficult to estimate the nature of the change in this parameter. Thus, it is possible to say that the architecture of the autoencoder is adequate and the neural network works correctly.

The next step is to test the ability of the superimposed autoencoder to predict data that was not part of the training. To assess the accuracy of the reconstructed data, it was used the MSE (mean squared error) function.

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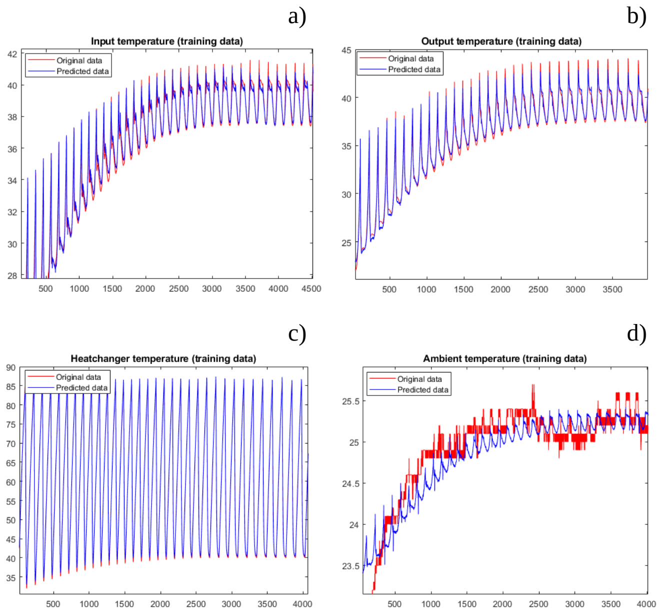

Fig. 4 Reconstruction of training data features a) Input temperature; b) Output temperature; c) Heat exchanger temperature; d) Ambient temperature

First, the autoencoder was tested for prediction on the new error-free data. The test error-free dataset contains 5419 samples and 10 features. Reconstruction plots for the same 4 features are shown in Fig. 5.

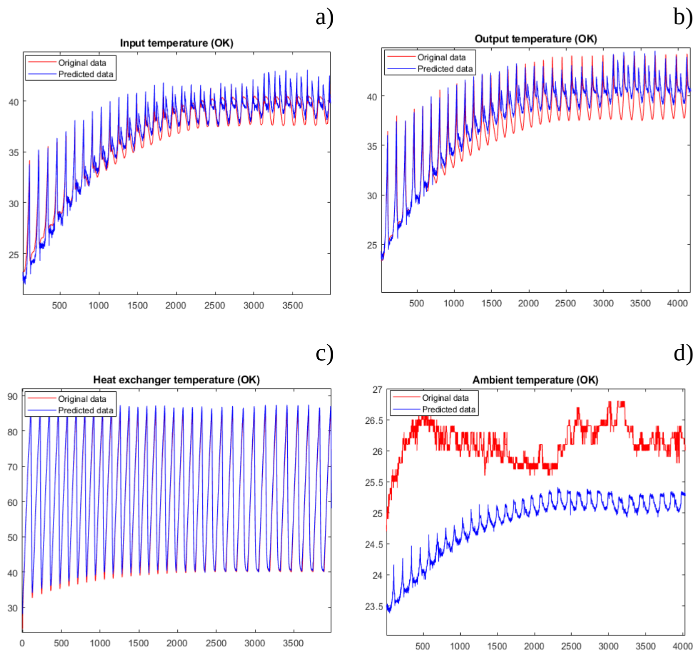

Fig. 5 Reconstruction of no-error data features a) Input temperature; b) Output temperature; c) Heat exchanger temperature; d) Ambient temperature

Next, the model input was fed with data that may be perceived as erroneous. In this case, the error appeared in the premature cooling of the working fluid due to the external environment. This error is mainly seen in the variation between the input temperature and the ambient temperature (see Fig. 6). The dataset containing the anomaly contains 5523 samples. The values showing anomalous behavior are between 3700 and 3800 measurement steps.

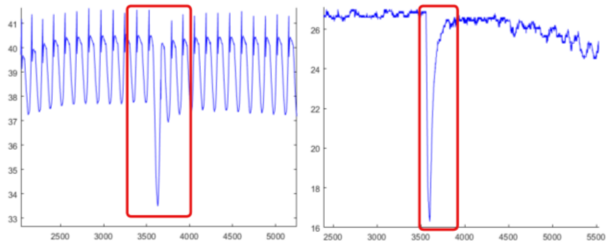

Fig. 6 *Anomaly in feature patterns behavior*

The sphere of interest of the model behavior, in this case, is whether this error is reflected in the sign of the parameter sensing waveform and in the computation of the model accuracy metric. The result plots of the prediction on the error data for inlet and outlet temperature, heat exchanger temperature, and ambient temperature are shown in Fig. 7.

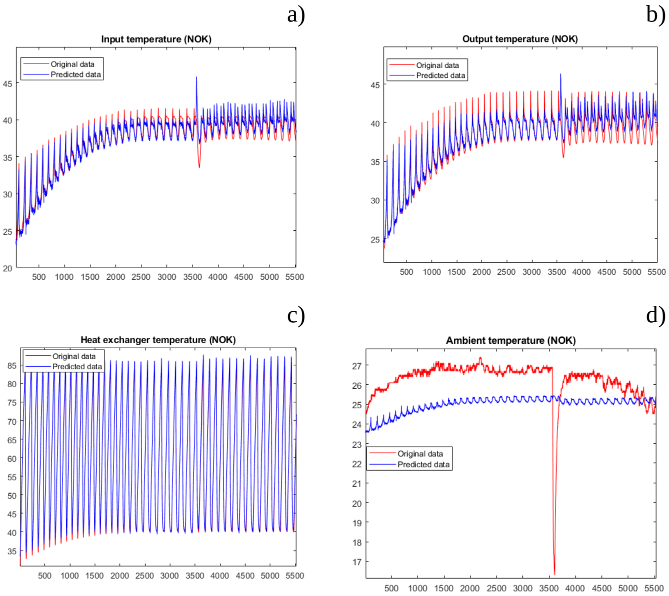

Fig. 7 *Reconstruction of anomaly data features a) Input temperature; b) Output temperature; c) Heat exchanger temperature; d) Ambient temperature*

The calculated MSE metrics for each parameter and dataset are shown in Table 1.

Table 1: *Mean-squared error metrics*

	Input temperature	Output temperature	Heat exchanger temperature	Ambient temperature
Training dataset	0.1755	0.1911	0.1914	0.0779
No-error dataset	0.7863	1.8765	1.0808	1.5030
Anomaly dataset	0.8643	1.3275	0.7792	2.8067

5. Results and discussions

In this paper, 4 parameters of the test equipment were monitored: the temperatures at the input and the output to the heat exchanger, the temperature of the heat exchanger, and the ambient environment temperature.

The superimposed neural network was tested on two test datasets, one of which contained examples of the anomalous behavior of the system. As it can be seen in Fig. 4, Fig. 5 and Fig. 7(a-c) the presented autoencoder model shows good results when reconstructing the dependencies between parameters on the new data. The success of the model is mainly shown when reconstructing a signal with a repeating pattern (inlet, outlet, and heat exchanger temperatures). The performance of the ambient temperature reconstruction is low (see Fig. 5d, Fig. 7d) as this parameter is generally difficult to predict and estimate.

The ability of the model to detect anomalies can be seen in Fig. 7(a,b). If there was an unexpected change in the waveform of the basin data, the waveform of the predicted value also changed its behavior for the parameters on which the anomalous behavior was occurring.

The occurrence of an anomaly is also indicated by an increase in the MSE value compared to the error-free dataset (see Table 1). The decrease of the MSE value in the anomalous dataset for the outlet temperature and heat exchanger temperatures can be explained by external conditions. Each of the datasets used was collected on a different day and the same climatic conditions could not be ensured in the location where the data collection took place.

6. Conclusions

Development and improvement of the proposed model would be possible by training the model on a larger amount of error-free data to cover a larger range of temperature parameters. The accuracy of prediction and detection of anomalies could also be improved by using the ambient temperature as a complementary parameter, increasing the overall accuracy of the model. The exact influence of this parameter on model accuracy is the subject of further research.

The ability to detect anomalies is powerful when R2F data are not available and provides an opportunity to estimate indicators of non-failure operating conditions. With the availability of data on errors and anomalous device states, the purposed model can be combined with classifier layers to classify existing anomalies. These factors show that autoencoders have perspectives for use in predictive maintenance tasks.

Acknowledgments

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