Artificial Neural Network Approach for Estimating Operating Parameters for Predictive Maintenance of Hydraulic Circuit

Ivan Kuric, Daria Fedorova(✉), Ivan Zajačko, Vladimír Tlach, Vladimír Stenchlák, and Andrej Bencel

Department of Automation and Production Systems, Faculty of Mechanical Engineering, University of Zilina, Univerzitná 8215/1, 010 26 Žilina, Slovakia
daria.fedorova@fstroj.uniza.sk

Abstract. This paper deals with the problem of model interpretability of neural network black box models in the terms of predictive maintenance. A testing device for the evaluation of predictive AI models has been presented. The experiment consisted in testing a feedforward neural network model, which was designed for the approximation of a complex multiparametric function and prediction of the monitored parameter (temperature of the working fluid in the tank). Favorable results were obtained for predicting the value of temperature in the working fluid tank based on the other simulation parameters and the simulation run time. Verification of the reliability of the prediction was carried out by additional neural network testing on new data. Correlation surface plots were also plotted and analyzed for the extracted dependencies between the parameters used for the prediction of the parameter of interest using the neural network. The achieved results have perspectives for processing the results obtained by neural network prediction in the field of predictive analytics and maintenance.

Keywords: feedforward neural network · predictive maintenance · correlation surfaces

1 Introduction

Maintenance of machinery and equipment is important to ensure reliable operation and prevent unplanned downtime. Unplanned machine and equipment downtime can have a major impact on production, product quality, and overall operational efficiency. In addition, repairs following unplanned downtimes are usually more costly than preventive maintenance, which allows problems to be identified and failures to be prevented before they occur. For this reason, the importance of maintenance to the industry can hardly be underestimated.

The main objective of maintenance is to keep machinery up and running, which means ensuring that the production process runs as smoothly as possible, minimizing production downtime, and eliminating the negative consequences of machine downtime.

V. C. M. Leung et al. (Eds.): Qshine 2023, LNICST 574, pp. 391–406, 2024.
https://doi.org/10.1007/978-3-031-65123-6_29

Also, maintenance objectives include attaining and prolonging the planned technical life of production machines, minimizing hazards for environmental damage, and preventing work accidents and damage to the health of employees (Červeňan 2015; Petra Marková 2008).

Nowadays, the maintenance of machinery and equipment is increasingly associated with modern technologies and analytical methods. Predictive maintenance, which uses operational data on the current state of machinery and equipment, makes it possible to identify potential problems in systems before a breakdown or failure occurs. This method thus helps prevent costly repairs and reduces unplanned production downtime (Quattrocchi et al. 2021).

Predictive maintenance uses a variety of technologies and methods to collect and analyze data from technical systems. One of the most widespread technologies is sensors that collect data on system operating parameters (condition monitoring) (Janssens et al. 2016; Liu et al. 2009). Based on this data, various data analysis methods can then be applied to identify patterns and dependencies between parameters.

For condition-based and predictive maintenance applications, several different approaches can be divided into three main categories:

– model-based, usually models based on the physics of faults;
– based on condition monitoring data;
– knowledge-based, relying on the judgment of an expert in the field (Fink 2020).

One of the most advanced methods of predictive analysis is the use of neural networks. Compared to statistical prediction models, ANN-based models have a distinct advantage in that they approximate nonlinear complex functions well. At the same time, however, they are criticized for their difficult interpretability (they are mostly black box models) (Dang et al. 2019; Kumar and Garg 2018; Fathi et al. 2021; Mustafaraj et al. 2011).

It is the interpretation of the data that is key to properly designing a predictive model for a reliable maintenance system. Therefore, this paper deals with the interpretation of the proposed forward feedforward neural network (FFNN) model that approximates a complex multiparametric function of the dependence of the temperature in the water tank on the other operating parameters of the test equipment. The results of this analysis should then be used to develop a predictive maintenance system that will be able to identify potential problems and propose solutions before a system failure or outage occurs.

2 Experiment Preparation

This research deals with verifying the ability of the feedforward neural network (FFNN) to approximate the function of several variables with sufficient accuracy and to reveal possibly hidden dependencies between the input variables and the output. This is necessary to increase the quality of the subsequent interpretation of the neural network model. The neural network will be designed, trained, and validated in MATLAB software.

3D graphs representing selected dependencies between input and output variables will be plotted to verify the relationships between variables, as well as to reveal dependencies that might otherwise be hidden.

2.1 Testing Device

The testing device was designed to generate data sets of sufficient size for training and validation of proposed neural network models for predictive maintenance tasks. The control part is represented by two microcontrollers, one of which is responsible for controlling the working cycle of the device (heating-cooling). The second microcontroller is responsible for collecting data about the current state of the device. In Fig. 1 a schematic diagram of the simulation device is shown.

A set of sensors is used to acquire data. A set of sensors located on the device allows for sensing the temperature of the liquid at three points of the hydraulic circuit (at the input to the heat exchanger, at the output, and in the tank), the temperature of the heat exchanger, flow and pressure in the system, and electric current and voltage in the electric 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. The time of each measurement is also recorded.

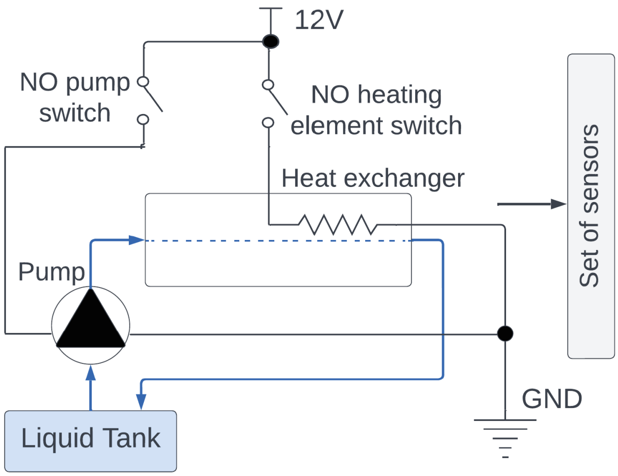

Fig. 1. Schematic diagram of the simulation device.

2.2 Purposed Neural Network Architecture

Based on the parameters that the test equipment can measure, it was decided to design a feedforward neural network that would be used to approximate the function

$$t_{tank} = f(t_{inp}, t_{out}, t_{HCH}, t_{amb}, RH, U, I, p_{sys}, Q, T) \quad (1)$$

where t_{tank} – tank temperature, °C; t_{inp} – heat exchanger input temperature, °C; t_{out} – heat exchanger output temperature, °C; t_{HCH} – heat exchanger temperature, °C; t_{amb}- ambient temperature, °C; RH – relative humidity, %; U – voltage in the system, U; I – electrical current in the system, A; Q – working fluid flow rate, L/hour; T – operating time, min.

A feedforward neural network is a type of neural network in which data passes only unidirectionally from the input neurons to the output neurons. The input data is the input to the network, where it is linearly combined using weights and biases on each neuron and passed through an activation function that produces an output on each neuron. The output from the input neurons passes sequentially through multiple layers of hidden neurons, with each layer transforming the input data into a new representational space. In the end, the output data is recomputed based on the weights and biases of the output neurons.

The neural network proposed in this paper is a shallow neural network, which is composed of an input layer (10 neurons, each representing one of the parameters). The hidden layer is composed of 100 neurons and the logistic sigmoid is used as the activation function. In the output layer, there is one neuron with a linear activation function, and it represents the predicted value of t_{tank}. The proposed neural network structure is shown in Fig. 2.

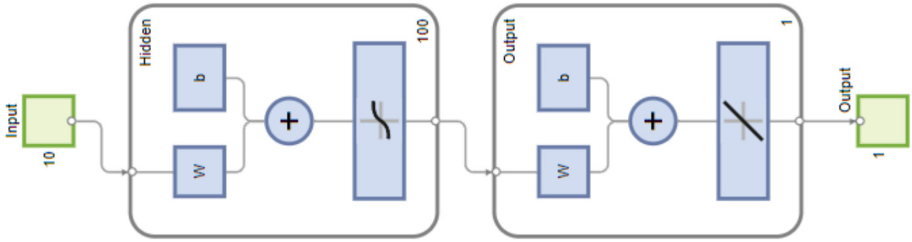

Fig. 2. The proposed neural network diagram

2.3 Methodology for the Verification of Neutron Network Results

After the training, the values of correlation coefficient R and mean square error (MSE) will be calculated, and based on these metrics the rationality of further use and validation of the proposed model will be decided. The model is considered reliable if the value of R is greater than 0.95 and the value of MSE is less than 0.1. Also, the model will be additionally tested on a new test dataset and will also be evaluated based on R and MSE metrics. The root main squared error (RMSE) will be calculated for additional model verification to detect large deviations in data.

3 The Experimental Realization

The experimental part of the paper focuses on training and validation of the neural network to visualize the dependencies of the parameter under study on the selected input variables. The experiment will be performed on two datasets that were obtained from the testing device.

After training and verification of the neural network, the obtained results will be used to calculate and visualize the dependences of the investigated parameter t_{tank} on the selected input variables. The visualization of these dependencies is used to understand the influence of each input variable on the parameter under study and to additionally verify the ability of the proposed neural network model to approximate the specified function.

3.1 Data Gathering

For the implementation of the experiment, two datasets using the proposed test equipment were collected. Each dataset contains 10 measured device operating parameters and also the time of each measurement is recorded. The training dataset contains 5419 measurements. The interval between each measurement is 5 s (the whole dataset contains about 7.5 h of monitoring device operation). The test dataset contains 5523 samples and corresponds to 7.7 h of device operation. Preprocessing of the datasets consisted in filtering out erroneous values and adding to the dataset a parameter describing the operating time for each measurement.

3.2 Training and Testing Neural Network

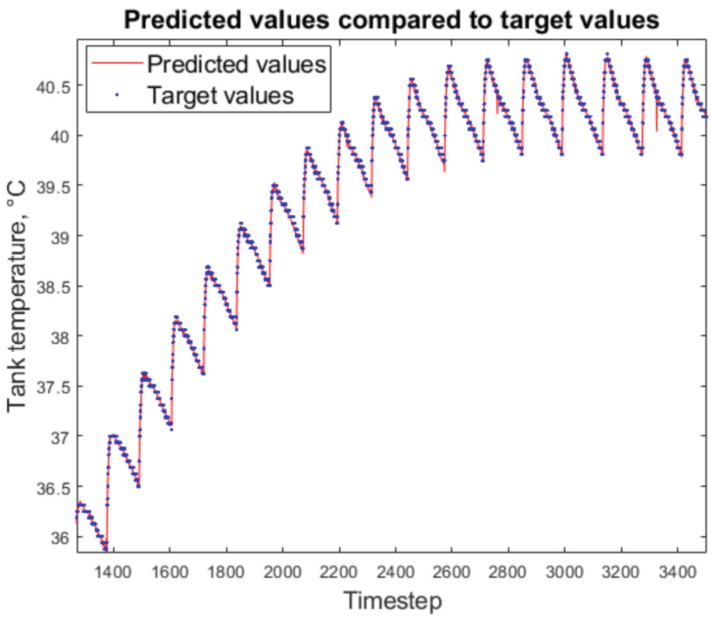

Fig. 3. Comparison between predicted and target values of the tank temperature (training dataset)

For the neural network training, all the measured temperatures in the test device system, the ambient parameters, the electrical parameters of the control part, the parameters of the working fluid flow, and the operating time were chosen as the input parameters.

Table 1. Evaluation metrics

Dataset	MSE	RMSE	R
Training dataset	0.0008	0.0276	0.9998
Testing dataset	0.0599	0.2448	0.9987

The target parameter is the temperature in the working fluid tank. Graf in Fig. 3 shows the comparison between target values and predicted values for t_{tank}.

The Levenberg-Marquardt algorithm was chosen as the training algorithm. The MSE is a statistical metric used to measure the accuracy of estimates or predictions in machine learning and data analytics models. MSE has been calculated as the average of the squared differences between the predicted (estimated) values and the actual values.

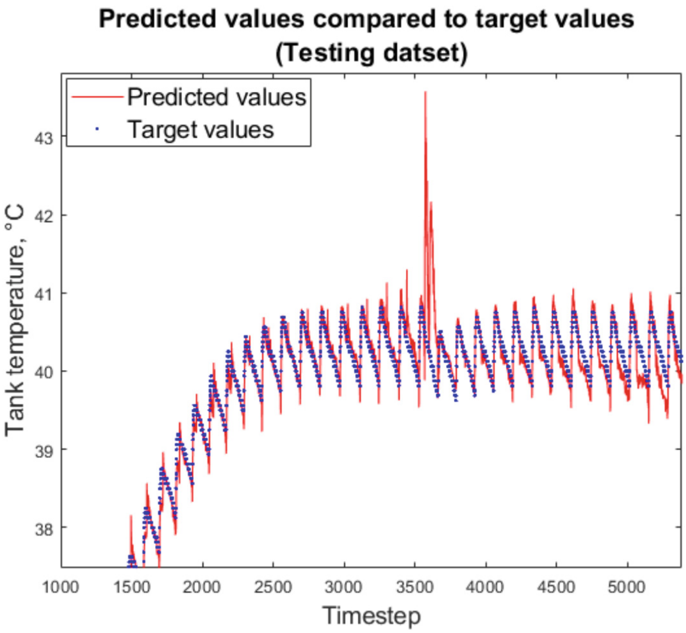

Fig. 4. Comparison between predicted and target values of the tank temperature (testing dataset)

After obtaining favorable training results (see Table 1), the model was tested on a test dataset to ensure the accuracy and robustness of the neural network. Graphs were also plotted for the predicted values and R and MSE were calculated. The MSE value for the training dataset is represented by small values, which indicates a good ability of the proposed model to predict the values of the observed parameter. The MSE for the test dataset is also a small number, confirming that the network makes accurate predictions on new data.

A correlation coefficient is a number that expresses the degree of dependence between two variables. It is used to measure how strongly and in what direction one variable changes concerning the other. As can be seen in Table 1 the positive correlation between the real estimated parameters is almost perfect for the two datasets.

The RMSE measures the difference between the predicted output of the model and the actual output, and it is calculated as the square root of the average of the squared differences between the predicted and actual values. RMSE is more sensitive to large outliers than the MSE and can be a better measure of the model's performance when there are large errors in the predictions.

It can be seen in Table 1 that for the test dataset, the values of MSE and RMSE are several orders of magnitude higher than when the given metrics for the training dataset. This can be explained by the unexpected premature cooling of the test device during its running cycle. In Fig. 4, the model changed its behavior pattern abruptly, which can be considered as a detected error in the device overfitting. Apart from this factor, the model is still able to predict the observed t_{tank} value, as indicated by the high value of the correlation coefficient R.

4 Correlation Surfaces

Correlation surfaces can be used to identify patterns and relationships in datasets that may be useful in a variety of fields. They are effective in predicting or explaining results and are also useful for identifying factors with the strongest correlation.

On a correlation surface plot, areas of high positive correlation are shown by the peak and areas of high negative correlation are shown by the valley. A flat area shall be used to show areas with little or no correlation.

4.1 Choosing the Investigated Parameter Dependencies

The test device is capable of sensing 10 parameters (including the investigated parameter t_{tank}) and one more parameter (operating time) is calculated by recording the actual measurement time.

Plotting all possible dependencies of t_{tank} on the other parameters would not be rational due to a large number of these dependencies. Moreover, most of them would be irrelevant from a logical point of view and would unnecessarily increase the computational and interpretation complexity.

Therefore, 5 dependencies were selected which, with a preliminary view, should be relevant to verify the ability of the proposed network to predict the values of the specified variable. In the following, a list of these dependencies and the expected results after their representation will be presented.

1. *Input temperature, output temperature.* Since the hydraulic circuit of the system is closed, it is expected that at other constant parameter values, the parameter under investigation will increase its value as the values at the inlet and outlet of the heat exchanger rise.

2. *Heat exchanger temperature, operating time.* The operating cycle of the device is set as follows: the heating elements heat the heat exchanger to a temperature of 85 °C. Next, the heating is switched off and the pumping of the working fluid starts, cooling the heat exchanger and heating the working fluid. The heating is restarted when the heat exchanger temperature drops below 40 °C. Hence, the expected behavior of the t_{tank}, in this case, is an increase as the operating time increases and as the heat exchanger temperature increases.
3. *Flow rate, operating time.* The flow rate of the working fluid directly affects the cooling of the heat exchanger by the working fluid contained in the tank. However, the values of the fluid flow are different from zero only when the water pump is switched on. As the working fluid heats up, the cooling of the heat exchanger will take longer and thus the fluid flow values will be at their maximum values for a longer time.
4. *Ambient temperature, heat exchanger temperature.* Increasing the ambient temperature should generally increase the temperature of the working fluid while increasing the cooling time of the heat exchanger.
5. *Ambient temperature, current.* By monitoring the electric current, the status of the water pump can be monitored. The eclectic current sensor senses the total current in the circuit. An increase in current means the pump is running. Thus, the working fluid is pumped and the heat from the heat exchanger is directed to the working fluid tank. The ambient temperature in this case should influence the rate of temperature increase of the fluid in the tank.

5 Dependencies Evaluation and Discussion

The correlation surfaces were plotted using Matlab software based on training dataset with the aim to evaluate neural network prediction and approximation ability. The observed t_{tank} parameter is located on the Z axis, X and Y axes represent the parameters that are varied in each case.

5.1 Influence of Input and Output Temperatures on Tank Temperature

As expected, the temperature in the tank increases when the temperature values at the output of the heat exchanger rise. The input temperature of the heat exchanger generally has a similar effect on the tank temperature.

However, in Fig. 5 one can see the valleys which indicate the negative correlation between the given and the observed parameter. This can probably be explained by the lower temperature of the fluid in the tank at the beginning of the experiment. That is, by the beginning of pumping the fluid, the value of the temperature at the input of the heat exchanger has decreased.

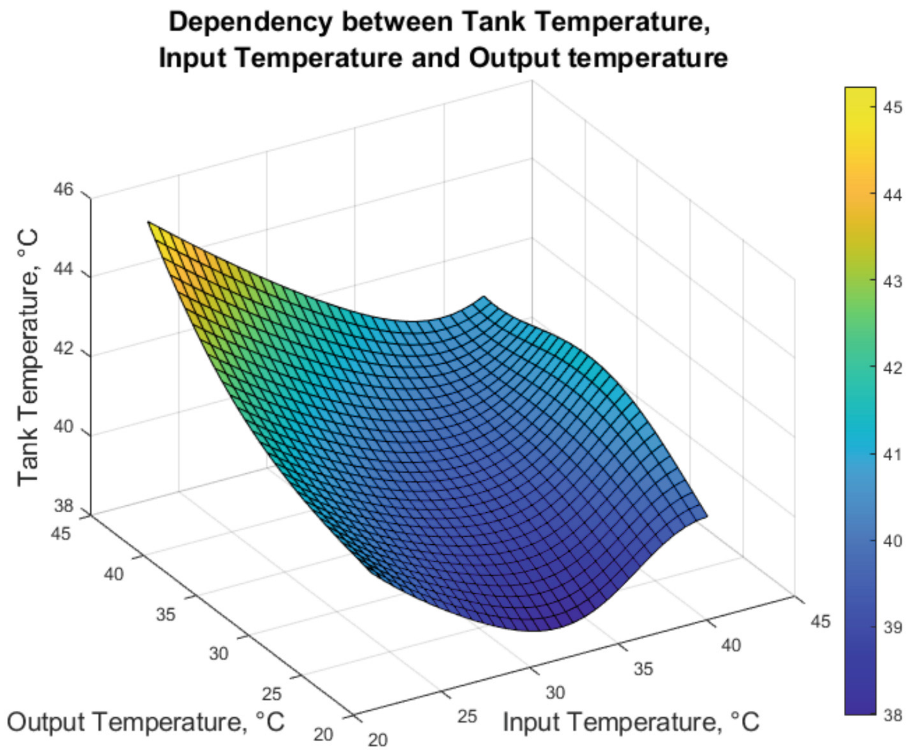

Fig. 5. Dependency between tank temperature, input, and output temperatures

5.2 Influence of Heat Exchanger Temperature and Operation Time on Tank Temperature

Since the investigated system is a closed system, over time the observed temperature in the tank will only increase, as can be seen in Fig. 6. At the beginning of the experiment the temperature in the tank rises more steeply than closer to the end of the measurements, which can be explained by the already higher temperature of the working fluid and thus more complicated cooling of the heat exchanger.

5.3 Influence of Flow Rate and Operation Time on Tank Temperature

As mentioned in 5.2 due to the closed nature of the analyzing system, by increasing the measurement time, the temperature of the working fluid will steadily rise. The dependency graph is shown in Fig. 7. The slight decrease of the parameter under study between times of 350–400 min can be explained by the fact that a higher working fluid temperature causes the heat exchanger to cool more slowly and thus the working fluid temperature tends to align slightly with the ambient temperature.

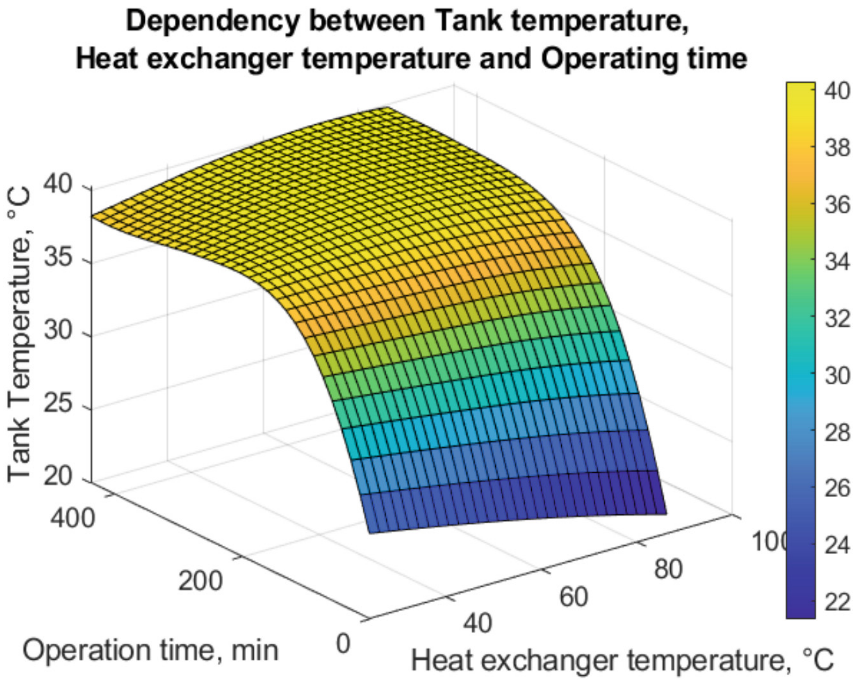

Fig. 6. Dependency between tank temperature, operation time and heat exchanger temperature

5.4 Influence of Heat Exchanger Temperature and Ambient Temperature on Tank Temperature

For this dependence, it can be seen in Fig. 9 that an increase in ambient temperature causes a decrease of the temperature in the tank, which goes against the expected behavior of the model. However, a more detailed analysis is needed.

In the test device, which is used in this experiment, a DHT11 sensor is used to measure the ambient temperature. The DHT11 sensor is capable of sensing with an accuracy of ±2 °C (Guangzhou Aosong Electronic Co. 2022). It can be seen that the change in ambient temperature over the entire time of the experiment is in the range of 24.7 °C to 26.8 °C. Thus, the range of change in the ambient temperature value is less than the measurement uncertainty. Hence, the effect of the parameter on the tank temperatures is negligible and this dependence is irrelevant.

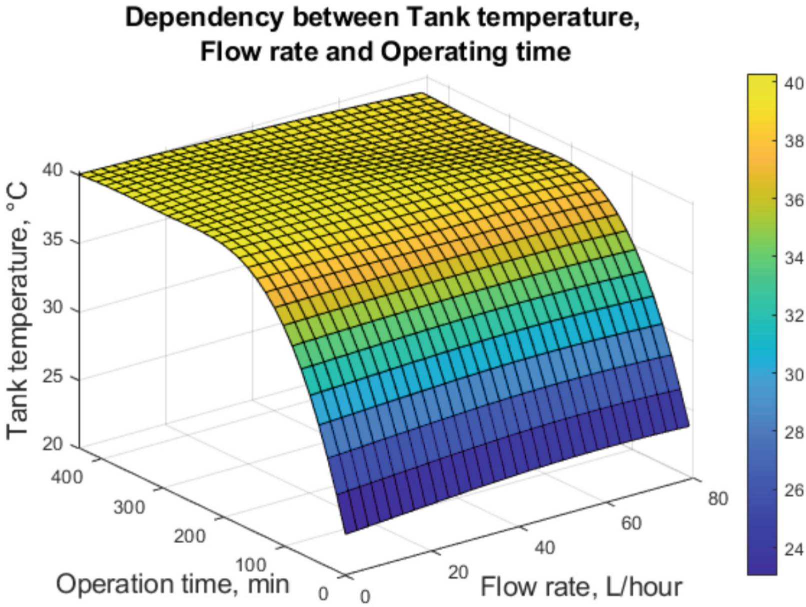

Fig. 7. Dependency between tank temperature, flow rate and operating time

As can be seen in the scheme in Fig. 8, the heated water underflow tube from the heat exchanger is located in the right corner of the water tank, as well as the suction tube. The liquid temperature sensor in the tank is located in the left corner at the end of the water flow in the tank. The flow of the heated water is shown in Fig. 8 by red arrow.

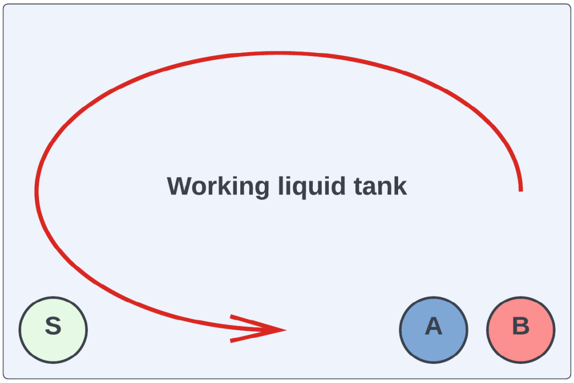

Fig. 8. Working liquid flow in the liquid tank. A – Suction tube, B – Underflow tube, S – Tank temperature sensor

Therefore, the moment the heat exchanger temperature (86 °C) is reached, the temperature in the tank at the sensing point is still lower than the heat exchanger temperature. After the pump is switched on, the liquid in the hydraulic circuit starts to flow. The flow of heated water with some heat loss reaches the tank temperature sensing positions with a time delay. By the time the tank temperature reading takes place, the heater temperature has already dropped. Further, the whole cycle is repeated with the working fluid temperature in the tank increasing steadily. This effect is clearly seen on Fig. 9.

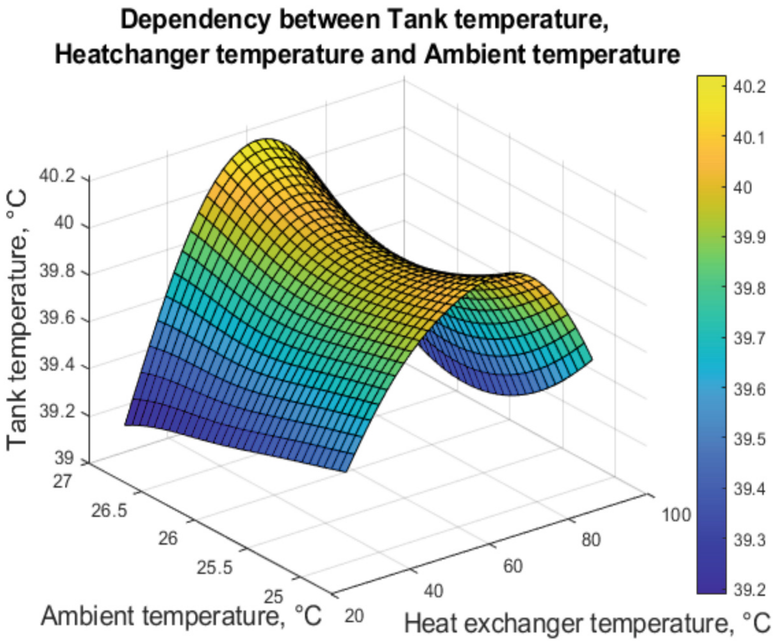

Fig. 9. Dependency between tank temperature, heat changer temperature and ambient temperature

5.5 Influence of Ambient Temperature and Current in Electrical Circuit on Tank Temperature

As mentioned in the previous paragraph, since the measurement uncertainty of the ambient temperature sensor is larger than the range of values of the change of the parameter during the measurement, the investigation of the parameter is irrelevant in the case of this article. More interest is encouraged by the dependence of the temperature in the tank on the electric current (Fig. 10).

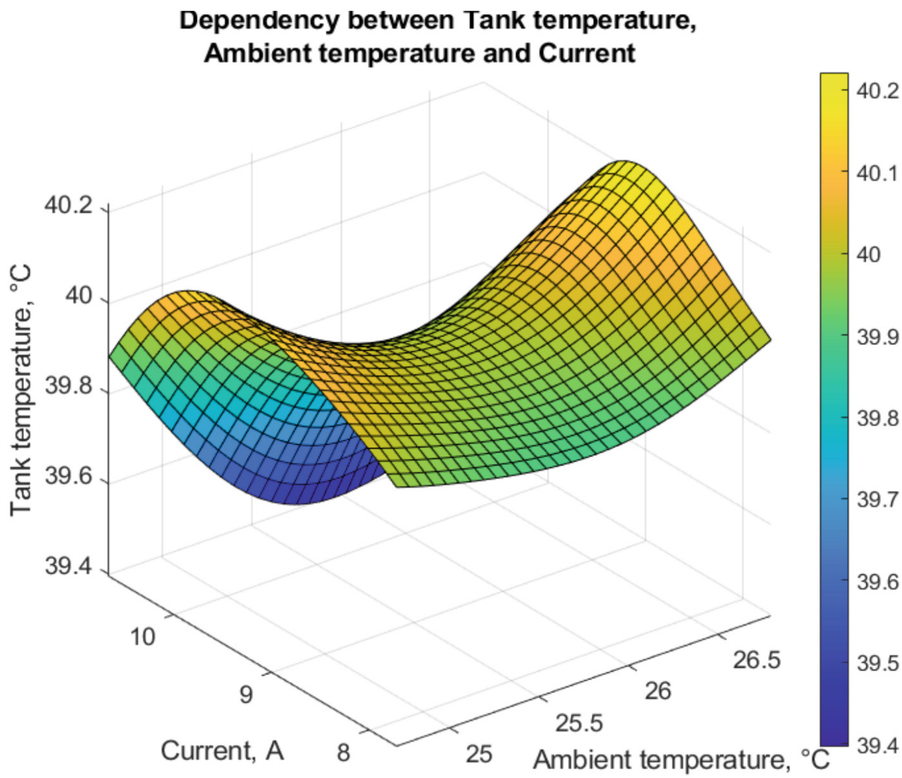

Fig. 10. Dependency between tank temperature, current and ambient temperature

The electric current sensor measures the current throughout the system. The effect of current on tank temperature is not directly definable but can be explained by the nature of the operating cycle of the test equipment. The graph in Fig. 11 shows a section of the waveforms of the change in the value of the electric current and flow rate in the system over the time of operation of the device. The fluctuations of the current values around their maximum and minimum values are explained by soft power supply used in testing device.

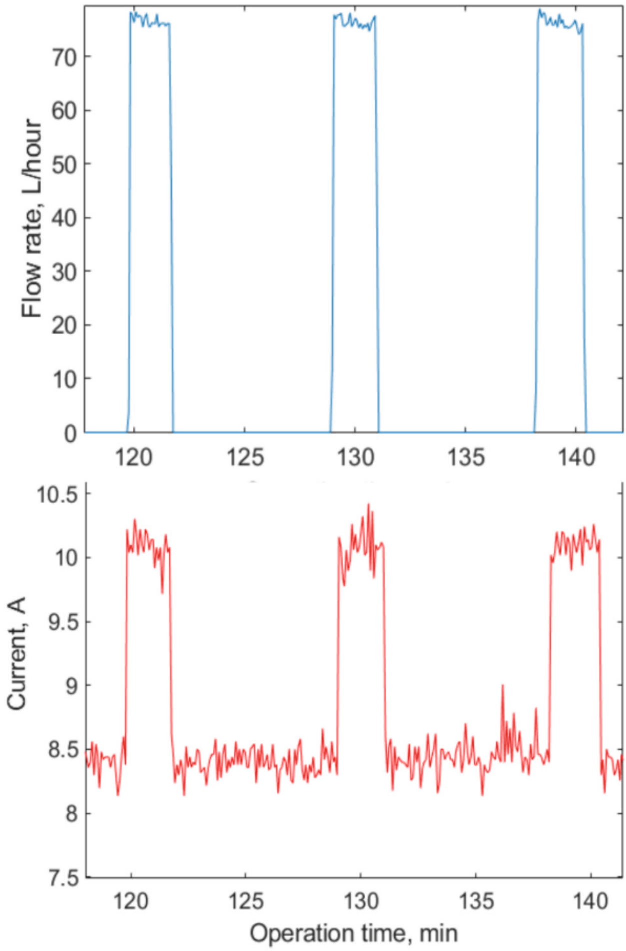

Fig. 11. Electric current value and flow rate changing in the system

The electric current increases when the pump is switched on. By switching on the pump, a current of the working fluid is generated in the system. This causes the heated water from the heat exchanger to start moving further down the hydraulic circuit and into the tank, increasing the overall temperature in the tank. This positive correlation can also be seen in Fig. 10 and Fig. 12. The strongest positive correlation between the tank temperature and electrical current is when the electric current takes values between 8.5 and 9.5 A.

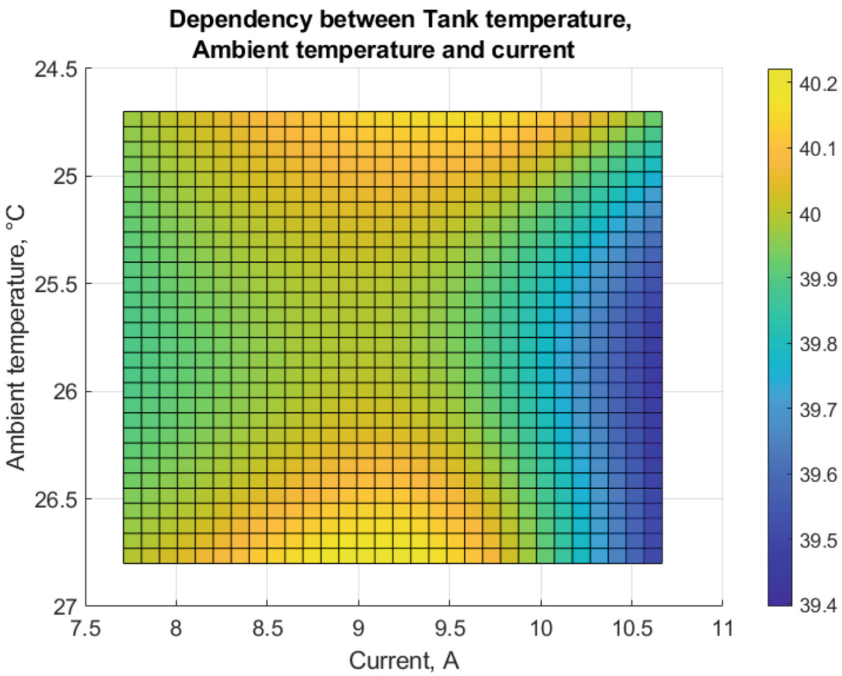

Fig. 12. Dependency between tank temperature, current and ambient temperature (2D view)

6 Conclusions

In the present work, a neural network was proposed to approximate a complex multi-parametric function that describes the dependence of one investigated parameter of the test equipment on its other operating parameters.

The proposed model can reliably predict the temperature of the working fluid in the tank based on the operating time, fluid temperatures in the hydraulic circuit (at the inlet to the heat exchanger and the outlet from the heat exchanger), the temperature of the heat exchanger, the flow rate and pressure in the system and the electric current and voltage in the electric circuit.

The accuracy of the model was verified using the test dataset and the numerical metrics R (R = 0.9998 for the training data and R = 0.9987 for the test dataset) and RMSE (RMSE = 0.0276 for the training dataset and RMSE = 0.2448 for the test data) as well as by displaying the extracted parameter dependencies using 3D correlation plots.

The analysis of the plots shows that the fluid temperatures in the hydraulic circuit, the heat exchanger temperature, and the operating time of the testing device have the most influence on the investigated parameter. The influence of ambient temperature could not be investigated with sufficient attention, since the sensor used does not offer sufficient reliability of the sensed data at the specified experimental conditions. However, replacing the DTH11 sensor with another more accurate ambient temperature sensor would allow the incorporation of ambient temperature as an additional refinement parameter of the prediction system.

The research has benefits for the field of descriptive analytics and for developing complex predictive maintenance systems that are based on artificial intelligence models.

Acknowledgement. The outputs of paper was supported by grant VEGA 1/0470/23 “Research of implementation methods and means of artificial intelligence in systems of automated quality control of products with volatile quality parameters”.

References

Červeňan, A.: Systém údržby. CKV Consult, Bratislava (2021). Accessed 8 Nov 2023. ISBN 978-80-971986-0-2. https://www.sjf.stuba.sk/buxus/docs/docs/edicne/Udrzba_farebna_final.pdf

Dang, X.H., Shah, S.Y., Zerfos, P.: Seq2graph: discovering dynamic non-linear dependencies from multivariate time series. In: Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019, pp. 1774–1783 (2019). https://doi.org/10.1109/BIGDATA47090.2019.9006103

Fathi, K., van de Venn, H.W., Honegger, M.: Predictive maintenance: an autoencoder anomaly-based approach for a 3 DoF delta robot. Sensors **21**, 6979 (2021). Accessed 26 Jan 2023, ISSN 1424–8220. https://doi.org/10.3390/S21216979

Guangzhou Aosong Electronic Co., Ltd. DHT11 Datasheet (2022). Accessed 4 Apr 2023. https://pdf1.alldatasheet.com/datasheet-pdf/view/1440068/ETC/DHT11.html

Janssens, O., et al.: Convolutional neural network based fault detection for rotating machinery. J. Sound Vibr. **377**, 331–345 (2016). ISSN 0022–460X. https://doi.org/10.1016/J.JSV.2016.05.027

Kumar, V., Garg, M.L.: Deep learning in predictive analytics: a survey. In: 2017 International Conference on Emerging Trends in Computing and Communication Technologies, ICETCCT 2017, vol. 2018-January, pp. 1–6 (2018). https://doi.org/10.1109/ICETCCT.2017.8280331

Liu, J., Wang, W., Golnaraghi, F.: A multi-step predictor with a variable input pattern for system state forecasting. Mech. Syst. Signal Process. **23**(5), 1586–1599 (2009). ISSN 0888–3270. https://doi.org/10.1016/J.YMSSP.2008.09.006

Mustafaraj, G., Lowry, G., Chen, J.: Prediction of room temperature and relative humidity by autoregressive linear and nonlinear neural network models for an open office. Energy Build. **43**(6), 1452–1460 (2011). ISSN 0378–7788. https://doi.org/10.1016/J.ENBUILD.2011.02.007

Marková, P.: Spoľahlivosť, bezruchovosť a udržovateľnosť meracích zariadení. Automa 58–59 (2008). Accessed 12 Dec 2021. https://automa.cz/Aton/FileRepository/pdf_articles/36674.pdf

Quattrocchi, G., Iacono, A., Berri, P.C., Dalla Vedova, M.D.L., Maggiore, P.: A new method for friction estimation in EMA transmissions. Actuators **10**(8), 194 (2021). Accessed 23 Jan 2023. ISSN 2076–0825. https://doi.org/10.3390/ACT10080194