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Analysis and prediction of leak detection in the low-pressure heat treatment of metal equipment

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Highlights

- The infiltration method is not effective in predicting furnace leaks.
- The prediction of furnace leaks is possible with the help of a Lambda probe.
- Artificial neural networks are useful in predicting furnace leaks.
- The predictive furnace leak detection model can be used on-line.

Abstract

The low-pressure heat treatment of metals enables the continuous improvement of the mechanical and plastic properties of products, such as hardness, abrasion resistance, etc. A significant problem related to the operation of vacuum furnaces for heat treatment is that they become unsealed during operation, resulting from the degradation of seals or the thermal expansion of the construction materials. Therefore, research was undertaken to develop a prediction model for detecting leaks in vacuum furnaces, the use of which will reduce the risk of degradation in the charge being processed. Unique experimental studies were carried out to detect leakages in a vacuum pit furnace, simulated using the ENV 116 reference slot. As a consequence, a prediction model for the detection of leaks in vacuum furnaces- which are used in the heat treatment of metals- was designed, using an artificial neural network. (93% for MLP 15-10-1) was developed. The model was implemented in a predictive maintenance system, in a real production company, as an element in the monitoring of the operation of vacuum furnaces.

Keywords

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vacuum heat treatment, vacuum furnace leaks, predictive maintenance, artificial neural networks.

1. Introduction

Metal heat treatment processes are a very important element of the manufacturing processes of products in industries such as the energy, automotive, aviation and mining industries etc. The process of hardening, carburising and/or nitriding is often the last process in the production cycle and allows the reproducible properties of the processed details, such as the surface hardness, core hardness or thickness of the diffusion layer to be achieved. The key to obtaining the assumed properties of the processed details is to maintain identical conditions for the implementation of heat treatment processes in the process chamber of the furnace, such as operating pressure, heating time, temperature, amount of technical gas etc. Even a slight change of parameters inside the vacuum furnace, during the heat treatment process, may result in irreversible damage to the charge and/or to the furnace. Both in the energy and mining industries, due to large dimensions and high production costs, the value of the charge to the furnace may exceed the value of hundreds of thousands of euros. The relevance of the problem may be proved by the scope of application of the details processed, for example in control systems, gears, heat exchangers in

aeroplanes and cars, drive shafts for wind turbines, gears with large modules, elements of drill bits and cutters in mining machines, drive transmission systems, dies, surgical instruments etc.

Low-pressure carbonisation processes are usually carried out within temperatures ranging from 950°C to 1020°C at a pressure of approximately 5x100 mbar. In the tests conducted, the measured pressure values are given in millibars, where 1mbar = 100 Pa due to the use of this unit of measurement in economic practice in the field of vacuum technology. In low-pressure carburising processes, it is necessary to maintain the stability of the process, which guarantees obtaining a precise and repeatable thickness of the carburised surface layer within the specified tolerance range. Possible leaks may result in a change in the parameters of the heat treatment process as well as damage to the charge, as a result of failing to meet the technological requirements expected.

Predictive maintenance is an important component of the Industry 4.0 Concept, especially when using production resources where failures do not occur suddenly and the risk of their occurrence increases over time. An example of such a progressive failure may be a leak in a vacuum furnace. Due to changes in the temperature of the con-

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struction of the furnace chamber and the wear of some elements, such as the seal in the furnace cover during operation, the furnace may become unsealed. Since modern vacuum furnaces are equipped with highly efficient cascade pumping systems consisting of a mechanical pump and a Roots' pump, pressure build-up in the vacuum furnace due to leaks is often virtually unnoticeable. However, as a result of leaks, the composition of the atmosphere inside the furnace chamber changes, on account of a higher oxygen content, which may lead to damage to the charge or failure to achieve the assumed parameters in the carburising process and, as a result, not achieving all technological requirements.

The implementation of predictive maintenance methods into industrial practice is one of the key assumptions of the Industry 4.0 Concept [13][15]. The progressive automation and digitisation of production processes requires the implementation of systems that will enable states of emergency to be diagnosed in advance. This approach makes it possible to:

- reduce losses associated with damaged parts as a result of failures,
- reduce unplanned downtime,
- reduce the maintenance costs incurred, regarding specialised, technical personnel, such as automation engineers and mechanics.

Systems for monitoring the parameters of complex technical systems are particularly important where these are situated in remote regions of the world and where access to qualified engineering staff is limited. Currently, data on monitoring the operational parameters of devices is stored in databases of ERP or MES systems. The Industry 4.0 Concept assumes real-time monitoring and recording of machine operating parameters and stores them in the form of big data sets in the Cloud. Multi-criteria data analysis with the use of artificial intelligence methods will enable the construction of efficient algorithms that will allow failure conditions to be predicted and thus, effectively prevented due to the inspection and repair of production resources. Research related to the development of the structure of a predictive maintenance system, based on the monitoring of real-time data within the reference model of industry architecture (RAMI 4.0) and DSR (Design Science Research) to reduce costs and operations, were led by Sahba et al. [24]. Predictive maintenance models, based on mathematical programming and deep learning allow the technical condition of individual elements of the production system to be predicted [12]. Machine learning methods based on machine performance analysis and monitoring of production environment variables are used in many of the studies carried out, in order to predict the emergency conditions of production systems [6][5][17][27][29]. A very important aspect of the implementation of predictive maintenance into industrial practice, is the analysis of big data sets, based on computationally efficient algorithms [31]. Another approach involves the construction of mathematical models to calculate maintenance rates for any schedule of time up to failure [20]. An important issue regarding maintenance management, based on prediction methods, is an approach based on multi-criteria decision making, integrated with the traditional method of analysing failure mode, effects, and criticality (FMECA) [1].

Low-pressure carburising is a long-lasting and energy-consuming heat treatment process, especially considering its requirement to obtain thick carburising layers, i.e., over 2.00 mm. One of the important parameters that influence the stability and repeatability of the process is the low oxygen content in the vacuum furnace chamber. The most common cause of the deterioration of this parameter is a leak in the furnace, which results in air entering the furnace chamber. The issue of leakage, in devices operating in high vacuum conditions is an important area of research and the subject of scientific publications [4] [9]. There are many methods for testing the leakage of vacuum devices, such as the pressure increase or decrease test, the leak test with gas-sensitive vacuum gauges, the test by immersion in various formulations or spraying with foam, the Krypton 85 test, the high fre-

quency vacuum test, test with chemical reactions and dye penetration [21]. An important method for testing the tightness of technical objects is the tracer gas method. The most popular tracing gases are helium, ammonia, hydrogen, nitrogen and semi-precious gases. A commonly used method of leak detection is the helium method, so-called [13] [28]. Helium is very well suited to the leak detection of vacuum devices because it is a non-toxic, non-flammable gas and does not form explosive mixtures with other gases. It is also neutral to the environment and does not enter into chemical reactions with other substances. The use of helium is not limited by the range of temperatures or pressures as it is a very temperature stable gas, which facilitates the testing of objects in environments with extremely high or low temperatures. Helium is the gas - right after hydrogen- with the smallest unit particle which enables penetration of micro-fractures in materials, therefore helium tests are very accurate. The relatively low price of helium compared to other noble gases should also be noted. The method itself is relatively simple and consists in connecting a so-called helium detector to the object being studied, while the operator dispenses a small portion of helium to any possible leak. The test object must reach a high, negative pressure. The method requires a detector with high accuracy, viz., the detection of leaks at the level of 5×10^{-12} mbar l/s. When using a helium detector, it is also possible to approximate the location of the leak. Another method for detecting leaks in vacuum furnaces is the so-called infiltration method, which consists in heating the furnace to a certain temperature at a specific negative pressure - usually as low a pressure as possible and then, as it slowly cools, calculate the value of the infiltration, i.e., the decrease in the value of the vacuum level, within a specific timeframe. The infiltration testing process allows leaks to be detected, however, it is long-lasting (several hours to several dozen hours) and does not allow the leak to be located. In general, the leak test should be preceded by the identification of possible leaks using the helium method.

Based on an analysis of the results of the literature on the subject, the infiltration method was selected for detecting leaks in vacuum furnaces with experimental tests being carried out to analyse leakages in pit furnaces for specific settings of the ENV 116 standard slot.

The use of various tools such as the Markov Process, Bays Networks, artificial neural networks or simulation methods, based on the Monte Carlo method for predictive maintenance purposes, has been the subject of publications by many authors [7][25]. Predictive maintenance methods use the Markov Process, Bays Networks, artificial neural networks and simulation methods based, for example, on the Monte Carlo method.

Many publications cover the use of machine learning methods for predictive maintenance, based on an analysis of machine performance and the variables of the production environment [5][17][27]. Part of the research concerns the acquisition and storage of data in the Cloud and the construction of a system platform for predictive maintenance [26]. Artificial neural networks are used, among other things, in order to analyse and classify data, both current and forecast, with the help of in-depth learning techniques and will enable images to be both recognised and reproduced. In the maintenance department, models are expected for detecting and forecasting future failures, in real time. [3] Based on an analysis of the literature, the most popular data-driven decision methods include the Support Vector Machine (SVM), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Random Forest, K-Nearest Neighbours and the Hidden Markov Model [22]. Currently, many methods, techniques and procedures, using intelligent production systems for maintenance workers, are based on deep learning techniques [17][32], however, there are still good examples of the use of artificial neural networks in maintenance, in the monitoring of tool wear, in the diagnosis of vibration in machining systems, in the thermal analysis of machines, in the analysis of other malfunctions affecting production, as well as in the diagnostics of finished products [9].

In the literature on the subject analysed, no model was found that could be used to predict the detection of leaks in devices used in the low-pressure heat treatment of metals. Therefore, research work was undertaken to design an effective leak detection model in vacuum furnaces, based on data obtained from the study of a working pit furnace.

The article presents the stages of a research experiment concerning the analysis of leaks with the use of a standard slot for various pressure and temperature parameters. Based on an analysis of the results of the experimental studies, a model for detecting leaks predictively, using artificial neural networks, was designed.

2. Research methods

2.1. Experimental work- testing furnace tightness- based on an analysis of the infiltration

The infiltration test is an effective, but relatively time-consuming method for obtaining knowledge about leakage in vacuum furnaces. The procedure for testing the tightness of the pit furnace, using the infiltration method, is shown in Figure 1.

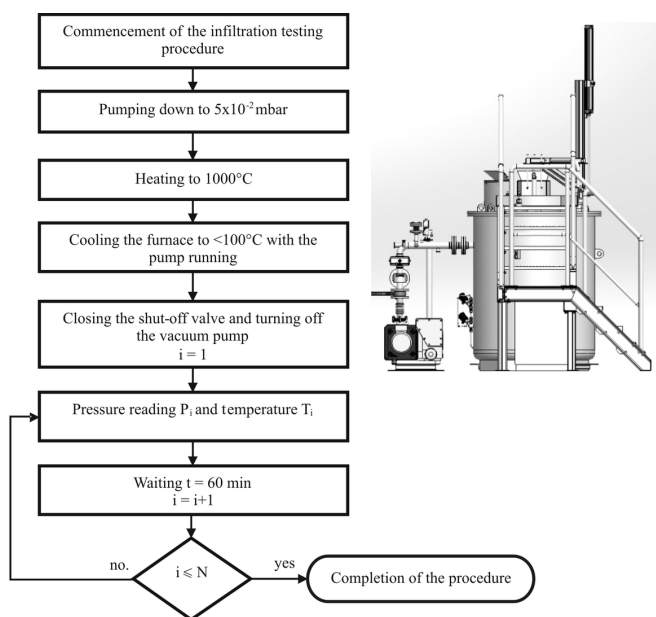


Fig. 1. The procedure for testing a leaking pit furnace, using the infiltration method

The longest stage in the infiltration test procedure here presented, is the cooling down of the furnace to a temperature of 50°C. Depending on the design of the furnace, that is, regarding the thickness of the insulation and the size of the heating chamber etc., the furnace cooling down process may take from several hours to several dozen hours. The control calculations for the infiltration test are performed, based on formula (1) shown below:

Table 1. Examples of the results of the first infiltration test for a leaky vacuum furnace.

V	t	P _b	P _e	T _b	T _e	N
[l]	[s]	[mbar]	[mbar]	[°C]	[°C]	10-3 [mbar·l/s]
1308	3600	1.40	4.06	42	42	967.83
1308	7200	1.40	6.87	42	41	995.00
1308	10800	1.40	9.79	42	41	1018.07
1308	14400	1.40	12.79	42	40	1037.80
1308	18000	1.40	25.12	42	39	1082.99
1308	21600	1.40	49.51	42	36	1102.87
1308	25200	1.40	74.52	42	34	1121.14

$$N = 1000 \cdot V \cdot \frac{P_e \cdot \left(0,5 \cdot \left(1 + \frac{273 + T_b}{273 + T_e} \right) - P_b \right)}{60 \cdot t} \quad (1)$$

where

- N - (leak rate) [mbar* l/s]
- V - volume of the furnace heating chamber [l]
- P_b - initial pressure [mbar],
- P_e - final pressure [mbar],
- T_b - initial temperature [°C],
- T_e - final temperature [°C],
- t - time [min].

The criterion for the tightness of the device, *vis-à-vis* the infiltration test, was set at 5,0 10⁻³ [mbar·l/s].

Table 1 shows examples of the results of the pit furnace infiltration test wherein a leak was detected.

The results presented in Table 1 differ many times from the criterion adopted, therefore the device tested shows increased leakage. After a review of the structure of the device and replacement of the valves, the infiltration test was carried out again. The test was performed with a slightly higher final temperature. The results are presented in Table 2.

As can be seen from the data presented in Table 2, the minimum indicator, adopted and established for the infiltration test, was exceeded over 100 times, thus indicating a leaking device. After re-analysis of tightness with the use of a helium detector and the sealing of the structural elements having been replaced, the infiltration test was carried out again; this gave satisfactory results. Table 3 presents the results of an infiltration test for a furnace which meets the criteria for leakages.

According to the analysis of the infiltration tests carried out, the method is not only effective, but is also long-lasting and may require several repetitions in the case of unsatisfactory results. In production conditions, it is also quite expensive, because it requires shutting down the heat treatment device for several hours. These devices are heavily loaded with orders in most enterprises and constitute bottlenecks in the manufacturing process. It is very important that, before starting an infiltration test, a helium test is carried out, in order to eliminate possible leakage in the device. Due to the specific features of the infiltration test, i.e., its long duration, furnace shutdown and high energy costs, this method cannot be used for a maintenance predictive system. Therefore, research work was undertaken to design a pit furnace leakage prediction model, using artificial neural networks.

2.2. Data collection and analysis

The Lambda probe is a sensor commonly used in the automotive industry to analyse the oxygen content in exhaust gas. The voltage generated by the sensor is lower than the higher oxygen content in exhaust gas, while the small amount of oxygen ions in the exhaust gas generates high voltage. To test for leakages in a pit furnace, the standard EVN116 slot (gas dosing valve) was used, which enables

Table 2. Examples of the results of the second infiltration test for a leaky vacuum furnace

V	t	P _b	P _e	T _b	T _e	N
[l]	[s]	[mbar]	[mbar]	[°C]	[°C]	10 ⁻³ [mbar·l/s]
1308	3600	1.46	2.85	76	75	504.47
1308	7200	1.46	4.35	75	74	525.88
1308	10800	1.46	5.90	74	72	538.53
1308	14400	1.46	7.42	72	71	542.02
1308	18000	1.46	8.91	71	70	542.51
1308	21600	1.46	10.36	70	69	539.76
1308	25200	1.46	11.80	69	68	537.59
1308	28800	1.46	13.17	68	67	532.93
1308	57600	1.46	23.01	67	58	495.93
1308	86400	1.46	31.70	58	52	462.59

Table 3. The results of the infiltration test for a furnace with a tight vacuum

V	t	P _b	P _e	T _b	T _e	N
[l]	[s]	[mbar]	[mbar]	[°C]	[°C]	10 ⁻³ [mbar·l/s]
1308	3600	0.238696	0.244000	43	43	2.00
1308	7200	0.238696	0.249304	43	42	1.98
1308	10800	0.238696	0.255091	43	42	2.04
1308	14400	0.238696	0.259913	43	42	1.98
1308	18000	0.238696	0.265700	43	41	2.02
1308	21600	0.238696	0.271004	43	41	2.01
1308	25200	0.238696	0.276308	43	41	2.01
1308	28800	0.238696	0.282095	43	40	2.03
1308	57600	0.238696	0.287399	43	40	2.03
1308	86400	0.238696	0.292704	43	40	2.02

the leak rate to be determined manually. Figure 2 shows the test site (Figure 2).

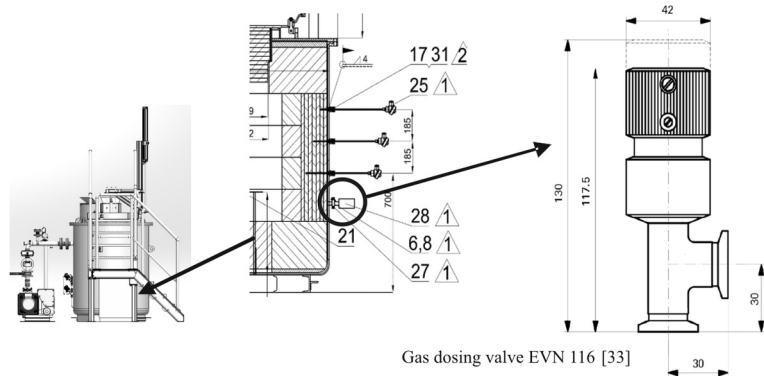


Fig. 2. Test stand for testing vacuum furnace leakage

As can be seen from the characteristics presented, setting the slot to 100 results in a horizontal leak at a level of $0.5 \cdot 10^{-3}$ mbar·l/s, but when the slot is set to 200, the leak is at a level of $0.8 \cdot 10^{-3}$ mbar * l/s. The test programme included an analysis of the characteristics of changes in the Lambda probe indications, depending on the size of the reference gap for different temperatures in the heating of the pit furnace. The following activities were planned for the purpose of conducting research experiments:

- setting a specific leakage for the reference slot, without opening the slot,
 - setting the maximum heating temperature T_{max} ,
 - creating a vacuum in the furnace at the P_{min} level,
 - heating the furnace to temperature T_{max} with the pump running,
 - keeping T_{max} for 15 min with the pump running,
 - closing the pump shut-off valve and turning the pump off,
 - opening reference slot t_1 ,
 - closing reference slot t_2 ,
 - turning the furnace off.

The tests were carried out at different heating temperatures: 500°C (loading the charge), 800°C (near temperature for hardening) and 1000°C (vacuum carburisation temperature). Figure 3 shows the temperature diagrams and the pressure and Lambda probe readings during heating to a temperature of 500°C, with the vacuum pump working, in order to determine the reference characteristics of the Lambda probe for a tight furnace.

The furnace was started at 7:20 a.m. at a temperature of 28°C; the target temperature of 500°C was reached after 60 minutes. The heating ramp was approximately 8°C/min. The vacuum in the furnace chamber was $7 \cdot 10^{-3}$ mbar. As can be seen from the diagram of the Lambda probe readings, taken during pumping out the furnace, the amount of oxygen ions in the furnace atmosphere decreased, which resulted in an increase in the voltage to approximately 880 mV.

Experiments at the test site (Figure 2) were then carried out. They simulated furnace leaks, with the standard slots set to 100, 150, 200 and 250, respectively, according to the characteristics of the EVN 116

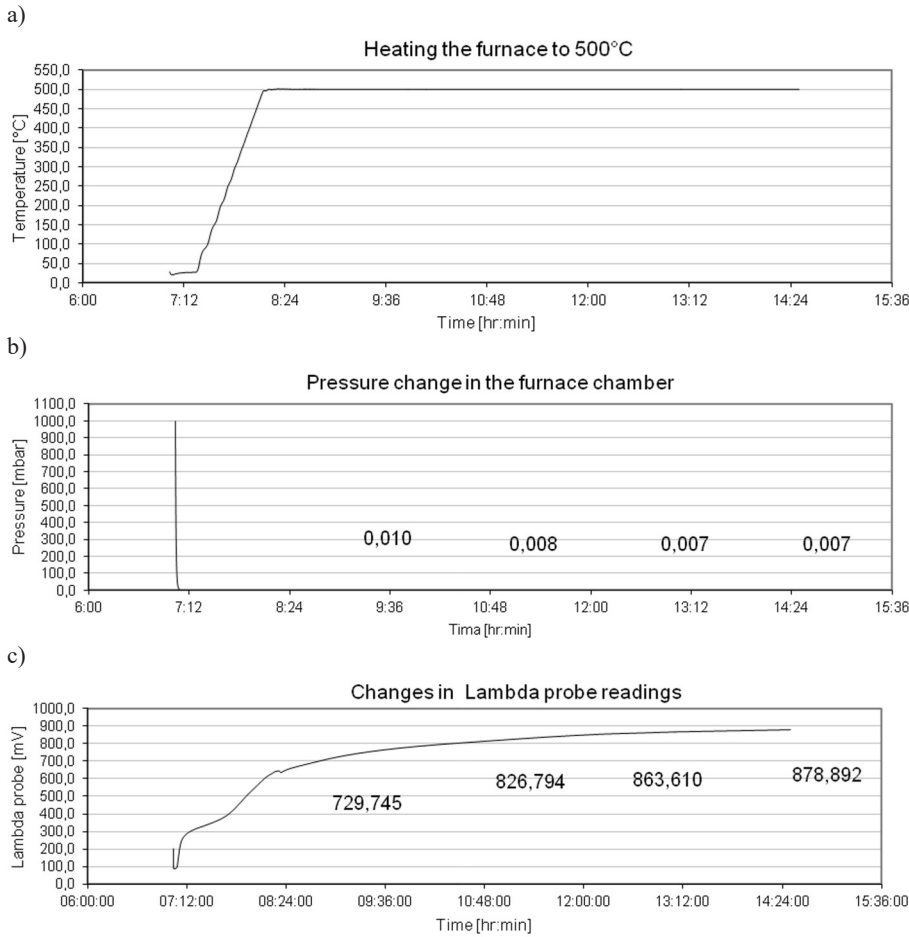


Fig. 3. Changes in a) temperature in the furnace chamber; b) pressure; c) voltage of the Lambda probe for a tight furnace

standard slot in which the numerical codes of the manual setting of the standard slot correspond to the specified leak (the so-called “digital display”, Figure 4), in the leakage range from approximately 10^{-3} do 10^{-2} mbar·l/s.

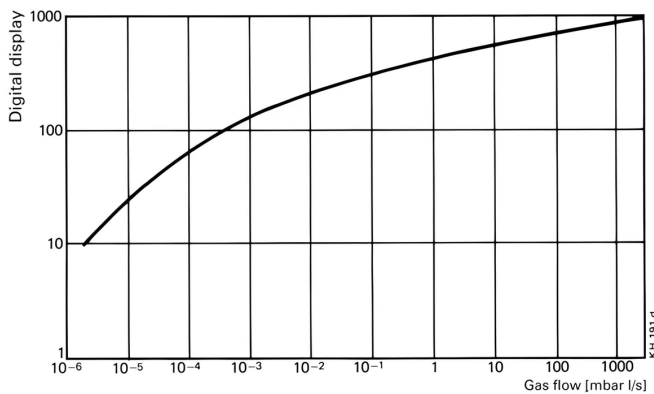


Figure 4. Characteristics of EVN 116 standard slot [33]

Changes in the furnace pressure for the individual settings of the reference slot and simulated voltage, as well as for the Lambda sensor readings are shown in Figure 5. As can be seen from the diagram presented, differences in the Lambda sensor readings for different sizes of the device leak are already visible 30 minutes after the opening of the standard slot. Table 4 shows the values of pressure and indications of the Lambda probe, which were recorded at equal intervals every 30 minutes, after opening the reference slot. Based on the data presented in Table 4, it is possible to diagnose any leakage in the device after 30 minutes and determine its size.

Analysis of the data obtained as a result of the conducted experimental tests (Table 4) shows that for increasingly larger leaks in the ENV 116 slot, the Lambda probe generates a correspondingly lower voltage.

The data received in the form of 1600 measurements concerning parameter values: y - Lambda probe voltage, x1 - temperature in the Furnace chamber, x2 - working pressure in the furnace chamber (values in bar), x3 - housing temperature, x4 - water flow in the cooling system, x5 - insulation temperature 1, x6 - insulation temperature 2, x7 - water flow in the cooling system of current passages, x8 - insulation temperature 3, x9 - water temperature at the inlet of the cooling system, x10 - gas pressure of the pneumatic system, X11 - temperature of the current bushing, X12 - heater current 1, x13 - heater current 2, X14 - heater current 3, x15 - partial pressure in the furnace chamber (values in millibars) constituted the basis for building a leak detection prediction model in vacuum furnaces using artificial neural networks.

3. Test results

The basic element of artificial neural networks are neurons, each of which is an autonomous processing unit. Each neuron carries out its own simple calculations and the structure, consisting of a large number of neurons, facilitates the multiplication potential of these calculations. The task of the neurons is to operate on the input data and present the results computed by the function activation. The neuron also describes a bias, which is an element that models

Table 4. Lambda probe indications [mV] for various ENV 116 slot leaks

time	digital display			
	100	150	200	250
00:00	835	826	818	813
00:30	840	831	822	809
01:00	844	835	824	806
01:30	849	839	826	802
02:00	852	842	828	799
02:30	855	842	828	795

the threshold above which the neuron sends an impulse, that is, an adjustment of the activation threshold value. The artificial neural network thus designed has parameters (weights) that must be assigned initial values. The role of the activation function is to determine the degree of excitation of the neuron, on the basis of the values reaching it. Based on the function used, the output value of the neurons is calculated.

The model was built using an artificial neural network due to its utility in both reactive and preventive maintenance as well as predictive maintenance. The model was designed on the basis of real data obtained from the operation of a vacuum furnace. An artificial neural network was chosen because using it facilitates, among other things, data classification and identification, the forecasting of wear in machine elements [9], the forecasting of the abrasive wear of cutting tool blades and the monitoring of machines and devices in action. The ANN type of unidirectional MLP multilayer neural network was selected (Multi-layered Perceptron) [23]. The network consists of neu-

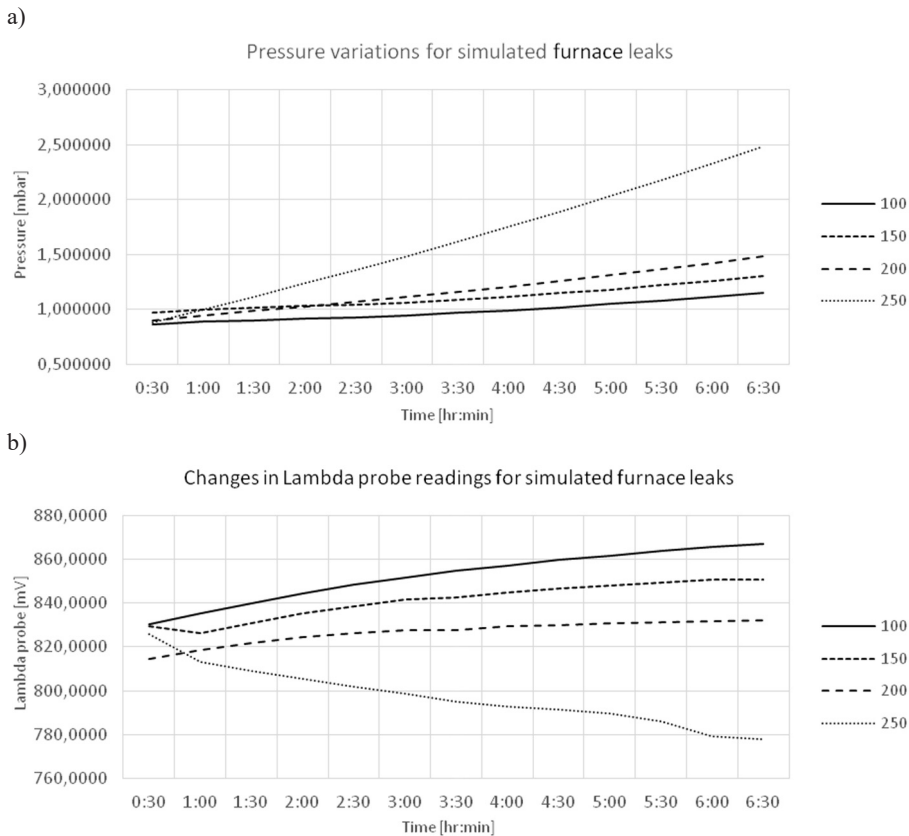


Fig. 5. Changes in the readings of the pressure sensor and the Lambda sensor for different levels

rons arranged in layers. Each of the neurons computes the weighted sum of its inputs; the excitation level thus determined becomes an argument for the transition function (activation function) that computes the output value of the neuron. For a unidirectional multilayer network, determining the appropriate number of hidden layers and the number of neurons in individual layers is not a simple issue. [2].

In order to build the model, an artificial neural network with a logistic activation function, a sigmoid unipolar function (formula 2) was used, due to the form of data on the Lambda probe indication for a tight furnace (Figure 3c).

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

where: x – is the input value of the activation function, e - Euler's number. The activation function is especially useful in artificial neural networks with back propagation. The function maps the interval $(-\infty, \infty)$ to $(0, 1)$ [19].

The weighting factors were determined in the process of training neurons through supervised learning. To generate a neural network Statistica, ver. 13.3 was used. The neural network model used in the study is shown in Figure 6.

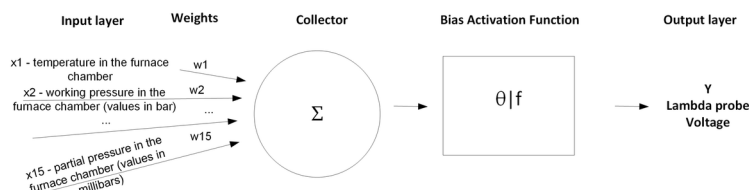


Fig. 6. MLP network structure for leak detection prediction in vacuum furnaces.

where:

$w_1...w_{15}$ - weights

Y - Lambda probe measurement value

Table 5 compares the MLP network, with the activation logistics function, in terms of the network quality achieved, for training, testing and validation, respectively and the error function. The best model was the MLP network with the structure 15-10-1, where 15-10-1 refers to the number of inputs (15), the number of neurons in the hidden layer (10) and the number of output networks (1).

The leak detection prediction model in vacuum furnaces was then verified with the use of ANN MLP 15-10-1 for the data presented in Appendix no. 1. Tests were carried out while the vacuum furnace was working and the actual results were compared with the forecast obtained (Table 6).

In Figure 7 a prediction model for the detection of leaks, in devices for the heat treatment of metals, has been presented.

4. Discussion

The aim of the study was to formulate a prediction model for detecting leaks in vacuum furnaces using artificial neural networks. The research required experiments to be conducted on a vacuum furnace in actual operation, followed by work related to the acquisition and analysis of data and the use of an appropriate ANN structure. The research was conducted in the R&D Department of SECO/WARWICK S.A. using a

pit vacuum furnace. Table 7 presents the main characteristics indicating the originality of the research results obtained and the contribution made to the research on leakage in vacuum furnaces. In particular, the approaches to the detection of furnace leakages were described, taking into account: (1) the methods used, (2) effectiveness, (3) verification in business practice. According to the present authors' knowledge, there is no approach, in existing studies, integrating the results of experimental work on the detection of leaks in a pit furnace using the ENV 116 reference slot with the use of artificial neural networks.

Technical devices that work in high vacuum conditions and are subjected to large temperature changes, become unsealed after a certain period of time. This can be due to various reasons, such as seal wear, damaged valves, leaks due to expansion and contraction of the metal parts of the furnace etc. Leaks can occur suddenly, as a result of a fault, or gradually, as a result of the normal operation of equipment. It is possible to prevent gradual leakage of the heat treatment device by continuously monitoring selected parameters. As currently used, pumping systems for obtaining a high vacuum in furnace chambers are very efficient, therefore the occurrence of even a large leak may not be registered by the pressure sensors. Due to the economics of heat treatment processes and for the avoidance of damage to the charge, it is important that the prediction of potential leakage occurs before actual treatment is required, such as carburising or quenching, so that the charge is not degraded. This can be achieved by using artificial intelligence methods. The study demonstrated the usefulness of an artificial neural network and its effectiveness in supporting the prognosis of furnace leakage (93% for MLP 15-10-1). The model designed for the detection of leaks in vacuum furnaces (Figure 6) can be integrated in systems supporting the operation of the maintenance department. Such adaptation can even be done online, if all the features / input values taken into account can be changed and controlled online.

Table 5. Artificial neural networks for leak detection in a vacuum furnace

Network name	Quality (learning)	Quality (testing)	Quality (validation)	Error (learning)	Error (testing)	Error (validation)	Learning algorithm	Error function
MLP 15-7-1	0.980799	0.751166	0.828486	177.310	158.8133	86.2470	BFGS 40	SOS
MLP 15-10-1	0.983770	0.751710	0.933961	184.058	245.6714	174.4568	BFGS 42	SOS
MLP 15-12-1	0.563121	0.462774	0.514705	3191.967	399.8066	433.7868	BFGS 4	SOS
MLP 15-14-1	0.966649	0.571415	0.575219	308.369	256.8963	249.1537	BFGS 48	SOS
MLP 15-13-1	0.973078	0.568790	0.681975	249.102	304.1500	156.2498	BFGS 41	SOS

Table 6. Comparison of actual values with the values forecast for leakages in a vacuum furnace

Time	Lambda probe voltage - actual value [mV]	Lambda probe voltage - forecast value [mV]	Error
15:45:00	727,2063	793,5139	-66,3076
16:00:00	743,9453	795,6114	-51,6661
16:15:00	755,042	793,7966	-38,7546
16:30:00	763,1294	792,5906	-29,4612
16:45:00	769,8062	793,7554	-23,9492
17:00:00	775,2605	792,3767	-17,1162
17:15:00	779,8684	794,0572	-14,1888
17:30:00	783,9121	794,9163	-11,0042

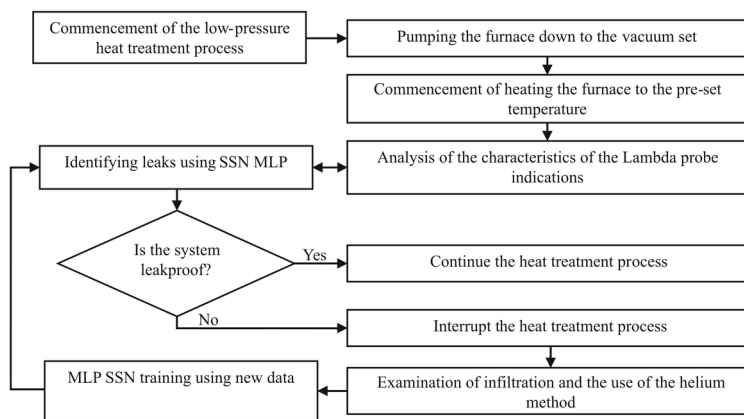


Fig. 7. Prediction model for detecting leaks in vacuum furnaces

5. Summary and conclusions

The low-pressure heat treatment of metals is most often carried out in the last phase of a production cycle. Inadequate heat treatment parameters, such as too much oxygen in the furnace chamber or too high a pressure, caused by leaks in the furnace, may lead to production shortages or the production of products with lower strength and reliability. Leakage in heat treatment equipment cannot be completely eliminated as it is process-specific, *vis-à-vis* the thermal expansion of metals, damage to the seal resulting from the operation of the furnace etc.

The article proposes a model for predictively detecting leaks in vacuum furnaces with the use of artificial neural networks. As a result of the experimental tests conducted, consisting in simulating the leakage, the Lambda sensor readings were determined for various settings of the standard slot size. The prediction model formulated for the detection of leaks in vacuum furnaces, as used in the heat treatment of metals using an artificial neural network (93% for MLP 15-10-1) will allow leakage in the heat treatment equipment of metals- *already in the heating phase*- to be detected before the start of the carbonisation or hardening processes, thus protecting the load against damage.

As part of further research and development work on the predictive maintenance of metal heat treatment devices, work will be carried out on detecting the conditions preceding burnout of the furnace heating elements, resulting from an increase in the level of carbon deposits on the heating elements and current passages and from low-pressure carburising processes.

Authors' contributions

SK: developing the concept of the article, planning research experiments, conducting research experiments, developing a predictive model for a vacuum furnace leak detection system, writing the content of the article.

JPM: developing the concept of the article, conducting research experiments, developing a predictive model of a vacuum furnace leak detection system, writing the content of the article.

MB: carrying out research experiments.

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