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AN ANALYSIS OF THE OPERATING PARAMETERS OF THE VACUUM FURNACE WITH REGARD TO THE REQUIREMENTS OF PREDICTIVE MAINTENANCE

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Abstract
The Industry 4.0 Concept assumes that the majority of industry's resources will be able to self-diagnose; this will, therefore, enable predictive maintenance. Numerically controlled machines and devices involved in technological processes should, especially, have the facility to predict breakdown. In the paper, the concept of a predictive maintenance system for a vacuum furnace is presented. The predictive maintenance system is based on analysis of the operating parameters of the system and on the algorithms for identifying emergency states in the furnace. The algorithms will be implemented in the monitoring sub-system of the furnace. Analysis of the operating parameters of vacuum furnaces, recorded in the Cloud will lead to increased reliability and reduced service costs. In the paper, the research methodology for identification of the critical parameters of the predictive maintenance system is proposed. Illustrated examples of the thermographic investigation of a vacuum furnace are given.

Keywords
Predictive maintenance, vacuum furnace, Industry 4.0, self-monitoring, thermo-visual investigation.

Introduction

Predictive maintenance is a very important component of the Industry 4.0 Concept. Predicting the breakdown of machinery is crucial for implementing such ideas as the massive customization of flexible and autonomous manufacturing systems. Predictive maintenance is an advanced method for the improvement of maintenance which is based on the Markov Process, the Bayesian Network, Artificial Neural Networks and the Monte Carlo Simulation, etc. [1] However, all methods need historical data about the exploitation and breakdown of manufacturing resources. The monitoring of manufacturing resources and the collection and analysis of data, for improving manufacturing processes, belong to the concept of data-driven, 'Smart' manufacturing which is compatible with the Industry 4.0 Concept [2]. There are already a number of studies examining 'big data' in manufacturing enterprises [3–5]. Bahga and Madisetti proposed CloudView, for storing, processing and analysing the massive amount of data on the maintenance of machinery, collected from a large number of sensors embedded in industrial machines, in a Cloud computing environment [6]. Chen describes the rationales and needs for integrated and intelligent manufacturing systems, including the analysis of 'big data' for the requirements of predictive maintenance [7]. Baptista et al. proposed integration of the auto-regressive moving average (ARMA) methodology, with data-driven techniques to predict fault events [8]. Lee et al. proposed the methodology of implementing cyber physical systems for predictive production systems [9, 10].

Selcuk presents new trends and techniques in the field of predictive maintenance and proposes implementing a method for a predictive maintenance programme in industry [11]. Susto et al. proposed using a multiple classifier machine learning methodology for predictive maintenance. The proposed solutions enable dynamic decision rules to be adopted for maintenance management. Hashem et al. analysed the limitations of time-based, equipment maintenance methods and the advantages of predictive or online maintenance techniques in identifying the onset of equipment breakdown [12]. Hashemian and Beam analysed three major predictive maintenance techniques, defined in terms of their source of data and described as the existing sensor-based technique, the test-sensor-based technique and the test-signal-based technique [13]. They present examples of detecting blockages in pressure sensing lines using existing, sensor-based techniques. Okoh et al. developed the through-life performance approach which ensures that a manufacturing system needs to undergo maintenance, repair and overhaul before breakdown occurs [14]. Horenbeek and Pintelon propose a dynamic, predictive maintenance policy for multi-component systems that minimises the long-term mean maintenance cost, per unit of time. They compare the developed, dynamic predictive maintenance policy to five other conventional maintenance policies [15]. Raaza and Ulansky propose mathematical models to calculate the maintenance indicators for the arbitrary distribution of time to breakdown [16]. Efthymiou et al. present a review on predictive maintenance methods and tools and present an integrated predictive maintenance platform for manufacturing systems [17]. Kłos and Patalas-Maliszewska propose the use of simulation methods for evaluating the performance of a predictive maintenance system [18]. Mori and Fujishima introduce a remote monitoring and maintenance system for machine tool manufacturers [19]. Dong et al. present the monitoring and maintenance of equipment systems for mine safety. They establish a predictive maintenance system which is based on the technology of the Internet of Things, in order to change the existing method for the maintenance of coal mining equipment [20]. In the literature, many decision-support tools have been proposed, based on the computer-simulation method for effective maintenance operations. Ni and Jin propose mathematical algorithms and simulation tools in order to identify data-driven, short-term, throughput bottlenecks, the prediction of windows of opportunity for maintenance, the prioritisation of maintenance tasks, the joint production-scheduling and maintenance-scheduling of systems and the management of maintenance staff [21]. From the above, short overview of the literature presented, the fact remains that predictive maintenance will be very important over the coming years for the development of the industrial sector.

In the paper, the research concept for developing a predictive maintenance system, dedicated to the vacuum pit furnace, (Fig. 1) is presented. The research project is undertaken in conjunction with the R&D Department of the SECO/WARWICK S.A. Company and funded by the European Union and the National Centre for Research and Development in Poland.

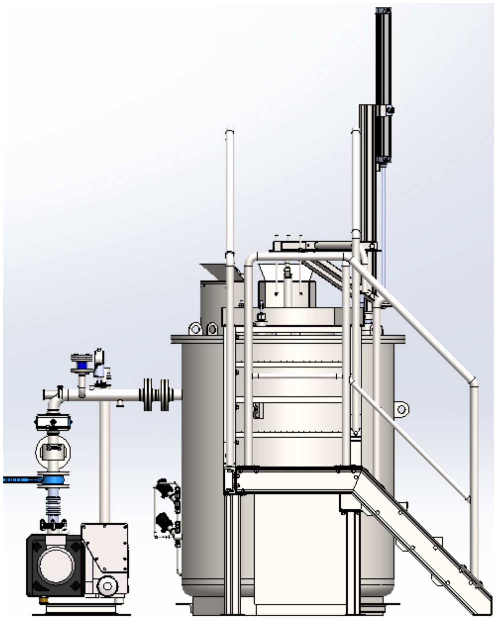

Fig. 1. The vacuum pit furnace [22].

The SECO/WARWICK company has been developing vacuum furnace technology, specifically for the aerospace, energy, defence, medical, machine, automotive, tool and hardening plants for over 25 years. The main result of the research project is the significant improvement of the vacuum furnace by equipping it with the facility to self-diagnose which enables potential breakdowns to be predicted. The self-diagnosis system will allow the exchange of data, obtained from a vacuum furnace, with other process line devices, in accordance with the Industry 4.0 Concept. Analysis of the operational data of vacuum furnaces, recorded in the Cloud, will increase the efficiency of warranty and post-warranty service, improve operational parameters and enable better equipment to be built more cheaply, in the future. In the next chapter, the main assumptions of the research project are presented.

The assumptions of the research project

The vacuum furnace is a very complex and technologically advanced device in which such special technological processes as annealing, solution heat treatment, brazing, sintering, gas and oil hardening, carburizing, nitriding and other processes are implemented. Heat treatment is often the last stage of the technological process in the production cycle. In many cases, the value of the processed workpiece may exceed the cost of the device, for example, in the heat treatment of very expensive, responsible elements, such as construction pipes in heat exchangers for nuclear reactors. Enterprises responsible for heat treatment always take the risk of financial loss due to disturbances in the heat treatment processes carried out. The most common reasons for the damage or destruction of a processed batch, in addition to the human factor, are breakdowns and abnormalities in the operation of the heat treatment equipment. Accumulated breakdown costs may include batch costs, repair costs, start-up costs and downtime costs.

The vacuum furnace comprises the following sub-systems, viz., control, heating, pumping, cooling, pneumatics, gas and insulation. In the first step of the project, a measuring system is developed for analyzing the operating parameters of all sub-systems. For the proper selection of measurement system components, or sensors, a detailed analysis is carried out on the functions and potential breakdowns of the sub-systems. The methodology of the analysis of the predictive maintenance of a vacuum furnace is presented in Fig. 2. In this first step, the most frequent breakdowns in an individual system should be identified. In order to identify potential breakdowns, an analysis (FMEA) of the breakdown mode and of the effects on the product and process, is undertaken. On the basis of such an analysis, the risk of breakdowns and the impact on the whole heat treatment process is determined. In the next step, the symptoms of the potential breakdowns, along with the measurement methods for those symptoms, should be determined. This step is very important for the maintenance prediction process and requires intensive research. Some breakdowns, such as leaks in the pump sub-system or disruption to the cooling sub-system, could be simulated but some symptoms could show up only by the long-term use of the vacuum furnace, such as with the degradation of the heating elements or the insulation. The research results, that is, the signals obtained from all sensors, will be collected in the Cloud database and, based on an analysis of the data, the prediction algorithms will be prepared. In the next step, the algorithms should be tested, in practice, based on the standards of the heat treatment processes implemented. The validation of the predictive maintenance algorithms is the last step in the methodology proposed. Validation will be based on testing the effectiveness of the algorithms in industry and increasing reliability in vacuum furnaces.

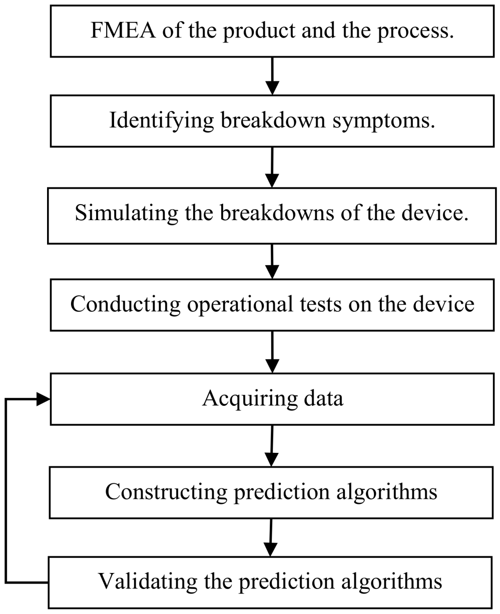

Fig. 2. The methodology for analyzing the predictive maintenance of a vacuum furnace.

The process of validating prediction algorithms is both permanent and adaptive. Predictive maintenance algorithms will be improved on the basis of the analysis of '*big data*' obtained from the monitoring of many devices. In the next chapter, the example of the initial research and the analyses of the operating parameters of the vacuum furnace sub-systems, are presented.

Examples of investigation by thermography

Initial research of vacuum furnace sub-systems includes thermographic analysis. Together with the device constructors and service workers, the set of markers on the device is applied. The markers are allocated to the critical point of all sub-systems of the vacuum furnace. Thermographic investigation is performed at an ambient temperature of 22.4°C and an air humidity of 36% using an FLIR T420 thermal camera; the thermographic analysis of the shell of a furnace is presented in Fig. 3.

Fig. 3. Thermographic investigation of the shell of a vacuum furnace.

As can be seen from the picture, there is no insulation damage, nor are there any thermal bridges. The investigation was conducted 3 times, while the furnace chamber was being heated; part of the cooling sub-system is presented in Fig. 4. The temperature of the water in the cooling system, measured using the thermal camera, was compared to the temperature indicated by the sensor, mounted on the water input and output pipes.

Fig. 4. Thermographic investigation of the cooling sub-system.

The effectiveness of the pumping sub-system is highly important, both for the power consumption of the furnace and for the quick removal of the vacuum, as well as for the correct completion of the technological processes. Investigation of the temperature of the pumping sub-system (Figs 5 and 6) enable the effectiveness of the device to be evaluated. Many operating parameters rely on the proper functioning of the pumping sub-system such as the quality and purity of the oil and the air- tightness of the furnace.

The efficiency of the pumping system could be also affected by leaks in the pipework or leaks in the furnace chamber. Another factor affecting the efficiency of the pumping system is the limited airflow through the filter which might have become contaminated with use.

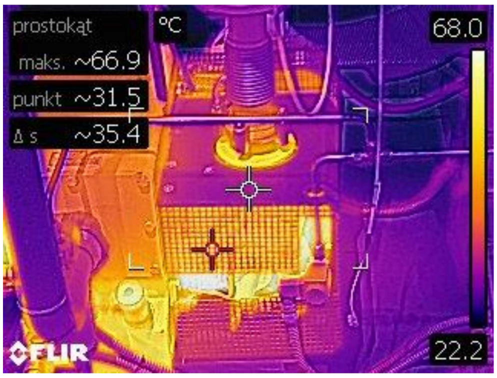

Fig. 5. Thermographic investigation of the pumping sub-system.

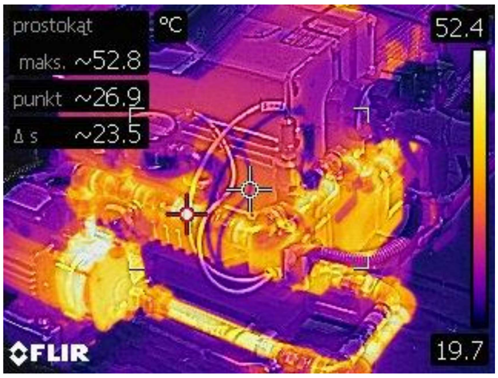

Fig. 6. Thermographic investigation of the pumping sub-system.

The temperature distribution in the electrical control panel has an impact on the whole control sub-system and quality of the data measured. Too high a temperature can also affect the control process. An example of the distribution of the temperature in the electric control panel is presented in the Fig. 7. Analysis of the distribution of the temperature in the control panel could result in recommending a better allocation of the components of the control sub-system.

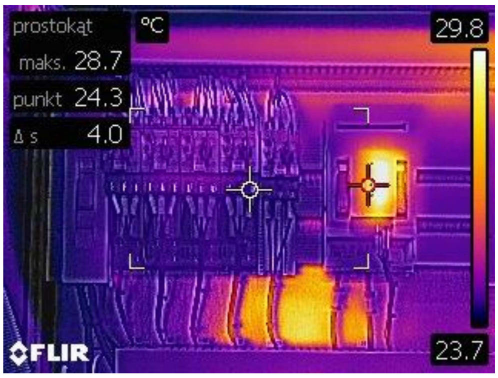

Fig. 7. Thermographic investigation of the electric control panel.

Analysis of the data of a simulated breakdown in a vacuum furnace

The simulation of the system breakdown is prepared using a gas dosing valve with separate shut-off valve EVN 116. The gas dosing valve EVN 116 is presented in the Fig. 8.

Fig. 8. The gas dosing valve EVN 116.

The device enables the calibration gap in the vacuum furnace to be set. The characteristics of the calibration gaps are presented in the Fig. 9.

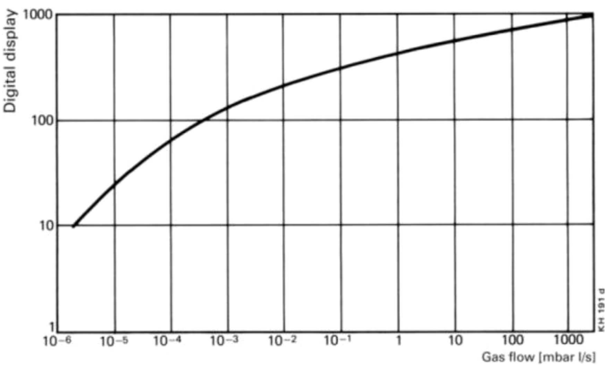

Fig. 9. The gas flow characteristic of the calibration gap [23].

To guarantee the tightness of the vacuum furnace, an infiltration test is conducted. The value of infiltration I is calculated on the basis of the formula (1):

$$I = 1000 \cdot V \frac{P_e \cdot \left(0.5 \cdot \left(1 + \dfrac{273 + C_b}{273 + C_e}\right) - P_b\right)}{60 \cdot T}, \quad (1)$$

where V – volume of furnace chamber, P_b – beginning pressure, P_e – end pressure, C_b – beginning temperature, C_e – end temperature, T – waiting time.

The results of the infiltration test are presented in Fig. 10. The vacuum furnace was cooled from a temperature of 1000°C – 72°C and only the final, 7 temperature measurements are presented on the chart (104°C – 72°C).

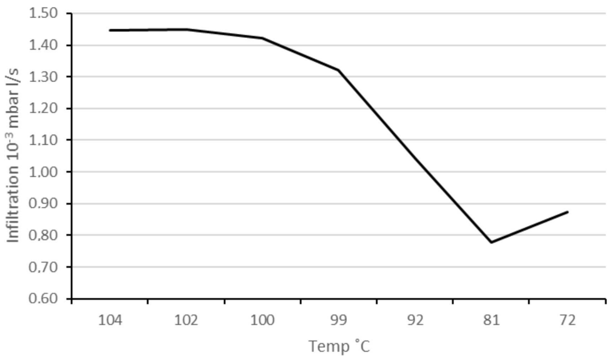

Fig. 10. The result of the infiltration test.

The results of the infiltration test were very good; as the temperature decreased, the infiltration value also decreased.

The vacuum furnace breakdown test was made using the calibration gap. The device was set to 999, opened for short intervals of several seconds and then closed. The furnace's vacuum pump was in constant operation. Any leaks in the furnace are registered immediately by the vacuum sensor (see Fig. 11).

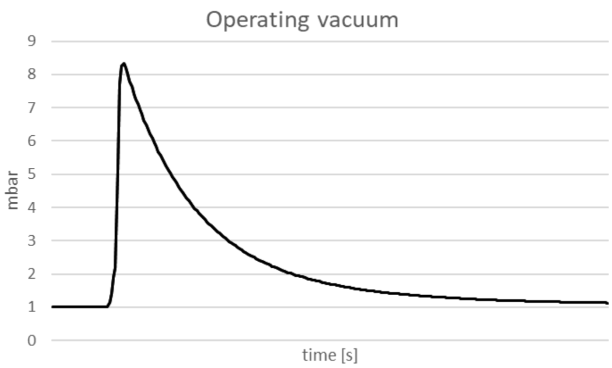

Fig. 11. Leaking in the vacuum furnace, registered by the vacuum sensor.

At the same time, the Lambda probe sensor reacted activated and showed the presence of oxygen in the furnace chamber. The values registered by the Lambda probe sensor are presented in mV. After closing the calibration gap, the operating vacuum returned to the beginning value for a short time, but the presence of oxygen continued to register for some time thereafter (see Fig. 12).

Leaking in the vacuum furnace could be also registered by the vacuum pump's total power sensor, with power consumption being immediately increased to reduce the pressure in the furnace chamber (see Fig. 13).

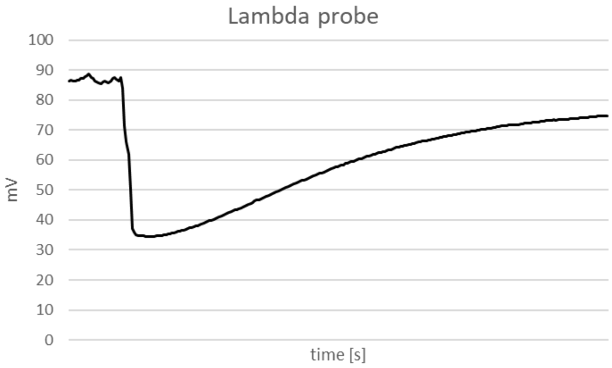

Fig. 12. Leaking in the vacuum furnace registered by the Lambda probe sensor.

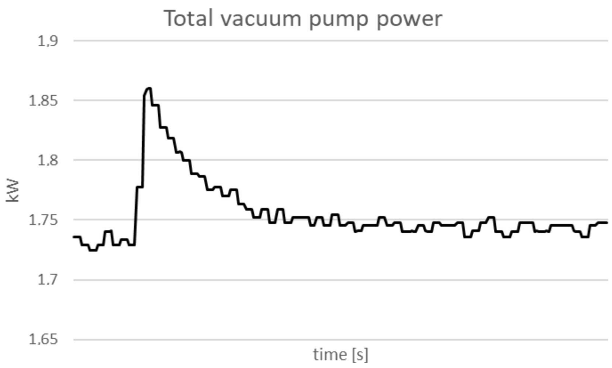

Fig. 13. Leaking in the vacuum furnace, as registered by the vacuum pump power sensor.

The test presented will be repeated for the different settings of the calibration gap, in order to find the critical values for the detection leakage in a furnace.

Conclusions

In the paper, only some of the assumptions of the research project for building a predictive maintenance system, dedicated to vacuum furnaces, are presented. The methodology for analyzing predictive maintenance for vacuum furnaces is proposed. As a part of the research, analysis was carried out on the construction of a pit furnace and the existing solutions for measurement systems. The functioning of most of the furnace's important sub-systems have been analysed. Based on the FMEA analysis of processes, detection methods for breakdowns of particular sub-systems have been planned. In order to determine the design requirements for the *'Smart'* measurement system, an analysis of planned, heat treatment operations was carried out, using a prototype vacuum furnace and a thermographic investigation of the sub-systems of the furnace was conducted. The research conducted was only part of the planned research programme which included:

- the durability of heating elements (change of resistance, degradation of the oxide passive layer),
- the degradation of the external insulation layer and the change in its thermal conductivity,
- the change in the resistance of culverts and ceramic supports used for fixing heating elements,
- the *rôle* of vacuum pumps and the development of a mathematical model that allows control of the impact of the deposit.

Of great importance in implementing the predictive maintenance system of the vacuum furnace, would be investigation into the methods used, *vis-à-vis* batch quality. During production processes, the charge is often contaminated with coolant or oil. The heating treatment results in the formation of hydrocarbons and carbon compounds which are detrimental to the functionality of the device.

The main advantages in the implementation of the research project will be:

- a reduction in service costs,
- a reduction in the 'human factor' – *so-called* – related to the supervision, breakdown and servicing of the vacuum furnace,
- a reduction in the costs of unplanned downtime in production lines where vacuum furnace systems are installed,
- a reduction in energy and material losses, resulting from the reduction in the number of vacuum furnace breakdowns,
- an increase in the economic benefits for furnace users, due to the effective use of production capacity and the timely delivery of products.

Implementation of the findings of the project will, in the long term, result in the replacement of existing atmospheric furnaces on today's market, with deep vacuum furnaces; this will be in line with the Industry 4.0 Concept.

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