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Analysis of Anomalies in the Thermal-Mechanical Fatigue Process Using Selected IT Tools

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Abstract

The article uses the results obtained during the tests of a wide group of metal alloys using a device operating by the Coffin method. The measure of resistance to thermal-mechanical fatigue is the number of cycles that the sample withstands before a macrocrack occurs, at a fixed current and temperature range. The device offers the possibility of working in two modes of sample mounting. The first mode allows the sample to freely elongate parallel to its axis, while the second mounting mode limits this elongation by using a transducer. The aim of the publication is to present possible solutions for anomaly detection. Anomaly detection concerns traps that may occur during the measurement process. Advanced machine learning methods were used to analyze and detect anomalies in data regarding thermal fatigue resistance. Isolation Forest and One-Class SVM algorithms were used for anomaly detection, which allow for effective identification of unusual patterns in the data. The conducted research confirmed the usefulness of one of the selected methods in the process of anomaly identification using the example of elongation.

Keywords: Thermal-mechanical fatigue, Vermicular cast iron, Coffin method, Isolation Forest, One-Class SVM

1. Introduction

Thermal fatigue is the process of degradation of mechanical parameters, the formation and development of structural defects and damages (cracks) as a result of changes in internal energy under the influence of a periodically changing temperature field. For this reason, various modifications are introduced in the metallurgical process, consisting of, for example, prior crushing of graphite contained in cast iron or introducing additional elements such as chromium, nickel, molybdenum or aluminum into the alloy, which modify the properties of this material [1, 2]. To study the influence of chemical composition modification and the method of cast iron processing on strength parameters, it is necessary to conduct thermal fatigue tests of standard samples of casting material. Due to the multitude of factors influencing the material's resistance to thermal fatigue under the influence of a periodically changing temperature field, there are currently no standard solutions for devices for conducting this type of tests [3-5]. Some solutions are based on the general solution presented by Coffin, in which the tubular sample is fixed in a rigid holder in a frame that is non-deformable in relation to the sample [6]. Thermal fatigue rarely occurs in its pure form, more often it is a combination of: cyclic mechanical stresses (thermal-mechanical fatigue), corrosive processes (thermal-corrosive fatigue), abrasion, etc., which causes the wear mechanism to be different compared to creep. In the literature, one can find certain dependencies of thermal fatigue resistance on material properties, the values of which should be as high as possible for: thermal conductivity, strength, elongation, and the values of properties as low as possible for: modulus of elasticity, expansion. However, these estimates are very general and difficult to apply [7, 8]. For this reason, tests were carried out to use selected computer tools for predicting phenomena occurring during the thermal fatigue process. Prediction, often called the prediction of future events based on the analysis of historical and current data, is an important tool in many industries, including casting production. This process involves the analysis of large data sets, which allows for the prediction of future results and making decisions based on them. Thanks to prediction, it is possible to optimize production, minimize risk, reduce costs and increase efficiency [9, 10].

Another interesting topic is the evaluation and detection of deviations from the typical thermal fatigue process. Detection of anomalies can be important in many aspects of casting production, for example, monitoring the chemical composition of the metal alloy. Deviations from established parameters can indicate that materials arriving at the production facility are defective, incomplete, of poor quality, or not as ordered. Real-time temperature monitoring during the melting process is also essential. Anomalies in temperature can signal furnace problems or irregularities in the molten metal. Analysis of the casting shape compared to expectations can help detect defects or deviations. Anomaly analysis can include examining the casting surface to detect defects such as cracks, pores, or excess material [11, 12]. Isolation Forest is a machine learning algorithm used for anomaly detection, also known as iForest. It was developed by Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou in 2008. Its unique method is to isolate anomalies, rather than building a profile of normal data, which is the typical approach in other anomaly detection techniques [13]. One-Class SVM (Support Vector Machine) is a machine learning technique for anomaly detection or classification tasks where only data from a single class is available. It is a specific case of the SVM algorithm, which is traditionally used to solve classification and regression problems with data from multiple classes. One-Class SVM focuses on finding a decision boundary around data from one class, in order to best separate this data from the rest of the feature space, where new, previously unseen data points may appear [14].

Thermal fatigue of iron alloys is a very complex issue. It covers many scientific fields, including: materials engineering, solid state physics, chemistry, thermodynamics, mechanics. A number of cast elements or finished mechanically processed products are operated in a variable temperature field with varying intensity. The development of the automotive, metallurgical (iron and non-ferrous metals), glass, shipbuilding industries, etc. has revealed new challenges for the development of increasingly better casting materials resistant to the effects of variable temperature fields. The possibility of using modern computer tools is an issue with great development potential. Some computer tools may be helpful for this purpose.

2. Description methodology and materials

2.1. Thermal-mechanical fatigue resistance measurement

The measurements were carried out on a device based on the L. F. Coffin method, in the temperature range of 100 - 800^{o}C (WP1 sample), for the warm8 sample a lower maximum temperature of 100 - 600^{o}C was assumed. In this method, heating is carried out by passing current through the tested sample. A constant current of 330 A was set, which flowed through a sample with a measuring section cross-section of 30.6 mm^2. The cooling rate was carried out at an average rate of 10^{o}C/s. The cycle consisted of heating and cooling. The heating and cooling rates are not the same. The heating rate is the highest at low temperatures and decreases until the peak temperature. Then, after a rapid initial cooling, an inflection point occurs with gradually slower cooling. The change temperature for time is not the same for each cycle. Additionally, slightly higher temperatures are achieved than at the set point (less than 20^{o}C).

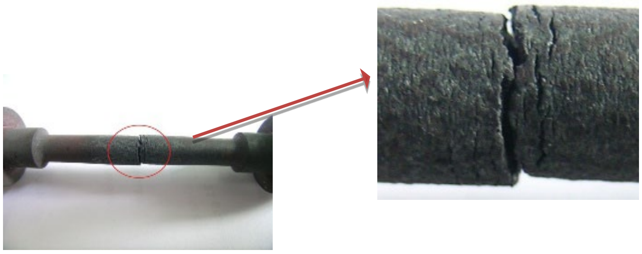

Fig. 1. Sample damage

The measure of resistance to thermal-mechanical fatigue is the number of cycles that the sample will withstand until a macro crack occurs at a given current and temperature range. The cycle measurement is completed when the sample is damaged as shown in figure 1. During the tests, the following sample parameters were recorded at 1 second intervals: temperature, force, elongation, resistance, current, resistance.

2.2. Algorithm parameters

Table 1 shows the parameters of the Isolation Forest algorithm, which were carefully chosen to provide optimal results for a given sample. For example, for the sample "werm8", the parameter analyzed was "Elongation". The time variable in this analysis is "Cycle". The algorithm uses 150 isolation trees and builds each tree using 256 data group. The window size, or the number of samples considered at one time, is 100.

Table 1.
Isolation Forest algorithm parameters

Name of the Tested Collection	WP1	werm8
Name of the Analyzed Variable	Elongation	
Time Variable	Cycle	
Number of Insulation Trees	400	150
Number of Samples for Building Each Tree	512	256
Window Size	100	100

Table 2 shows the parameters of the One-Class SVM algorithm, which have been carefully selected to provide optimal results for a specific sample. The name of the test is "werm8", and the parameter analyzed is "Elongation". The value of the parameter ν\nuν is 0.01, and the kernel used is "rbf" (radial basis function). These carefully selected parameters aim to maximize the efficiency of the One-Class SVM algorithm to identify anomalies in the data from this test as accurately as possible.

Table 2.
One-Class SVM algorithm parameters

Name of the Tested Collection	WP1	werm8
Name of the Analyzed Variable	Elongation	
Nu	0.01	0.01
kernel	rbf	rbf

Table 3 presents data on the chemical composition of the tested alloys. The WP1 sample was made of Maraging steel, while the werm8 sample was made of vermicular cast iron.

Table 3.
Chemical composition of selected samples

Chemical composition		WP1	Werm8
C	%,	0,02	3,75
Si		0,08	2,33
Mn		0,01	0,4
P		0,07	0,04
S		0,01	0,012
Mg		-	0,013
Ni		18,5	-
Mo		4,8	-
V		-	0,23
Ti		0,6	-
Zr		0,01	-
Co		9	-
Al		0,1	-
Sb		-	0,064

3. Description of achieved results of own researches

3.1. Identification of anomalies

During the thermal fatigue resistance test, the sample gradually degrades as shown in Figure 2. Figure 2a shows the microstructure of the warm8 cast iron before the tests, while Figure 2b shows the microstructure of the sample after the tests. Clear cracks and "burnt" graphite are visible. Such changes in the microstructure cause the material not to meet the basic design requirements. Depending on the sample material and process parameters, the test may last 57 cycles as was the case for the warm8 sample or 4000 cycles as was the case for the WP1 sample. In the case of nickel alloys, these materials are characterized by even higher resistance to thermal shocks. The thermal softening process takes time, causing a gradual decrease in mechanical and functional properties. An attempt to use computer tools to determine or identify events deviating from the norm, i.e. potential moments affecting strength parameters, was undertaken using two algorithms: Isolation Forest and One-Class SVM. In this work, an analysis of anomaly values was carried out in two sample samples: WP1 and werm8, in order to identify significant cases changes elongation during cycle and compeered to average value from thermal fatigue resistance test. Anomaly values are an indicator of deviations from the norm, which allows for the assessment of the degree of elongation or shortening of materials. Anomaly is identification on raw data. This data shows changes elongation samples.

In the case of the Isolation Forest algorithm, after receiving an HTTP POST request, the program starts by obtaining the following parameters: collection name in the database (collectionName), value key (valueKey), time key (timeKey), number of trees (nTrees), sample size (sampleSize) and window size (windowSize). Then, using the MongoClient client, a connection is established to the MongoDB database, from where the data is retrieved. Data from the database is transformed into a format useful for the Isolation Forest algorithm, and then the model is trained on their basis. The model evaluates the data group, returning results in the form of scores, which are the basis for identifying anomalies. Anomaly detection is implemented using a sliding window mechanism, which allows dynamic adjustment of anomaly detection thresholds depending on changing data patterns.

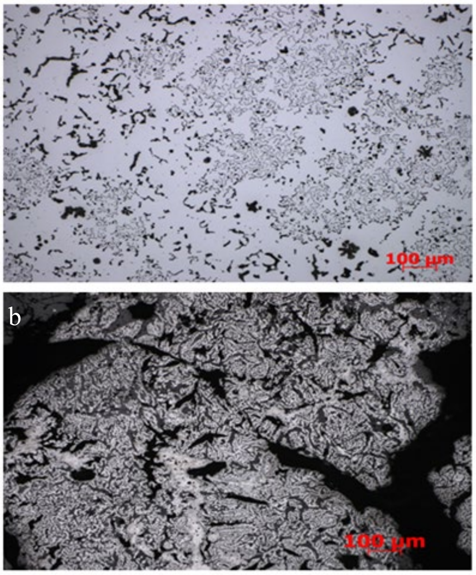

Fig. 2. Microstructure of werm8 cast iron: a) before the thermal fatigue resistance test; b) after the thermal fatigue test

This approach increases the adaptability of the model to evolving data conditions. The algorithm is equipped with error handling, so that in the event of unexpected problems (e.g. database connection errors or internal algorithm errors), it can react appropriately and inform the user about them. One-Class SVM for real-time anomaly detection was integrated on data from the MongoDB database. This algorithm implemented support vector machine (SVM) methods for one class, using child processes in Node.js to run Python scripts that process the data and return results. Variables and data structures, such as anomalies and values, are defined at the module level. They are used to store the results of data operations that can be used in different parts of the program. The One-Class SVM model is configured and trained using the passed parameters. It is important here to determine which parameters are most relevant to the analysis and how they affect the model performance.

Figure 3 shows the graph of elongation anomalies from cycles for the WP1 sample, which covers a wide time interval from 0 to 4000. The anomaly values in this sample range from 2.19 to 2.22, indicating significant elongation of the material. The graph shows that the data are not evenly distributed over a long period of time, with visible clusters of anomaly values in specific time intervals. The anomalies occurring in the initial period of the study can be explained by phenomena related to the deformation of the sample, while the final stage is related to material degradation and deformation decay. The middle anomalies was showing because measurement, was stope by technical pause. The anomalies occurring between 1000 and 1500 cycles are particularly interesting, they occurred well before the sample fracture.

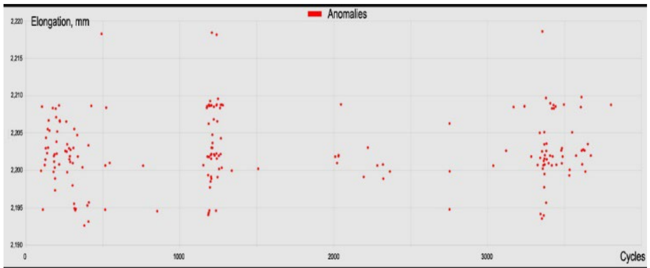

Fig. 3. Elongation anomaly graph from cycles for sample WP1 determined using the Isolation Forest algorithm

Figure 4 shows the graph of elongation anomalies from cycles for the werm8 sample, which covers the interval from 0 to 40. This is significantly shorter than in the case of the analysis presented in Figure 3. The anomaly values for this sample are negative and range from -0.02 to -0.03. The data in the graph are scattered over the entire time axis, with a visible accumulation at the end of the studied interval. This phenomenon concerns a significant reduction in elongation before the sample breaks.

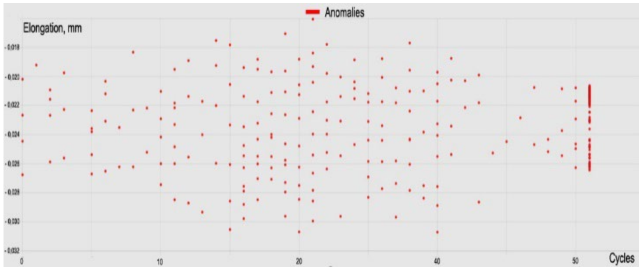

Fig. 4. Elongation anomaly graph from cycles for the werm8 sample determined using the Isolation Forest algorithm

Figure 5 shows the graph for the WP1 sample covering a wide time interval from 0 to 4000. The anomaly values in this sample range between 2.10 and 2.45, which indicates significant deviations in the material. Similarly to the analysis of anomalies using the Isolation Forest algorithm, Figure 5 shows a clustering of anomalies at the final stage of the thermal fatigue resistance testing process.

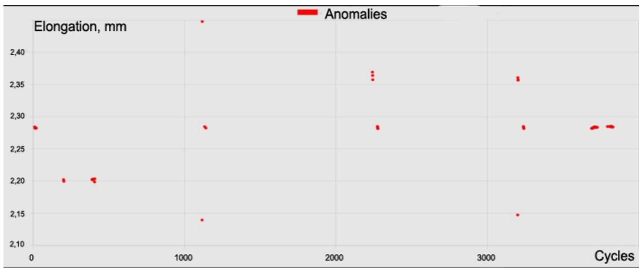

Fig. 5. Elongation anomaly graph from cycles for sample WP1 determined using the One-Class SVM algorithm

Figure 6 shows the graph for the werm8 sample, covering the time interval from 0 to 45. The anomaly values for this sample range from -0.05 to 0.15, which indicates smaller deviations from the norm. The obtained results are difficult to interpret. This may be due to the significantly smaller amount of data than in the case of the WP1 sample.

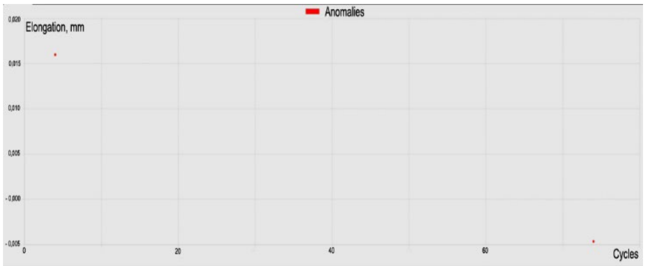

Fig. 6. Elongation anomaly graph from cycles for the werm8 sample determined using the One-Class SVM algorithm.

4. Conclusions

Compared to the One-Class SVM algorithm, the Isolation Forest algorithm achieved better results, providing more stable and precise anomaly values. The Isolation Forest algorithm proved to be more effective in identifying and classifying anomalies compared to the One-Class SVM, which suggests its greater suitability for analyzing the thermal fatigue resistance testing process. For both cases of the algorithms used, better results were obtained for the WP1 sample, which was characterized by a significantly larger number of cycles compared to the werm8 sample. The number of data suitable for training the algorithms is therefore of great importance. However, it should be noted that in the case of the Isolation Forest algorithm, it was possible to identify the moment of approaching rupture of the werm8 and WP1 samples. Further research can focus on understanding the mechanisms leading to the observed deformations and on developing new materials with desirable mechanical properties. Moreover, comparative analyses with other samples can provide additional information on the influence of various factors on the behavior of materials, which is crucial for engineers and scientists working on innovative material solutions. The Isolation Forest algorithm, due to its efficiency, is a valuable tool in these analyses.

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