Neural network to diagnose lining condition

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Abstract. The paper presents data on the problem of diagnosing the lining condition at the iron and steel works. The authors describe the neural network structure and software that are designed and developed to determine the lining burnout zones. The simulation results of the proposed neural networks are presented. The authors note the low learning and classification errors of the proposed neural networks. To realize the proposed neural network, the specialized software has been developed.

1. Introduction

In the course of industrial production, dangerous and critical production facilities and machinery are used. Lined equipment, including torpedo ladle cars, hot-metal cars and steel ladles are considered to be critical equipment at heavy industry and machinery building facilities. Such equipment is classified as critical since consequences of accidents involving such equipment lead to multimillion losses for the enterprise and in some cases to human deaths, which is proved by a number of sources [1-3]. In order to prevent accidents with such type of equipment and maintain industrial safety at the production facility, a growing number of diagnostic operations and technologies to control technical condition of lined equipment are applied in production units which, in turn, require development of new and improvement of existing technical means and information technologies.

Nowadays there are different automated systems to monitor, diagnose and operate critical equipment at production units [4-6]. Existing automated systems possess a wide range of functions to diagnose and monitor the condition of critical equipment; however, as a number of sources claim [5-8], existing systems do not provide diagnostics of the given lined equipment in the real-time mode without stopping exploiting it. It should be mentioned that modern automated systems are unable to provide complete complex (qualitative and quantitative) automated evaluation of the lining condition, which leads to a low level of objectiveness and quality of the decisions taken while exploiting the equipment. Another important factor is that the existing systems are oriented to diagnose only certain equipment and their adaptation to a different production facility requires a lot of time and finance [9-10]. That is why, scientific research in the field of computerization and intellectualization of the lined equipment condition diagnostics is relevant.
2. The method to diagnose the lining condition
The existence of lining, which serves to protect from the impact of high temperatures of the internal content that might be over 1000°C, is a feature of an internal structure of critical lined equipment. The feature of diagnostics of critical lined equipment is that the changes in the condition of its lining can be determined by thermograms analysis which is obtained with help of the thermal method or laser scanners. Thermograms of the critical lined equipment in two-dimension space are presented as spot-like images with spectral allocation of colours. Thus the research of the lining condition based on thermograms is seen as recognition of a multicoloured spot-like image according to certain characteristics. Although the existing methods allow one to determine the lining burnout zones, they do not allow carrying out qualitative analysis of the burnouts (determination of the depth and the area of the burnout).

To diagnose of the lining condition and to carrying out qualitative analysis of the lining burnout zones, the method, which includes the following main stages, is proposed:
1. Receiving the lined equipment thermogram by a thermal imager.
2. Thermogram image processing by the proposed neural network in order to determine the burnout zones and provide their qualitative evaluation.
3. Creation of the damaged areas map of the lining with classification of the burnout level.

The thermogram image processing includes pre-processing followed by its recognition by the proposed neural network. The pre-processing of the thermogram image is carried out using the method of adaptive transformation of local contrast and a Prewitt filter. Usage of the methods of pre-processing is based on their high efficiency to determine and highlight boarders of the lining burnout zones, which is proved in a publication [11-12].

After determining the boarders of the lining burnout zones, the second stage proceeds with determination of quantitative information parameters of the burnout zones of the lining. The following information parameters are the basis for analysis and recognition of the burnout zones in the lining:
1. The mass centre of the thermogram fraction which is a part of the lining burnout zone.
2. The distances matrix to the boarders of the determined burnout zone, measurements of elements of which are calculated in relation to the mass centre of the thermogram fraction. The distance matrix provides calculations for each angle of the thermogram fraction from 0 to 360.
3. The colour value of lining the burnout zone.

The suggested parameters characterise fractions of the thermogram that are zones of the lining burnout as the area of burnout will expand due to exposure to high temperatures; thus the mass centres will change depending on the level of burnout. The distances in matrix will also change in relation to the mass centre and the change of the colour in the mass centre of the fraction will characterise the depth of the burnout.

Thus, the proposed characteristics will be the input at the entrance to the neural network which is designed to classify the burnout levels of lining zones. To reduce the time for network training, it seems to be rational to decrease the number of meanings in the input sampling. Only those values of the distances matrix that describe the main angles related to the centre of the thermograms fraction with a burnout zone, namely 0, 30, 45, 60, 90, 120 and 180 degrees, are to be used as the input for the neural network.

3. Synthesis of the neural network to diagnose the lining condition
A multilayered neural network for classification of the burnout levels is used, which allows one not only to define the fact of lining burnout existence, but also to conduct qualitative evaluation of lining condition (evaluation of the area and depth of the burnout in accordance with the burnout level). The proposed structure of the neural networks is presented in figure 1.
After a structure for a neural network is selected, the network has to be trained. Training of a neural network in the course of action is conducted in accordance with the back propagation algorithm [13-14] with organizational changes induced during the training. After modification of the training algorithm, the training includes the following two stages:
- the first stage includes classical training of a neural network based on standard training sampling;
- during the second stage, only experimental data are used to train neural network.

Thus, at first, the neural network is trained with the help of only standard data, and after the error reaches the required level, the training of the network proceeds on the basis of experimental data, resulting in mitigation of the recognition error due to which a high level of the network operation accuracy is achieved.

In order to conduct training of a neural network on the basis of standard thermogram images, 480 images of lined equipment of different types (torpedo ladle cars and steel ladles) were used. The second stage involved usage of 620 thermograms received during an experiment conducted at Alchevsk Iron & Steel Works. In order to train the neural network to react to incorrect thermograms, thermograms of standard images distorted with noises were used for training purposes. For both control and test sampling, 180 images of thermograms of the following lined equipment exploited at Alchevsk Iron & Steel Works were used: torpedo ladle cars (type PM350), immovable mixers (type MC 1300), 100t and 50t ladles.

To measure the quality of the classification of lining burnout zones with the help of the neural network, the standard error was calculated:

$$E = \frac{1}{n} \sum_{i=1}^{n} (y_i - y(k_i))^2$$

where $E$ - error of the burnout level classification;
$y_i$ - value of the $i$ exit of the neural network when recognising the thermogram;
$y(ki)$ - value of the $i$ standard exit of the neural network.

22 neural networks with different structures were created in the course of the work. Table 1 provides information about the best results of recognition of images of critical lined equipment thermograms demonstrated by neural networks with different structures.
Table 1. Results of recognition of images of critical lined equipment thermograms by neural networks with different structures

| Pattern of neural network | Classification error | Optimal number of training epochs | Total number of thermograms | Number of correctly recognized thermograms |
|---------------------------|-----------------------|-----------------------------------|----------------------------|-------------------------------------------|
| 150-50-5                  | 0.443                 | 440                               | 590                        | 545                                       |
| 150-70-5                  | 0.304                 | 630                               | 590                        | 537                                       |
| 150-30-5                  | 0.351                 | 280                               | 590                        | 562                                       |
| 200-50-5                  | 0.308                 | 650                               | 590                        | 577                                       |
| 200-30-5                  | 0.406                 | 600                               | 590                        | 549                                       |
| 250-50-5                  | 0.258                 | 660                               | 590                        | 563                                       |

The optimal number of training epochs for created neural networks was determined in accordance with training and classification errors dependences, samples of which for the neural network pattern of 200-50-5 is presented in figure 2.

Figure 2. Training (E_L) and classification (E_G) errors dependences for neural pattern 200-50-5.

Thus usage of neural network allows one to determine of the lining burnout level, simultaneously conducting qualitative evaluation of the lining condition as each level of burnout is characterized by corresponding measurements of the hate area and the depth of the burnout.

To realize proposed neural networks, the authors developed the software (figure 3).

Figure 3. Developed software to determine lining burnout zones.
The developed software is implemented at the Alchevsk Iron&Steel Works and is used to diagnose the torpedo ladle cars (type PM 350) in order to determine the lining burnout zones.

4. Conclusion
The following results were received in the course of the study:

1. The neural network approach to determine the lining burnout zones was proposed.
2. The software, which realized the proposed neural network to determine the lining burnout zones, was developed.
3. Adequacy of the proposed approach is confirmed by the low value of the mean-square error of the neural network.

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