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Methodology of automatic quality control of aluminium castings

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Methodology of research

ABSTRACT

Purpose: Employment of the artificial intelligence tools for development of the methodology of the automated assessment of quality and structural defects in the Al and Mg alloys and the custom made computer software will make it possible to determine the quality of the manufactured element based on the digital images registered in the X-ray flaw detection examinations. The possibility to correlate the frequency and morphology of defects with the technological process parameters will make it also possible to identify and classify these defects and control the process to minimise and eliminate them.

Design/methodology/approach: The developed design methodologies both the material and technological ones will make it possible to improve shortly the quality of materials from the light alloys in the technological process, and the automatic process flow correction will make the production cost reduction possible, and - first of all - to reduce the amount of the waste products.

Findings: The merit of the project consists in the interdisciplinary joining of the knowledge in the area of light metal alloys, including Al and/or Mg, in the area of materials processing connected with the entire scope of problems connected with manufacturing of products and their elements, in the area of the automated low-pressure die casting, and also in the methodology of structure and properties assessment of the engineering materials with, among others, the X-ray flaw detection and computer image analysis methods.

Practical implications: The developed methodology of the automated assessment of quality and properties of the light Al and Mg based alloys may be used by manufacturers of subassemblies and elements of engines (e.g., car engine bodies made from the light alloys with the low-pressure casting in the sand moulds).

Originality/value: The project's effects will be shortening the time needed for analyses and elimination of manu subjective evaluation errors made by humans.

Keywords: Automation of technological process; Al-Si-Cu; Neural networks; Images analysis; Cast defects

1. Introduction

Castings from aluminium alloys are widely used in production of machines and devices made in the technological processes. Aluminium alloys are especially preferred in designs thanks to their good mechanical properties and possibility to make very complicated castings with high service properties. Thanks to the contemporary casting and heat treatment technologies, castings from the aluminium alloys have the suitably high mechanical properties and simultaneously decrease the part weight. Therefore, there are more and more frequently used in the means of transport industry [1-5].

The aluminium alloys technologies; those currently used and of those the future, consist mostly in casting to permanent (metal) moulds. However, the tendency has appeared in batch production lastly to come back to casting these alloys into the sand moulds too, made on the highly efficient automatic production lines [6, 7].

The images are used in materials examination methods that feature the information source on material's structure, processes taking place in it, and its properties. Images obtained with the flaw detection methods, e.g., radiological or ultrasonic ones, are used for detecting material defects developed on various stages of the technological process [8].

The specific character of images does not always allow using directly the methods and means of the classic image recognition and digital processing theory. The lack of the uniform theory and general approaches renders extremely difficult selection of image processing and recognition algorithms and acquiring the right assessment of their effectiveness. Computer assistance is used more and more often to optimise the image processing task and improve its efficiency. Computer "vision" features the relatively new image technology developing very rapidly. Its main goal is the desire to furnish the computer with the image recognition and processing potential comparable with the living organism endowed by nature with the power of seeing. This stands for furnishing the computer with the artificial intelligence algorithms, whose goal is providing it with the capability of the autonomous use of its own input sensors for detection of the spatial information [8, 9].

The artificial neural networks are used more and more widely to carry out many tasks. The advantage of the neural networks is their capability to learn and adapt to the changing condition, as well as their capability to generalise the acquired knowledge. Thanks to these properties they can be used in all cases in which employment of the traditional methods is confronted with big difficulties, analytical solutions are impossible or hard to attain, in problems calling for associating and processing the incomplete or inaccurate information. Therefore, neural networks assist humans often in the process of taking difficult, and sometimes complex decisions [10-13].

The contemporary computer image analysis systems are much weaker than the human sense of vision in the qualitative interpretation of the contents of images. However, their advantage is the speed of analysis, resistance to fatigue and the possibility to make measurements [14].

The automated non-destructive testing systems are introduced currently, which is aimed, among others, at increasing the efficiency, improvement of detection of discontinuity of objects, or acquiring the objective information about the condition of objects. Test results may be archived and presented, as needed. Employment of the automatic methods makes it also possible, among others, to speed up the measurements, make them fully automatic, improve their repeatability and gives also access to a big number of the geometrical parameters [8, 9, 15-17].

The commonly used automation in the technological processes, including the manufacturing processes, is aimed at limiting or substituting human activity by operation of self-regulating machines and carrying out the particular functions unattended [18-21].

2. Experimental procedure

Examinations were carried out on the car engine elements' castings, i.e., blocks and heads from the W319 aluminium alloy with the chemical composition shown in Table 1, close to the chemical composition of the EN AC-AlSi7Cu3Mg alloy (Tab. 2) according to the PN-EN standard [22].

Castings of engine blocks were made using the "Cosworth" method.

The closed control loop of the mould filling system in the "Cosworth" method ensures (Fig. 1) [6, 7]:

- purity of the alloy in the casting furnace,
- exact duration control for all operations,
- repeatable, systematic mould filling,
- registering information for each casting operation.

The "Roll-over" mould turning technique is used in the "Cosworth" process, shown schematically on Figure 2. The successive stages of this process are:

1. Fill mould with clean metal,
2. Roll over with positive pump pressure. Prevents core blows,
3. Drain metal from runner,
4. Remove mould. Casting solidification is optimised.

The defect detection examinations were carried out with the X-ray method for the castings of the six- and eight-cylinders car engine blocks made with the "Cosworth" method" The examinations were made on the Philips MGC 30 rentgenograph at voltage of 100 kV and current of 10 mA. Exposure time was always 10 seconds. Several hundred electronic photos were made with the size of 1760x2140 pixels, which were saved in the JPG format. The set of the defect detection photos of the analysed castings of the combustion engines' blocks and heads is the base for further analysis. Defects documented on 300 photos made

Table 1.
Chemical composition of W319 aluminum alloy

Mass fraction of the element, wt %							
Si	Cu	Mg	Mn	Fe	Ti	Zn	Ni
5-8	2-4	0,1-0,6	$\leq$0,8	$\leq$0,9	$\leq$0,25	$\leq$3	$\leq$0,35

Table 2.
Chemical composition of EN-AC AlSi7Cu3Mg aluminum alloy according to PN-EN 1706:2001

Mass fraction of the element, wt %							
Si	Cu	Mg	Mn	Fe	Ti	Zn	Ni
6,5-8	3-4	0,3-0,6	0,2-0,65	$\leq$0,8	$\leq$0,25	$\leq$0,65	$\leq$0,3

were detected in the examined castings. Photos with no casting defects were not used for further analyses. Selected photos confirming casting defects were reduced in size for documentation (Fig. 4). Classification of casting defects identified in castings of the combustion engines elements was carried out based on the ASTM E155 standard (Tab. 3).

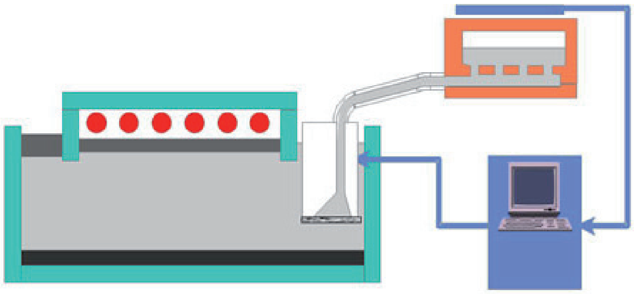


Fig. 1. Closed loop control system for mould fill

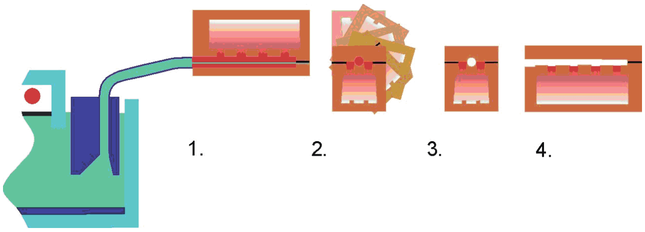


Fig. 2. The “Roll-over” mould turning technique

Table 3.
Types of the defects taken into consideration in classification

Symbol	Defect type	Number of classes
GH	Gas hole	1÷8
PR	Porosity	1÷8
SC	Shrinkage cavity	1÷8
SP	Shrinkage porosity	1÷8

The developed methodology pertaining to the automated classification of casting defects is a loopback of the technological process control based on data acquired from the process and the artificial intelligence methods used for that and from the developed computer programs. Schematic diagram of the system developed within the framework of this project is shown in Fig. 3, it consists from two logical blocks encompassing the procedure to improve the quality of castings of the car engine parts made from the Al-Si-Cu alloys of the PN EN AC-AlSi7Cu3Mg type.

Methodology of processing the information contained in images showing the examined castings of the engine blocks and heads, using the developed computer program, includes [15]:

- normalising parameters describing images of castings (size, scale),
- carrying out analysis of digital images showing sections of engine blocks and heads to extract casting defects from the image,
- calculation of areas, perimeters and geometrical coefficients of casting defects according to formulae,
- calculation of the geometrical values of casting defects, used as independent variable for the neural networks training.

Extracting images of defects consists in such data processing and further applying image analysis methods, so that the defect image is represented in 1-bit format, neglecting the objects which are the technological openings and are not defects (Fig. 5).

The block diagram of the data analysis for the developed methodology is presented in Fig. 6.

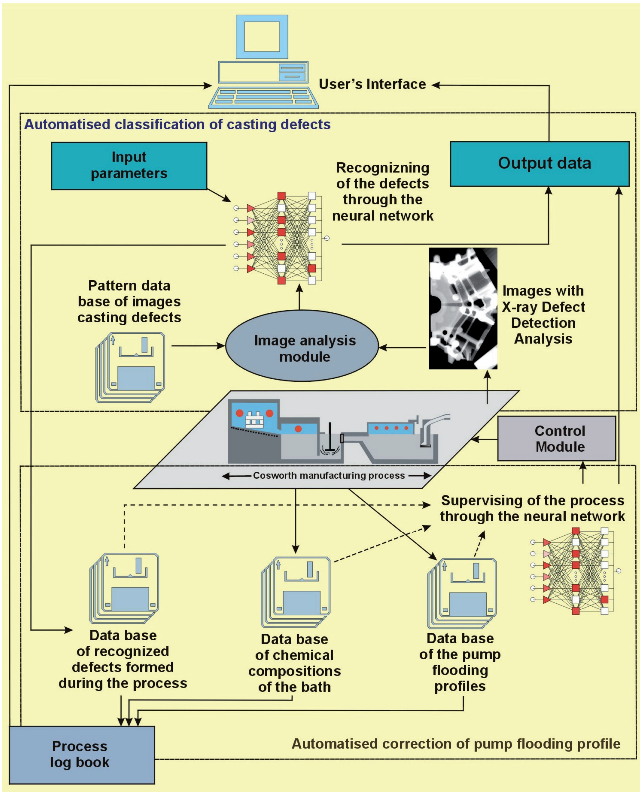


Fig. 3. Outline of the quality evaluation computer system and production process control

The interval estimation was used to evaluate the range in which values should stay of the geometrical coefficients describing the morphology of casting defects. In this way it was determined which objects in the image, after applying image analysis and after calculating the geometrical coefficients, are the casting defects. To do it, the confidence intervals for the average values were determined, assuming that the investigated values of the geometrical parameters have the normal distribution $N(\mu,\sigma)$. The confidence intervals for average values μ for the particular geometrical coefficients of the casting defects, i.e.: area,

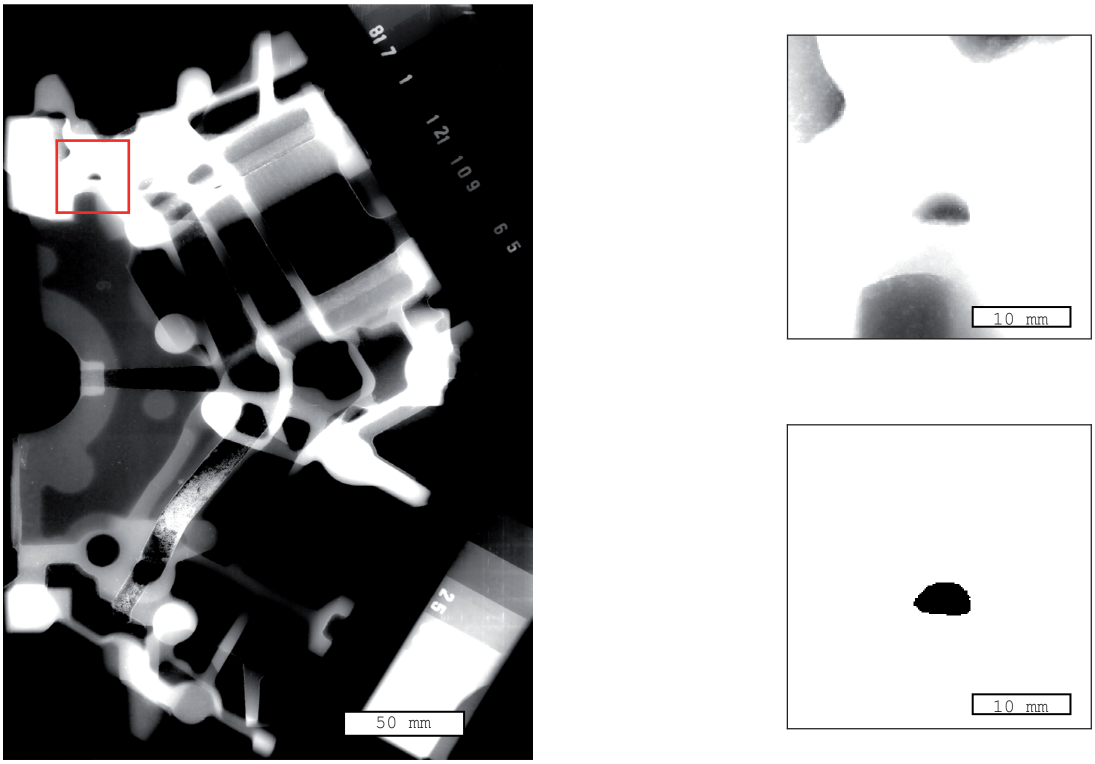


Fig. 4. The fragment of picture showing a section of car engine blocks

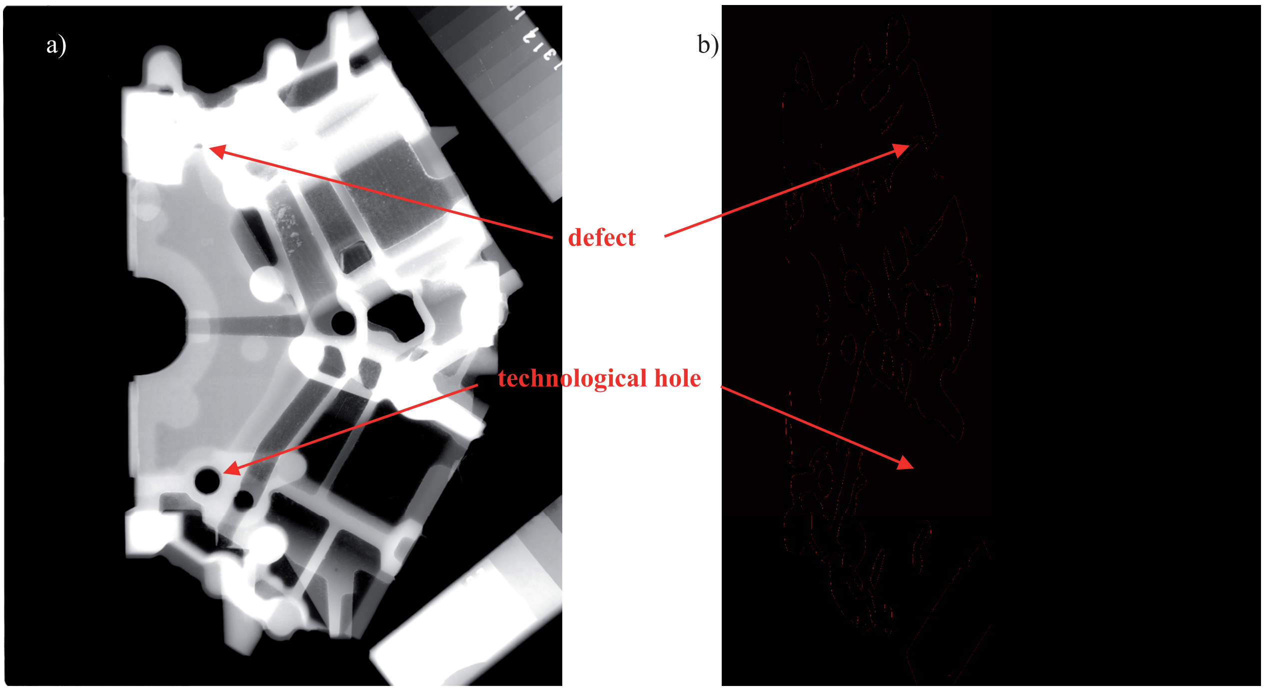


Fig. 5. The pictures showing a section of car engine blocks: a) before analysis, b) after analysis

perimeter, Feret diameters, roundness and circularity coefficients were calculated according to the formula:

$$P\left\{\bar{x} - t_{\alpha} \cdot \frac{s}{\sqrt{n}} \langle \mu \langle \bar{x} + t_{\alpha} \cdot \frac{s}{\sqrt{n}} \right\} = 1 - \alpha \tag{1}$$

where:

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i \tag{2}$$

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(x_i - \bar{x}\right)^2} \tag{3}$$

$1\text{-}\alpha$ – confidence interval,

t_{α} – value of the t Student variable read from the distribution tables for n-1 degrees of freedom,

$\bar{x}$ – arithmetic average, calculated for the particular geometrical coefficients, based on defects identified in the castings,

s – standard deviation, calculated for the particular geometrical coefficients, based on defects identified in the castings.

The neural networks were used for classification of defects developed in castings during the technological process, and for calculations the Statistica Neural Network 4.0 F software package was used.

The following quantities were used as the main quality coefficients of the model developed using the neural network for classification tasks:

- part of the correct classifications in %,
- concentration diagrams of the neural networks responses,
- histogram of the network forecast error for a particular casting defects class.

3. Discussion of the experimental results

Exemplary casting defects after image analysis and after calculating the geometrical coefficients for all defect classes are shown in Tab. 4. Values of the area and perimeter and of the coefficients calculated using them grow along with the given defect type class. The Feret coefficient, centricity, and the nondimensional shape coefficient assume very close values for different types and classes of casting defects.

he obtained analysis is of considerable importance in proper extracting of casting defects from X-ray images. Another important coefficient is the quality of the X-ray images because poor quality images (eg. overexposed images) affect the correctness of the analysis. Thanks to the applied analysis of sections of images of automotive engine blocks and heads it is possible to prepare such image of casting that enables to detect the edges of objects on images and furthermore to extract those that qualify as casting defects.

The obtained results (table 5) indicate the significant dependence between the defect classes and values of selected geometrical parameters describing casting defects such as: circumference, surface area, Feret diameters, nondimensional shape coefficient, circulatory coefficients and roundness coefficient. Also the obtained results indicate the lack of dependence between defect classes and Feret coefficient and centrality. The final number of the input variables was determined after employing the genetic algorithms.

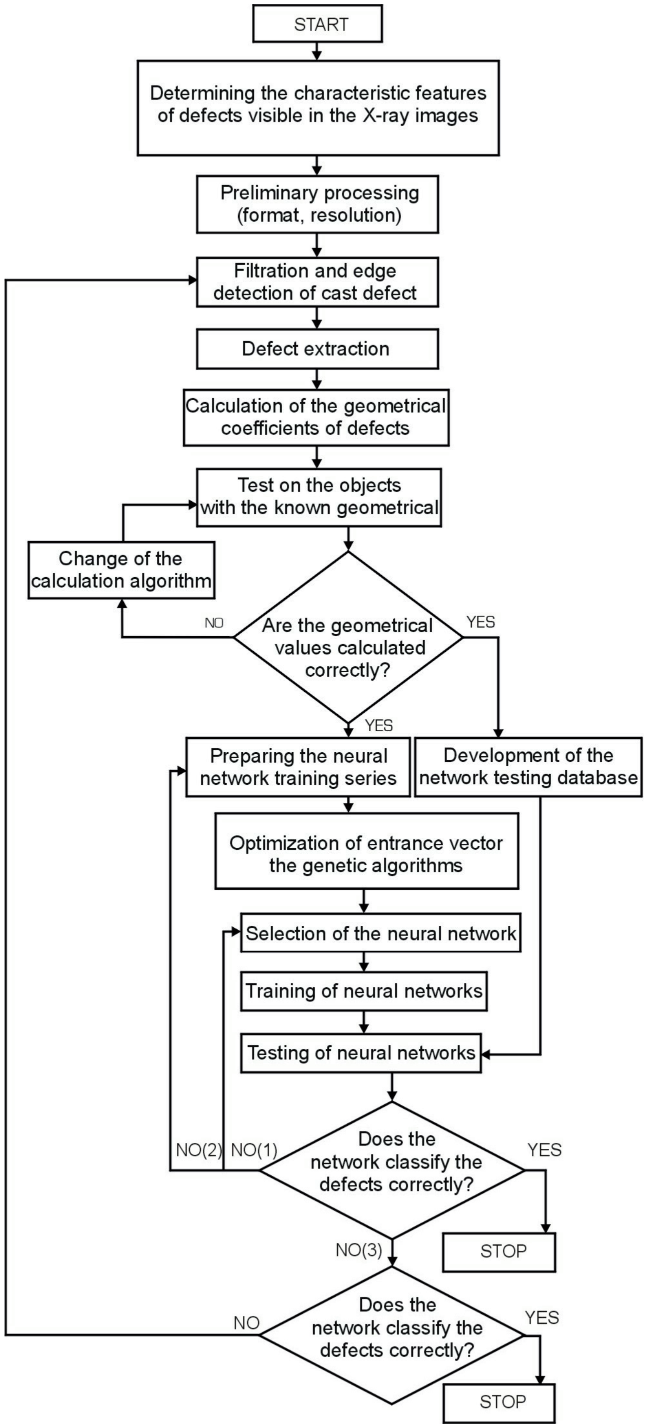


Fig. 6. Block diagram of the developed methodology of data processing pertaining to casting defects observed in the examined castings of the internal combustion engine elements from the Al-Si-Cu alloy

The best results of classification of defects obtained by applying multilayer perceptron (tab. 6) for which the best indicators of quality evaluation were obtained are shown on Fig. 7.

Table 4.
Value of geometrical coefficients of the example casting defects for individual classes

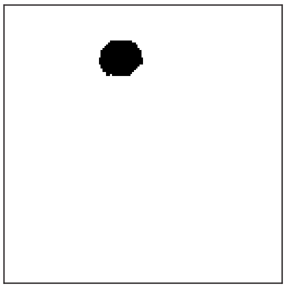
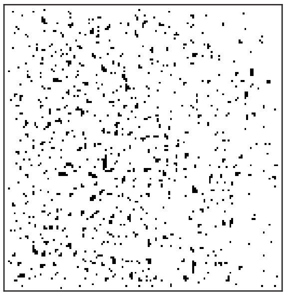
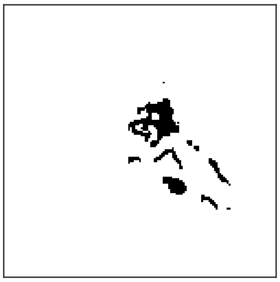
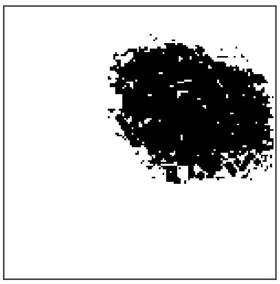
Image of casting defect	Type of geometrical parameters: defect circumference, L	defect surface area, S	horizontal Feret diameter, S_{Fx}	vertical Feret diameter, S_{Fy}	Feret coefficient, WF	nondimensional shape coefficient of the casting defect, BWK	circulatory coefficient of defect, R_{c1}	circulatory coefficient of defect, R_{c2}	Malinowska coefficient of defect, WM	centrality coefficient, C_t	Defect class
	71,2	368	24	19	1,3	1,1	21,6	22,7	0	1,4	GH5
	1397,9	1224	144	145	1	127,1	39,5	445	10,3	1,1	PR5
	325,4	596	55	69	0,8	14,1	27,5	103,5	2,8	2,6	SC5
	648,2	4792	90	81	1,1	7	78,1	206,3	1,6	1,3	SP5

Table 5.
List of results of nonparametric tests of the significance of correlation for the defect class and calculated geometrical parameters of defects

Type of geometrical parameters	Size of N test	Correlation	Z test value	Significance level	Test result
Tau Kendalla correlation					
defect circumference (L)	330	0,367395	9,958256	0,00	essential
defect surface area (S)	330	0,398611	10,80438	0,00	essential
horizontal Feret diameter (S_{Fx})	330	0,354401	9,606052	0,00	essential
vertical Feret diameter (S_{Fy})	330	0,363593	9,85521	0,00	essential
Feret coefficient (WF)	330	-0,051604	-1,39872	0,161896	inessential
nondimensional shape coefficient of the casting defect (BWK)	330	0,188958	5,121715	0,00	essential
circulatory coefficient of defect (R_{c1})	330	0,399789	10,83629	0,00	essential
circulatory coefficient of defect (R_{c2})	330	0,365931	9,918571	0,00	essential
Malinowska coefficient of defect (WM)	330	0,190378	5,160197	0,00	essential
centrality coefficient (C_t)	330	-0,037578	-1,01855	0,308416	inessential

Table 6.
Characteristics of neural network applied for the classification of casting defect

It.	Geometrical parameters of casting defects applied for training neuronal network	Network structure	Training method	Number of training periods
1.	defect area (S), horizontal Feret diameter (S_{Fx}), vertical Feret diameter (S_{Fy}) circulatory coefficient of defect (R_{c1}), Malinowska coefficient of defect (WM)	MLP 5-27-108	Back Propagation, Conjugate Gradient Descent	465

Table 7.
List of error value and quality of applied neural network

It.	Type of neural network	Error of validation	Error of test	Quality of validation	Quality of test
1.	MLP 5-27-108	0,0322	0,0551	0,98	0,9393

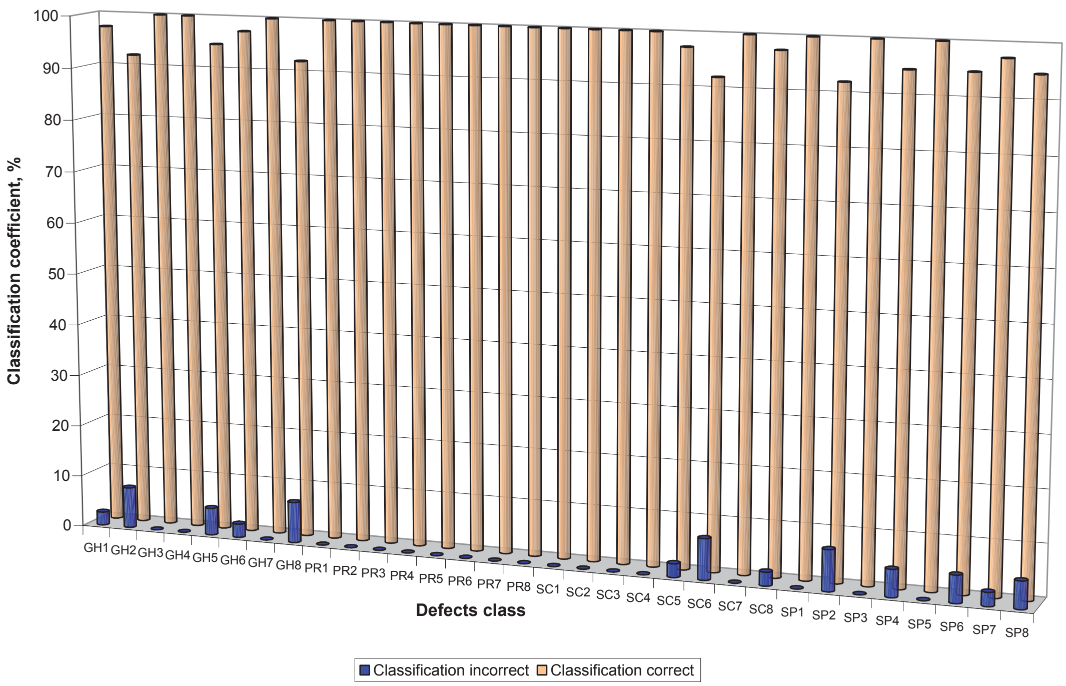


Fig. 7. The plot of defects and correct classifications in particular classes of MLP 5-27-108 network

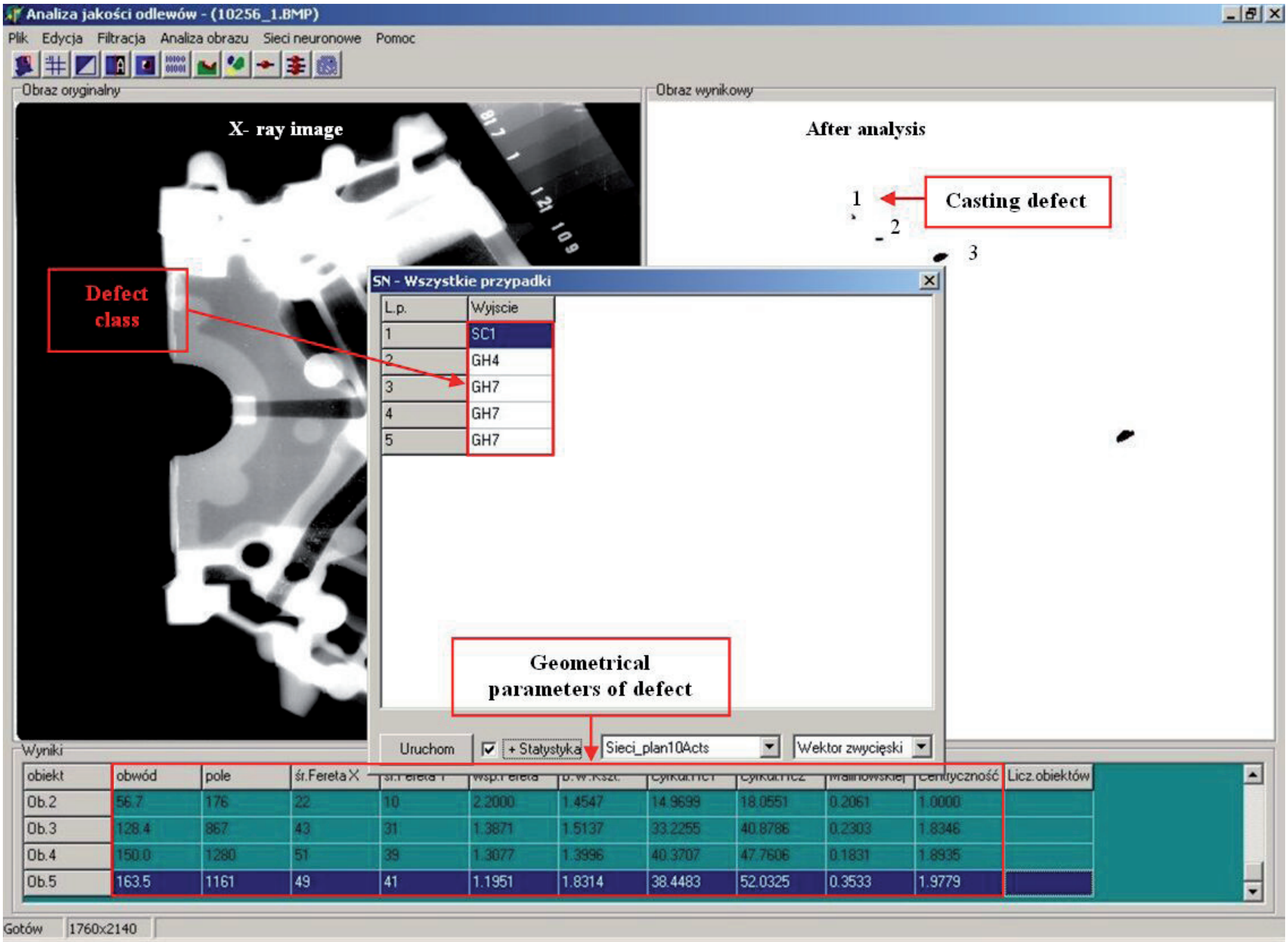


Fig. 8. The programme window for the assessment of class of casting defects

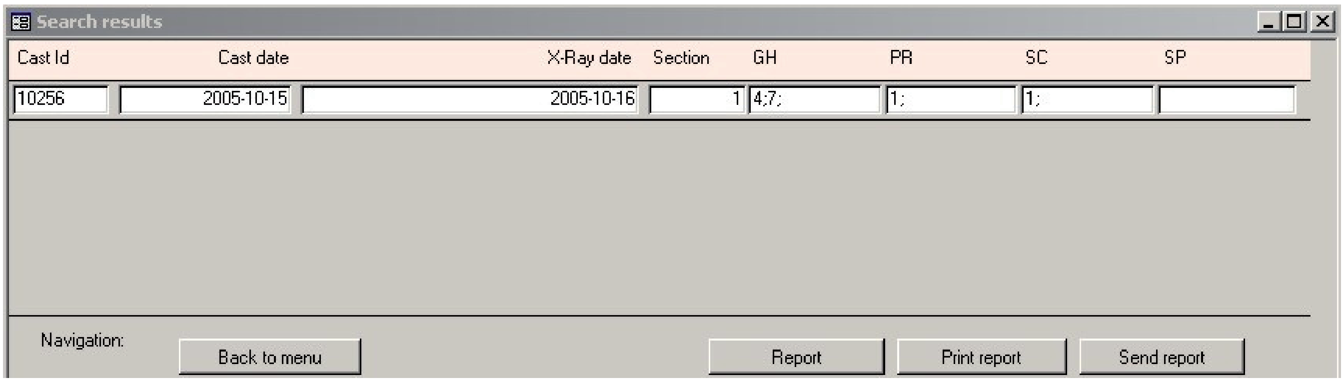


Fig. 9. The data base window with the information about tested casts

Quality of defects classification by the neural network used with the smallest error values is shown in Tab. 7. Increase of the number of the correctly classified casting defects grows after employing the developed methodology, and concentration of the error for the particular defects gets smaller.

The class of casting defect calculated by the neural network on the basis of the calculated geometrical parameters in casting defects applied for model construction should be characterised by the proper similarity to the size corresponding to the class of defect of the model included in ASTM standard. The applied

MLP 5-27-108 neural net enables the correct classification of casting defects, because the value of error classification is 2.63% for testing defects. The improvement of the activity of the prepared model was also possible thanks to genetic algorithms which enabled the increase of the amount of correct classifications of casting defects (Fig. 7). The advantage applying neural networks rather than the statistical methods is also the correct classification of various types of defects regardless of the similar values of geometrical parameters describing morphology.

Worked computer programme makes possible direct data concern testing casts. Program makes possible searching information about cast date, X-ray date and serching casts, in which detectd specified cast defects.

Computer program was developed to evaluate quality of castings in the automatic way (unattended). In Fig. 8 the image of the analysed casting is shown in the "original image" window and the identified casting defect in the "resulting image" window, as well as the calculated values of the geometrical coefficients of the defect. The defect class calculated using the neural networks is also shown in Fig. 8.

The developed computer program makes the examined castings data management possible (Fig. 9). The program makes it possible to search information about the casting manufacturing date, its X-ray examination date, and to filter the castings with the particular casting defects specified by the database user. The database makes it possible to search for castings in which the defects of the particular type and class were revealed by examination. In Fig. 9 program window is shown in which information about the examined castings are shown, namely: casting manufacturing date, X-ray examination date, and defect(s) class identified in the castings.

4. Conclusions

The computer system, in which the artificial neural networks as well as the automatic image analysis methods were used makes automatic identification and classification possible of defects occurring in castings from the Al-Si alloys of the W319 type, assisting and automating in this way the decisions about rejection of castings which do not meet the defined quality requirements, and therefore ensuring simultaneously the repeatability and objectivity of assessment of the metallurgical quality of these alloys. Correctly defined quality of products makes further possible such control of the technological process that the number of defects occurring in the castings may be decreased by the relevant process correction. Controlling the technological process basing on the information acquired from the computer system developed for determining the quality of products makes optimisation of this process possible and therefore, reduction of the number of defective casting, and in consequence reduction of costs and environment pollution.

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