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Prediction of Properties of Austempered Ductile Iron Assisted by Artificial Neural Network

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In the article it is presented wide range of parameters have been influenced on mechanical properties of austempered ductile iron (ADI). It is shown that to obtain precisions grade of ADI is very complicated process and it requires complex investigation. The article is the first step to determinate almost all parameters influence mechanical properties of ADI. It could be done by adapting artificial neural network (ANN). There are presented several results obtained on a special kind of ANN predicting properties of ADI.

Keywords: modelling, artificial neural networks, austempered ductile iron, mechanical properties.

1. INTRODUCTION

Making castings in austempered ductile iron (ADI) requires from the manufacturer at least some knowledge about the tools used in shaping the utilization features of products made from this material – the task related with determination of an effect of the technological process parameters (cast iron chemical composition and heat treatment parameters) on the properties of final product. In view of a complex nature of the phenomena taking place at the individual stages of the technological process of making ADI, the available knowledge in the form of research studies is not capable of approaching these problems in a way such as to cover all the related aspects and variations. The data given in reference literature quote some parameters of the heat treatment and values of the mechanical properties, but this is usually done very selectively, the data are often incomplete and collected from the laboratory tests only. For practical purpose this knowledge is not adequate, and hence not useful.

Therefore, a database was created, which includes data on the chemical composition and technical parameters of ADI, as well as a complementary information, i.e. the information on the number of the spheroidal graphite precipitates/mm^2 and parameters of the spheroidizing treatment. The data were taken from the available reference literature, from publications, and from laboratory investigation. A study was undertaken to provide the lacking experimental data, thus making up for a gap existing in this scope, as well as some data obtained directly by industrial trials.

The collected data were processed to a form of training sets and were used for modeling done by means of the Artificial Neural Networks (ANNs), to obtain a solution for relations of the type: parameters of technological process – properties of product manufactured by this process. This step should enable determination of a relationship between the large number of production- and material-related parameters changing in time and parameters responsible for casting quality. As a result of the conducted research it should be possible to predict the properties and select the best parameters of ADI technological process.

The features of the learning systems, and of ANNs in particular, make them an excellent and helpful tool in forecasting various consequences of a manufacturing process, and hence also in predicting the four principal mechanical properties investigated in ADI, i.e. tensile strength, proof stress, elongation and hardness.

The mechanical properties of ADI depend, among others, on the parameters of ductile iron heat treatment, i.e. on the temperature and time of austenitizing, and the temperature and time of austempering, on the cast iron chemical composition, the number and shape of spheroidal graphite precipitates, and casting technique [1, 2]. All of the above mentioned parameters are used as inputs to the network. By correct choice of the neural network it is possible to create a tool predicting the ADI properties, which are the resultant of interrelations between certain factors deciding about the final form of microstructure in this cast iron (e.g. austempering temperature, the density of spheroidal graphite precipitates, casting modulus).

For determination of the properties of products manufactured by a technological process it is necessary to interrelate the respective parameters, which often prove to be impossible without application of proper mathematical tools. Designing and controlling of manufacturing processes can be aided by the use of mathematical tools. In practice, we often have to do with processes of the “black box” type, whose physical nature is either unknown or very complex. Modelling processes of this kind consists in establishing a relationship between the input and the output (i.e. result) signals on the basis of a certain number of observed cases (regression problem).

This approach is also valid for the case of investigating an unknown process, when the target is to acquire the lacking link of knowledge from the results of laboratory experiments or technological trials. Tasks of this type are usually accomplished through application of the learning systems which, among others, also include the Artificial Neural Networks (ANNs).

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Recently, learning systems for exp. artificial neural networks (ANNs) that have been commonly used for this purpose. Their applications include, for example:

- predicting properties of products or materials on the basis of the parameters of the technological process involved;
- identifying the causes that lead to the appearance of manufacturing defects in products;
- designing based on the specific data which was collected in the industry and generalized by ANNs.

Some well-known cases of application of the learning systems in modelling of foundry problems were described in literature [3 – 5]. An example may be the use of fuzzy logic in determining a relationship between the temperature, time and mechanical properties of ADI. In these studies four fuzzy and “neuro-fuzzy” models were used to design the predicting models. The results of those studies have proved their full applicability in processes of this type [6]. Another example of an effective application of the tools based on learning systems is predicting of hardness and determining the content of retained austenite, on which, as we all know, numerous properties of ADI depend, in function of the chemical composition and heat treatment parameters. In both cases, a model of the neural network, optimised within a Bayesian framework, was used, while the developed tools were successfully aiding manufacture of this cast iron grade [7, 8].

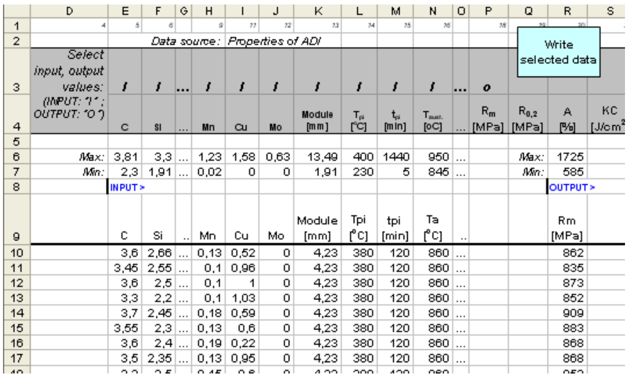
2. RESEARCH METHODOLOGY

2.1. Data sets

The data sets used in the present work were created basing on the results of the research described in literature. In this way, the first stage of the studies, covering a method of processing data of this type, a modeling technique using ANNs, and an analysis of the approximate results, was completed. The methodology, developed during preliminary studies, will be used in basic research on modeling an effect of the technological process parameters on ADI properties. The modeling will be done on a large number of the data, describing the whole research area. These will be the data collected from literature, experiments, and industry.

The training data are collected in the form of tables in calculation sheets, which greatly simplifies their use. An easy input and processing of the data collected during experiments, various forms of presentation of the results, a programming option enabling proper data formatting – these are but only some of the advantages of this solution.

A very important issue is to decide which parameters are to be selected as input and which as output (result) signals. Quite natural seems to adopt the properties of raw materials and process parameters as inputs to the neural network, while properties of the product should play the function of output values, but it may prove necessary to acquire some knowledge about other relationships as well. Therefore, a support software was created to enable an arbitrary configuration of the training data. Through the choice of input and output parameters (Fig. 1), a generation of the required training set directly from the collected database becomes possible.



	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	4	5	6		9	11	12	13	14	15	16		18	19	20	
2			Data source:			Properties of ADI								Write selected data		
3	Select input, output values:	I	I	...	I	I	I	I	I	I	I	...	o			
4	(INPUT: "I"; OUTPUT: "O")	C	Si	...	Mn	Cu	Mo	Module [mm]	T_{pi} [°C]	t_{pi} [min]	$T_{aust.}$ [oC]	...	R_m [MPa]	$R_{0,2}$ [MPa]	A [%]	KC [J/cm²]
5																
6	Max:	3,81	3,3	...	1,23	1,58	0,63	13,49	400	1440	950	...		Max:	1725	
7	Min:	2,3	1,91	...	0,02	0	0	1,91	230	5	845	...		Min:	585	
8		INPUT >													OUTPUT >	
9		C	Si	..	Mn	Cu	Mo	Module [mm]	Tpi [°C]	tpi [min]	Ta [°C]	..			Rm [MPa]	
10		3,6	2,66	...	0,13	0,52	0	4,23	380	120	860	...			862	
11		3,45	2,55	...	0,1	0,96	0	4,23	380	120	860	...			835	
12		3,6	2,5	...	0,1	1	0	4,23	380	120	860	...			873	
13		3,3	2,2	...	0,1	1,03	0	4,23	380	120	860	...			852	
14		3,7	2,45	...	0,18	0,59	0	4,23	380	120	860	...			909	
15		3,55	2,3	...	0,13	0,6	0	4,23	380	120	860	...			883	
16		3,6	2,4	...	0,19	0,22	0	4,23	380	120	860	...			868	
17		3,5	2,35	...	0,13	0,95	0	4,23	380	120	860	...			868	

Fig. 1. A fragment of program window generating the training data

Modeling was performed on selected sets of the training data, adopting for each configuration the chemical composition and heat treatment parameters as input data, and the tensile strength R_m and elongation A_5 or austenite content as output data. The artificial neural networks were trained on the prepared sets, adopting a general rule of repeated training for the same set of the training data (each network has been trained 10 times). Utilizing only the data given in literature, training was done without any further verification. The verification would require creation of a separate verifying set with data strictly representing the investigated relationships. A relatively small number of the available data as well as a source of their origin made the creation of a correct verifying set impossible.

2.2. Artificial neural networks

The networks had the MLP-type architecture with one hidden layer having calculated minimum amount of neurons. To improve the learning results, the training method called “simulated annealing” has been applied, combined with the conventional back-propagation method. The simulated annealing method was used for a better selection of the initial values of the synapses while the back-propagation phase of the learning decreased the network error. For data which included verification (testing) sets the learning process automatically ended when the error calculated for the verification set started to grow. For the data without verification sets the criterion for ending of the learning session was the mean square error change in a single iteration less then $5 \cdot 10^{-6}$.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

The results of training the selected artificial neural networks (trained many times) were analyzed on the results of training this network which was characterized by the least root-mean- square error over the entire training cycle. The average errors of output value prediction results obtained from the ANNs were identified, taking into consideration their proportion in the characteristic value ranges.

Figure 2 represents the training data configuration for modeling an effect of predetermined parameters on the ADI tensile strength R_m, and Figure 3 presents the distributions of prediction errors for these data.

INPUT >													OUTPUT >
C	Si	S+P	Mg	Mn	Ni	Cu	Mo	Module [mm]	T_{pi} [°C]	t_{pi} [min]	T_a [°C]	t_a [min]	R_m [MPa]

Fig. 2. A set of *configuration 1* (the training data set contained 321 records)

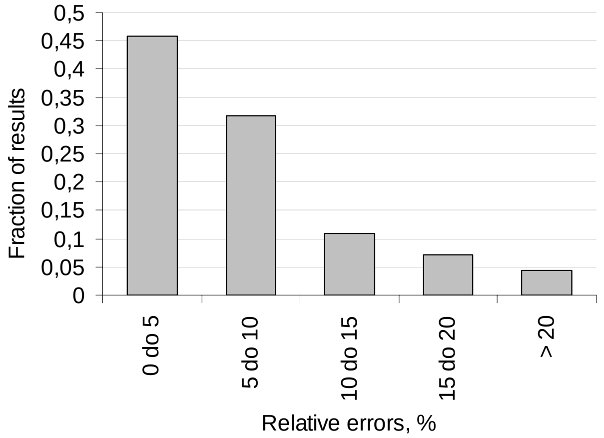


Fig. 3. The comparison of output prediction errors obtained from the ANNs (minimum errors from 10 training sessions) for the *configuration 1* data

It follows from the diagram that the ANN is correctly modeling the value of R_m, a definite majority of the results exhibit an error below 10 %. The reason of the observed prediction errors may be different sources of origin of the successive training data records.

The quality of the trained network can also be estimated through direct comparison of modeling results with the training data. Figure 4 shows an example of such analysis where points represent the, ordered in a decreasing sequence, values of the output (training) data, and circles are the ANN responses to these data. It can be easily seen that the ANN correctly predicts the values of R_m, but in spite of this some irregularities are still present in a range of 600 – 800 MPa.

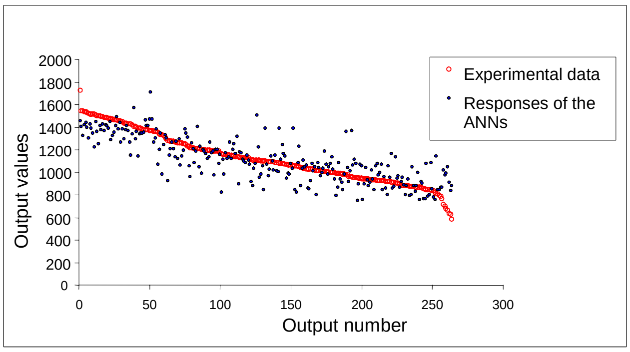


Fig. 4. Comparison of the training data and ANNs responses for the *configuration 1* data

This means that the network was not sufficiently well trained to correctly predict the results in this range (e.g. either because the number of the training data was too small, or because the training data suffered a distortion which blurred the result).

A measurable effect of modeling with the use of ANNs is the possibility of asking some questions to obtain the required knowledge. One of the means for this type of action is graphical representation of the searched relationships, e.g. of an effect of the austempering temperature on the tensile strength R_m of ADI. Figure 5 shows an example of ANNs application. The plotted curve was generated by the correctly trained ANN answering the questions with values of other input data locked at a constant and predetermined level. It can be stated that the character of the obtained curve is consistent with expectations.

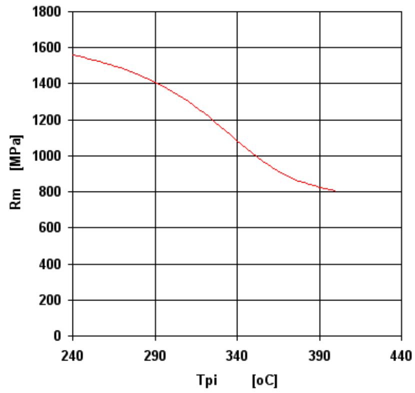


Fig. 5. A result of ANNs modeling R_m

The values of elongation predicted by ANNs trained with the *configuration 2* data (Fig. 6) exhibit large errors (Fig. 7).

INPUT >													OUTPUT >
C	Si	S+P	Mg	Mn	Ni	Cu	Mo	Module [mm]	T_{pi} [°C]	t_{pi} [min]	T_a [°C]	t_a [min]	A [%]

Fig. 6. A set of *configuration* 2 (the training data set contained 317 records)

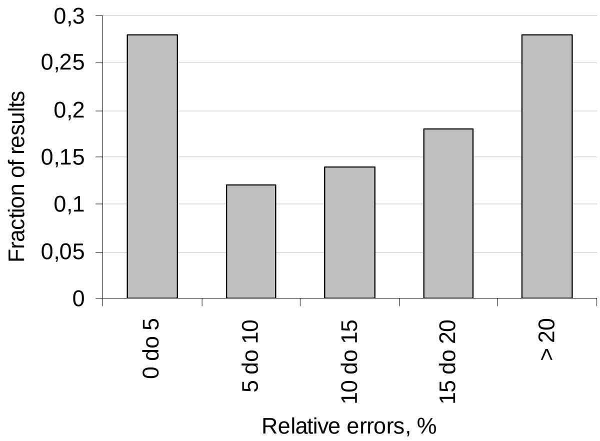


Fig. 7. The comparison of output prediction errors obtained from the ANNs (minimum errors from 10 training sessions) for the *configuration 2* data

An effect of modeling the complex relations is the observed, relatively large scatter of results predicted by ANNs (Fig. 8). The measured results of elongation A_5 usually exhibit an error resulting from the measuring methodology, which must have affected the obtained prediction results.

Searching for regularities between the variables present in production process is obtained through analysis of the data. This enables determining a set of the parameters which, when applied to the ADI production process, will make obtaining of the required properties possible. The input parameters for production conditions are usually determined wihin certain ranges of values, e.g. when making ADI, for a given chemical composition of the base material, obtaining of the required mechanical properties will be possible only by proper choice of the heat treatment parameters, that is, the parameters of austenitizing (T_a, t_a) and austempering (T_{pi}, t_{pi}).

The changes in the resultant values of the process can be taken into consideration even at the stage of process designing through analysis of signal groups performed by application of ANNs [9].

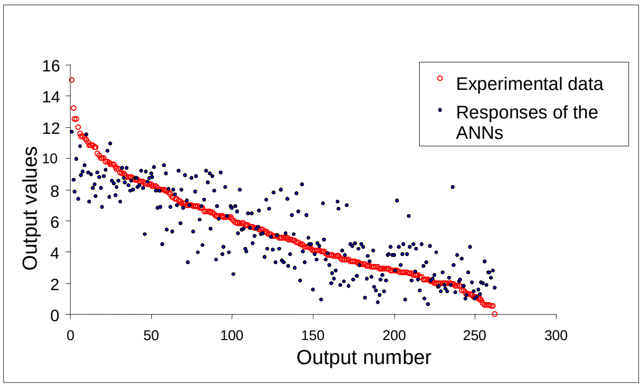


Fig. 8. The comparison of training data and ANNs responses for for the *configuration 2* data

Figure 9 shows an effect of the input data variability on the values of output parameters. By changing the input values within the range determined by the user it is possible to predict the range of changes in output values.

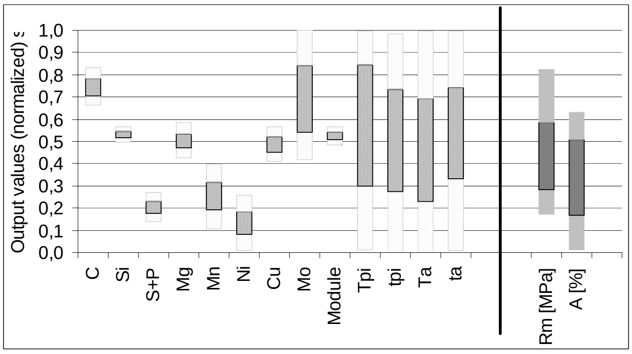


Fig. 9. Analysis of signal groups

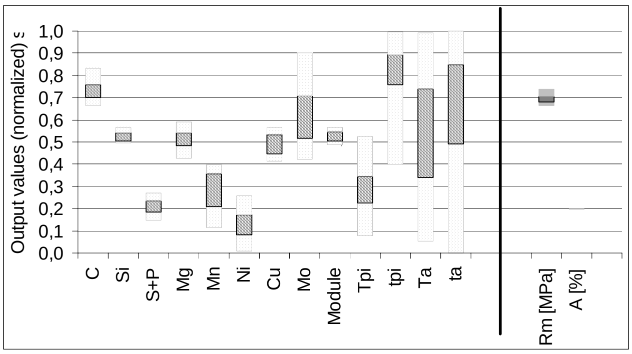


Fig. 10. Prediction of the output data for the expected result

Figure 10 shows another type of analysis, which allows predicting the admissible range of input values for output values required by the user. For the examined case, ANN indicated the range of input data required to obtain R_m = 1400 MPa and A_5 = 3 %. The described methods of analysis of the signal groups are at present at the stages of testing using both training data and test data.

Using ANNs it is possible to determine the technological process parameters which, for the preset properties of ADI, i.e. R_m and A_5, should additionally enable obtaining of the required metallographic structure. Some attempts at practical execution of this task are shown in Figures 11 – 12. The *configuration* 3 data (Fig. 11) cover the mechanical properties as input data in strict correlation with austenite content.

INPUT >													OUTPUT >
C	Si	Mg	Mn	Ni	Cu	Mo	T_{pi} [°C]	t_{pi} [min]	T_a [°C]	t_a [min]	R_m [MPa]	A [%]	Austenite content [%]

Fig. 11. A set in *configuration 3* (the training data set contained 115 records)

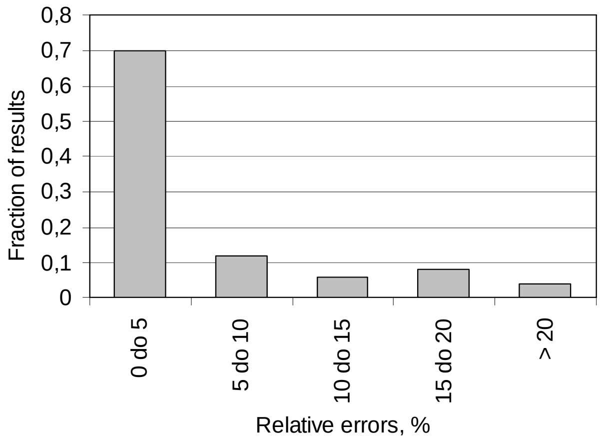


Fig. 12. The comparison of output prediction errors obtained from the ANNs (minimum errors from 10 training sessions) for the *configuration 3* data

4. SUMMARY AND CONCLUSIONS

The work done on predicting the ADI properties by artificial neural networks covers in a most general outline collecting of the training data, including chemical composition of the base ductile iron, heat treatment parameters, microstructure obtained by ADI austempering, and wall thickness, and mechanical properties obtained for the preset parameters. The data published in literature used in the preliminary investigation have been completed with the experimental data and the results of industrial trials.

The analysis discussed in the present work leads to a conclusion that the task can be successfully accomplished by application of ANNs.

The investigation should be repeated for a large number of the training data, and the obtained results should be verified for a definite production problem.

Modeling of the obtained data by means of the learning systems is expected to be helpful in designing a tool which would assist the ADI manufacturers. An advantage of the proposed solution is that the training process (through proper correlation with preset inputs) offers some complementary information, e.g. on the cast iron nodularity, the type of primary structure, heat treatment conditions, which the manufacturer may not have ready at hand The required data sets cover the parameters which every manufacturer of ADI castings can quickly have at his disposal.

REFERENCES

1. **Perzyk, M., Kochański, A., Kozłowski, J.** Significance Analysis of Production Parameters Asisted by Artificial Neural Networks *IIIth International Conference on Advances in Production Engineering* Wyd. PW, Warszawa, 1, 2004: pp. 43 – 53.
2. **Myszka, D., Kaczorowski, M., Tybulczuk, J., Kowalski, A.** Parameters of ADI Production and its Mechanical Properties *Archives of Foundry* 4/11 2004: pp. 355 – 364.
3. **Perzyk, M., Kochański, A.** Methodology of Detection of Casting Defects Causes by Neural Networks *Materials Science* (*Medžiagotyra*) (*ISSN 1392-1320*) 8 (4) 2002: pp. 375 – 379.
4. **Perzyk, M., Kochański, A.** Detection of Causes of Casting Defects Assisted by Artificial Neural Networks *Journal of Engineering Manufacture, Proceedings of the Institution of Mechanical Engineers* Part B 217 2003: pp. 1279 – 1284.
5. **Perzyk, M., Kochański, A.** Prediction of Ductile Cast Iron Quality by Artificial Neural Networks *Journal of Materials Processing Technology* 109 3 2001: pp. 305 –307.
6. **Arafeh, L., Singh, H., Putatunda, S.** A Neuro Fuzzy Logic Approach to Material Processing *IEEE Transactions On Systems, Man, And Cybernetics – Part C: Applications And Reviews* 29 (3) August 1999.
7. **Yescas, M. A.** Prediction of the Vickers Hardness in Austempered Ductile Irons Using Neural Networks *Int. J. Cast Metals Res.* 15 2003: pp. 513 – 521.
8. **Yescas, M. A., Bhadeshia, H. K. D. H., MacKay, D. J.** Estimation of the Amount of Retained Austenite in Austempered Ductile Irons Using Neural Networks *Materials Science and Engineering* A 311 2001: pp. 162 – 173.
9. **Kozłowski, J., Biernacki, R., Myszka, D., Perzyk, M., Kochański, A.** Application of Learning Systems to Prediction of Cast Metals Properties *Archives of Foundry* 4 (11) 2004: pp. 249 – 258.

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