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AUSTEMPERED DUCTILE IRON MANUFACTURING DATA ACQUISITION PROCESS WITH THE USE OF SEMANTIC TECHNIQUES

The aim of this work was to propose a methodology supporting the task of collecting the comparative data on studies of the mechanical properties of ADI. Collecting of research data is an important step in the process of finding the optimum design solutions for newly made products - experimental data allow us properly calibrate the manufacturing process of ADI to let the final product achieve the required properties. Parameters of the ADI production process, i.e. the time and temperature of austenitising and austempering, as well as the alloying elements added to ductile iron affect the ADI properties. The design process can use research data collected, among others, from the Web. As stated in the article, the process of data acquisition can be supported by semantic technologies, including ontologies which are descriptive logic formalism.

Keywords: Austempered Ductile Iron, thermal treatment, properties, process data, data integration, ontology.

1. Introduction

The technologically demanding process of the ADI, i.e. Austempered Ductile Iron, manufacture is a good example of how important the accurate information about various process parameters really is. As described further, various parameters such as temperature and time in different stages of the process, and also the chemical composition exert a strong influence on the final properties of this material. When new products are designed, it is necessary to decide on their final properties, which means choice of the process parameters. Therefore, it is so important to have access to the experimental and literature data on global research using new settings and options for the ADI treatment, in other words - the data that will allow appropriate selection of process parameters to produce the required grades of ADI.

2. Austempered Ductile Iron

ADI is the result of heat treatment carried out on the cast iron with nodular graphite. Excellent combination of properties obtained in ADI, including the strength, toughness and fatigue behavior, makes this material a successful substitute for steel or aluminum alloys. ADI has a high fatigue strength, higher than aluminum, is resistant to abrasive wear like steel, but most of all – its use can significantly reduce the cost of production. An important advantage for the automotive industry is also high damping capacity, as a matter of fact, by 40% better than that of steel [1]. Manufacturers are looking for new uses for this material - ADI is already present in the automotive, agricultural and railway stock industries [2]. ADI is generally recommended as a structural material because of the very encouraging cost of production of parts compared to the cost of other materials. First of all, it offers a very good castability, which enables complex shapes to be reproduced with higher yield and raw castings to have better dimensional accuracy. This, in turn, implies savings in machining [3].

2.1. Preparation of ADI

One of the stages in the ADI production is making the ductile iron with the addition of elements such as Mn, Ni, Cu, Mo, Cr, Sn, or with other elements allowing the formation of a pearlitic or pearlitic-ferritic structure and increasing the hardenability. The spheroidisation of cast iron consists in introducing into the melt appropriate amounts of magnesium, which result in the precipitation of graphite characterized by nodular morphology. The degree of refinement and the specific shape of graphite depend on the content of sulphur and residual magnesium, the latter one remaining in the alloy as one of its constituents. The specific behavior of this additive, i.e. its burning out in the liquid metal, is the reason why the structure of the resulting alloy has the best properties immediately upon completing the spheroidising treatment. Inoculation is usually carried out with FeSi or FeSi-based alloys. The aim of this treatment is to obtain more uniform distribution of graphite precipitates and larger number of nuclei. The chemical composition and initial structure of the ductile iron affect the heat treatment parameters. A typical course of the heat treatment consists in austenising at a temperature of 815-950 °C followed by austempering at a temperature of 230-400 °C [4].

Differences in the mechanical properties of specific ADI grades are associated with differences in the structure, resulting, in turn, from different heat treatment parameters.

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Modelling of ADI properties can be achieved through control of parameters such as the temperature of austenitising and austempering. This is best reflected in the tensile strength Rm - to - percentage elongation A ratio. During austempering, very important is the temperature of the process. If the cast iron is austempered at a temperature above 400 °C, it can be expected that, due to rapid transformation, carbides will appear in the structure and the cast iron will lose its ductility. Austenite content in relation to ferrite assumes the highest level in the temperature range of 350 to 370 ºC, and then the cast iron has the highest elongation and the lowest strength [5].

If the austempering temperature is reduced even more, the structure will contain martensite, which is the effect of transformation of residual austenite precipitated during cooling to room temperature. Besides temperature of the process, structure of the cast iron also depends on the time of the process. Particularly important is the optimum time of austenitising, ensuring on the one hand suitable enrichment of austenite in carbon (proper time of the process), and on the other hand preventing the decomposition of austenite and carbide evolution (too long time of the process). The high carbon content in austenite reduces the temperature of the start of martensitic transformation. Austempering carried out for the time of approximately 3 hours can lead to enrichment of austenite in carbon up to 1.8 % and 2.2 %. The resulting structure is composed of martensite, coarse precipitates of ferrite and residual austenite [6].

2.2. Development of various scenarios for the ADI production

The aim of the first stage of the work was to collect comparative data on the manufacturing process of ADI. Foundry Research Institute in Cracow has an experienced team of engineers conducting research on this material. Studies of this material are also conducted in nearly all parts of the world. The diversity of the experiments results in the development of new variants of the heat treatment, and thus in new ways to obtain the required properties of this material. In this work it was important to examine whether the data collected from the World Wide Web have any value for process engineer designing the manufacturing process of ADI.

In the following part of this study, the ADI grades designated as ADI-1 up to ADI-6 will be presented. They represent different chemical compositions of cast iron subjected to the heat treatment, which involves austenitising and austempering (TABLE 1). To obtain a minimum fatigue strength of 220 MPa, two variants of the heat treatment were proposed for two different chemical compositions (ADI-1, ADI-2, a total of 4 variants) [7]. For ADI-1 (containing Cu and Ni), the required fatigue strength can be obtained by austenitising at 900 °C for 90 minutes and ausferritising at 360 °C (variant I) or 320 °C (variant II) for 120 minutes. For ADI-2 (unalloyed), the required fatigue strength can be obtained by austenitising at 900 °C for 90 minutes and ausferritising at 360 °C (variant III) or 320 °C (variant IV) for 120 minutes.

Another scenario is related with the heat treatment of samples used for the tensile strength and fracture toughness testing. Important parameters are: tensile strength (min. 1000 MPa), yield strength (min. 950 MPa), fracture toughness (min. 50 MPa√m), and elongation. To obtain the specified combination of properties, two chemical compositions were selected (ADI-3 and ADI-4) [9], differing in the content of Cr. For the cast iron without chromium (ADI-3), four variants of the heat treatment were proposed (TABLE 1).

Studies carried out showed that ferrite grains nucleate at the austenite grain boundaries, which act as privileged sites for heterogeneous nucleation. At lower temperatures of ausferritising, carbon diffusion is slower, and the growth of ferrite retarded (nucleation of ferrite plates is more privileged than the growth), in this temperature austenite is less stability to which is the reasons why the microstructure obtained at lower ausferritising temperatures (260 °C, 288 °C) contains more ferrite (fine-grained in this case) and lower volume of austenite.

TABLE 1

Samples of variants of the ADI manufacture with breakdown into the obtained properties[8]

No.	austenitizing		austempering		properties					
	temp. (°C)	time (s)	temp. (°C)	time (s)	tensile strength (MPa)	elongation (%)	reduction of area (%)	hardness (HRC)	yield strength (Mpa)	fracture toughness (Mpa √m)
ADI4	871	7200	260	14400	1438	1,6	0,9	48	1250	55,2
	871	7200	385	7200	830	5,1	5,5	32	650	40
ADI3	871	7200	273	12600	1179	0,8	1,2	45	1137	55,2
	871	7200	385	7200	848	5,1	4,1	30	595	44,1
ADI1	900	5400	320	7200	350	-	-	-	-	-
ADI2	900	5400	320	7200	290	-	-	-	-	-
ADI6	900	5400	250	3600	1520	1,8	-	58	1410	-
	900	5400	425	3600	862	9,2	-	37	565	-

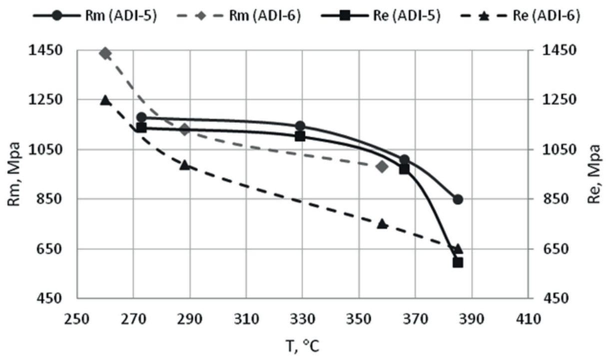

Fig. 1. The tensile and yield strength of ADI-5 and ADI-6 vs austempering temperature – an example

Closer analysis shows that ADI ductility increases with austenite volume increasing in the structure, while both the yield strength and tensile strength are decreasing (Fig. 1). Fracture toughness (stress intensity factor) reaches the highest value for the hardness of approx. 40 HRC, i.e. when the cast iron contains about 60 % ferrite and 25 % austenite. So, the optimum value is achieved when ausferritising is carried out at approx. 280 °C for approx. 3.5 h. Higher temperatures increase the segregation areas of elements such as Si, Mo, Mn, and in ADI-4 also of Cr. Further variants referred to ADI-5 [9]. The task was to develop the heat treatment regime for samples used in testing of mechanical properties and fracture toughness. Important parameters were: tensile strength (min. 950MPa) and fracture toughness (min. 45 MPa√m). To obtain the specified properties, one chemical composition (TABLE 1) and four heat treatment variants were selected. Examining the effect of the ausferritising temperature on fracture toughness it can be noticed that with temperature increasing to approx. 316°C, the fracture toughness initially increases and then decreases, while prolonged time of ausferritising increases this parameter.

The last scenario considered referred to ADI-6 [11]. The task was to develop the heat treatment regime for samples used in mechanical tests. Important parameters were: tensile strength (min. 950 MPa), elongation (min 3.5 %), and hardness (min. 40 HRC). To obtain the specified properties, one chemical composition and two heat treatment variants were selected (TABLE 1). The results show that at lower temperatures of ausferritising, the yield strength, tensile strength and hardness are lower. The yield strength and tensile strength decrease when the austenite and ferrite become coarse (higher temperatures of ausferritising).

The data collected and the conclusions drawn can be used in the design of technological process, but they can equally well serve the task of building intelligent systems, as has already been demonstrated in previous works of the authors using rough set theory [12] and the logic of plausible reasoning [13] and others related with diagnostics [14] or [15].

3. Ontology Driven Data Acquisition

Today, computers are becoming "smarter", are able to process more information, faster draw conclusions and make decisions. However, the manner in which the computer makes decisions is based on mathematics, and specifically on logic. Ontology in terms of computer science is also a logic formalism, because knowledge consists of inference, in other words, rules or aggregates, i.e. interlinked information. By contrast, the information consists of data linked by relations.

Ontology is a kind of proxy between a human and a computer. The task posed to a computer is to understand knowledge in a manner such as it is understood by a human. The problem is not understanding in the sense of syntax - because this has already been largely achieved - but in the sense of semantics, i.e. in the sense of understanding the links between concepts expressed in natural language and abstract ideas. Here, the main role is played by the *semantics* of inference. Ontology in computer science is a formal record of the definition of a certain part of the knowledge expressed in the form of a taxonomy of related classes. In other words, ontology is a semantic model of defined field of knowledge. Ontologies are computerized implementation of description logic [16]. The description logics (DL) were used in the creation of ontologies for the Semantic Web, in decision support systems, among others, in medicine, in database applications (query analysis and optimization), or in applications for natural language processing. The main tasks of inference implemented in the DL are: satisfiability, subsumption, equivalence and separability of concepts, finding/checking membership of an instance in a given class, checking consistency of the knowledge base. Description logics are by nature best suited to describe the classes of objects and reasoning about objects belonging to different classes, thus it seems quite natural to attempt to apply them to define standards for ADI grades. The description of the model of knowledge consists of facts about various alloys, e.g.:

$$hasTensileStrength(sample\,1, 800),\ hasHardness(sample\,1, 280)$$

The terminology, on the other hand, includes the definitions and axioms on the class hierarchy. Sample definition (for grade according to EN-GJS-800-8) in DL notation is as follows:

$$\begin{aligned}&PN-EN-GJS-800-8 \equiv \exists hasTensileStrength \cap \exists hasYieldStrength\\&\cap \exists hasElongation \cap \exists hasHardenss \cap \forall hasTensileStrength.\{800\}\\&\cap \forall hasYieldStrength.\{500\} \cap \forall hasElongation.\{8\}\\&\cap \forall hasHardness.Range1\end{aligned}$$

An important element of the definition is part with the universal quantifiers ("for all"). Its use enables checking the value of objects that are in different relations to the tested alloy (relations from the table, e.g. hasHardness). The definition also includes part with the existential quantifiers, which can be avoided if we assume that we do not have all the data. In this case, however, inference may be incorrect (e.g. the alloy can be mistakenly considered to meet the standard, even if some of its parameters - which are not examined - do not meet this standard). Additionally, in the case of numerical data, certain impediment occurs. In the basic version (without extensions that are in the study phase), Description Logics do not support arithmetic operations. Therefore, the numerical values used in the above definition are interpreted as objects of classes. Hence one can define the Number class and explicitly mention its instances (so it will be the representation of a finite subset of the numbers). In addition, for this definition, the value of hasHardness should belong to an interval, and does not need to be a specific value. In this case it is necessary to define a Range1 class in the form of:

$$Range1 \equiv \{260,261,262,263,264,...,318,319,320\}$$

Formalism is complicated for an inexperienced designer and requires participation of an expert. Also the DL syntax lacks dedicated editors. A better solution in this case is modelling of the DL-based ontology in an ontology editor, e.g. Protege. The ontology language, more expressive and deeply routed in the logic, is OWL (Web Ontology Language). There are numerous variants of the OWL language, in which the selection of specific limit constructs gives specific capabilities and complexity of reasoning. Significant variations of OWL are based on Description Logic languages [16]. Modelling capabilities are thus similar to the DL, but tool support for OWL language (including the Protege editor with integrated inference engine and the capability of adding plug-ins) is much more promising. Classes, relationships and objects are introduced by declarations, while their specifications are created using the constructors known from DL (intersection, sum, quantifiers, etc.):

Declaration :=' Declaration' '(' axiomAnnotations Entity ')'
Entity :=
'Class' '(' Class ')' |
' Datatype' '(' Datatype ')' |
'ObjectProperty' '(' ObjectProperty ')' |
' DataProperty' '(' DataProperty ')' |
' AnnotationProperty' '(' AnnotationProperty ')' |
' NamedIndividual' '(' NamedIndividual ')'

Important fact is that in the ontologies using OWL and RDF/S it is easier to store numerical data types. The axioms in the ontology, in analogy to the knowledge base stored in the DL, can relate to classes, relationships or objects. Using a table with the description of parameters of the experiments carried out at the Foundry Research Institute in Cracow, basic classes of the ontology were modelled in the Protege editor (figure 2).

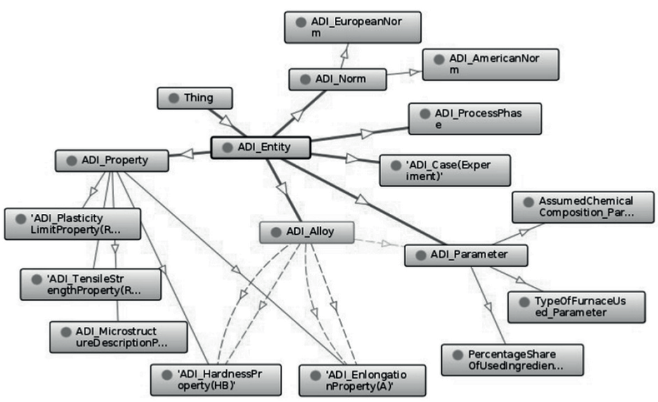

Fig. 2. Fragment of ontology describing experiments and properties of the manufactured cast iron

The above graphic corresponds to a record in the form of OWL Functional Syntax included in TABLE 2.

TABLE 2
A record in the form of OWL Functional Syntax

Ontology(
Annotation(rdfs:comment "ADI Ontology"^^xsd:string) (...)
Declaration(Class(:ADI_MicrostructureDescriptionProperty))
Declaration(Class(:AssumedChemicalComposition_Parameter))
Declaration(Class(:PercentageShareOfUsedIngredients_ Parameter))
Declaration(Class(:TypeOfFurnaceUsed_Parameter)) (...)
Declaration(ObjectProperty(:hasProperty)) (...)
AnnotationAssertion(rdfs:label "ADI_HardnessProperty(HB)")
SubClassOf()
AnnotationAssertion(rdfs:label "ADI_EnlongationProperty(A)")
SubClassOf()
AnnotationAssertion(rdfs:label "ADI_Property") (...)
AnnotationAssertion(rdfs:label "hasHardness")
SubObjectPropertyOf(:hasProperty)
ObjectPropertyDomain()
ObjectPropertyRange() (...))

3.1. Multi-Source-Data-Linkage framework

Searching for information to select process parameters and support the decision-making procedure is becoming nowadays more and more difficult due to the dispersion of research centers, a variety of sources (researchers, technologists, magazines, books, research reports, results of experiments), even in a niche so small as the production of ADI. Increasingly, all these sources of information can be found on the World Wide Web, but to accomplish this it is often not enough to use Google.com, and even if it is, the task may turn out to be quite difficult [18].

As indicated earlier, based on the literature, one can create a very accurate and reliable knowledge base. Semantic model of relationships existing between the data could reduce required experience of the technologist to evaluate the data found, and most of all – time needed. The authors propose the use of a genuine proprietary framework developed in the School of Information Technology and Electrical Engineering at The University of Queensland, named OGDL: Ontology Guided Data Linkage, which consists of the following steps [19]:

- *Stage 1* - Ontology Construction: Construct an ontology that is capable of describing the properties of data objects from different application domains.
- *Stage 2* - Key Discovery for Data Objects: Every data object represents a class of objects (facts) that has the same structure (set of attributes). A key is like a primary key in a relational data model that can be used to uniquely identify the objects/samples in a data source. So we can say that a data source is a collection of uniquely identifiable objects (samples) and every object is identified by a key.
- *Stage 3* – Key Linkage Validation for Multiple Data Sources. In OGDL approach we connect the keys from multi-source data according to the semantics defined in the ontology. For a given key in a data source, we check out its equivalent keys in ontology and then consider the

syntactical transformation between the key values. The syntactical transformation between the key values will qualify the link-ability of the data values such as the cardinality, granularity, range, unit, and scales. Sometimes the key equivalence may not be available. In this case, we need to consider the approximation between the key values with respect to the ontology.

In general, data linkage can be considered based on techniques either deterministic or probabilistic [20]. In deterministic approaches, a global schema is expected to be available to decide the link-ability between different data sources. However, it is difficult to obtain a global schema in most cases. In probabilistic approaches it is assumed that the relationships between data items of different sources can be established via a probabilistic model where two data items are linkable if they satisfy certain co-existence relationships. OGDL approach is a hybrid of these two approaches. In OGDL, we firstly construct an ontology using ontology discovery algorithms. Then we use a multi-faceted classification technique for performing structural analysis on multi-source data. This framework supports self-organization of contributing data sources through the discovery of structural dependencies, by performing multi-level exploitation of ontological domain knowledge relating to tables, attributes and tuples from a data source. The framework thus is able to discover schema structures across unrelated databases, based on the use of direct and weighted correlations between different ontological concepts, using record-matching technique for concept clustering and cluster mapping.

The process of mining structures existing among multiple databases is a significant task, with the aim to acquire the keys to make data items linkable. Accurate integration of internet available information can provide valuable insights that are useful for evidence-based key discovery. Traditional approaches use similarity scores that compare tuple values from different attributes, and declare it as matches if the score is above a certain threshold [21] or [22]. These approaches perform quite well when comparing similar databases with clean data. However, when dealing with a large amount of variable data, comparison of tuple values alone is not enough [23]. It is necessary to apply domain knowledge (expert, technologist) when attempting to perform data linkage where there are inconsistencies in the data. Furthermore, the creation of data linkages between heterogeneous data sources requires the discovery of all possible primary and foreign key relationships that may exist between different attribute pairs, on a global spectrum.

While conducting our research, we analyzed real-world data collected from a variety of sources (mentioned before). Findings from this analysis indicate that schemas of data that are invariant in time hold valuable information that aid the identification of semantically similar objects. The objective is to develop an ontology structure to provide an overview of all data. In OGDL, we exploit hidden relationships between data sources towards patterns discovery at different levels of data abstraction, including the schema and data instance levels. As some chains-of-relationships have stronger correlation weights than others, we focus on the identification of data correspondences between key attributes, together with its semantic information flow. OGDL approach is considered with the relationships that link keys such as candidate, primary, partial, and foreign key relational data (linkage) relationships. The final results are further integrated into data analysis tools to support sensible queries to discover meaningful and accurate facts among data objects of multiple sources.

There exist context-aware content mediators that for example allow multi-device and multi-user Web browsing that delivers partial view of each page to particular users. Content adaptation mediators operate on information as it flows and can add value to the information by enhancing the information (content is added or omitted), and/or transcoding it, and/or connecting various streams of information. However the existing approaches are quite limited in the types of information sources and the context information that they are able to use [24]. As a future extension our plan is to research adaptive user interfaces that provide generic mediators able to use any sources of information (and therefore suitable for a variety of applications) and also a variety of context information including user role, location information, and user preferences. The mediators need to be supported by Context Managers able to gather and evaluate context information and also appropriate meta information in the information sources. Such meta information (annotation, indexing) will need to be matched with the current context (including the role) to select appropriate interface adaptation and the content that it presents to particular users based on user preferences and their active roles. One of the requirements of such a mediation is that it is bi-directional i.e., both the request for information and the response are mediated.

4. Conclusions

The work presented here is a summary of the authors' studies of the mechanical properties and applications of ADI. In terms of the interdisciplinary knowledge it also enables specifying the use of a modern approach to data integration, which is the Agile Data Integration system. Collecting of research data is an important step in the process of finding the optimum design solutions for newly made products - experimental data allow us properly calibrate the manufacturing process of ADI to let the final product achieve the required properties. The design process can use the research data collected, among others, from the Web. As indicated in the article, the process of data acquisition can be supported by the semantic technologies.

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REFERENCES

[1] P. Skoczylas, A. Krzyńska, M. Kaczorowski, The comparative studies of ADI versus Hadfield cast steel wear resistance, Archives of Foundry Engineering **11** (2), 123–126 (2011).

[2] J.R. Keough, Austempered Ductile Iron (ADI) - A Green Alternative. American Foundry Society, 2010, USA.
[3] J. Tybulczuk, A. Kowalski, ADI. The properties and application in industry. Castings Atlas, 2003, Instytut Odlewnictwa, Kraków (in Polish).
[4] D. Myszka, T. Babul, Preparation of ausferritic iron in a vacuum oven with gas cooling, Archiwum Technologii Maszyn i Automatyzacji **30** (3), 34-42 (2010) (in Polish).
[5] D. Wilk-Kołodziejczyk, B. Mrzygłód, K. Regulski, Influence of Process Parameters on the Properties of Austempered Ductile Iron (ADI) Examined with the Use of Data Mining Methods, Metalurgija **55** (4), 849-851 (2014).
[6] T. Szymczak, G. Gumienny, T. Pacyniak, Effect of Vanadium and Molybdenum on the Crystallization, Microstructure and Properties of Hypoeutectic Silumin, Archives of Foundry Engineering **15**(4), 81-86 (2015).
[7] C. Zhin, S. Teng-Shih, Phase Transformation and Fatigue Properties of Alloyed and Unalloyed Austemperred Ductile Irons, World Conference on ADI: Conference on Austempored Ductile Iron (ADI) for Casting Producers, Suppliers and Design Engineers, 2002, Kentucky, USA.
[8] I. Olejarczyk-Wożeńska, A. Adrian, H. Adrian, B. Mrzygłód, Parametric representation of TTT diagrams of ADI cast iron, Archives of Metallurgy and Materials **57**, 981-986 (2012).
[9] L. Bartosiewicz, I. Singh, F.A. Alberts, A.R. Krause, S.K. Putatunda, The Influence of Chromium on Mechanical Properties of Austempered Ductile Cast Iron, Journal of Materials Engineering and Performance **4** (1), 90-101 (1995).
[10] [10]P.P. Rao, S.K. Patatunda, Dependence of Fracture Toughness of Austempered Ductile Iron on Austempering Temperature, Metallurgical and Materials Transactions A **29A**, 3005-3016 (1998).
[11] K. Aslantas, S. Tasgetiren, Y. Yalcin, Austempering retards pitting failure in ductile iron spur gears, Engineering Failure Analysis **11**, 935-941 (2004).
[12] S. Kluska-Nawarecka, D. Wilk-Kolodziejczyk, K. Regulski, G. Dobrowolski, Rough Sets Applied to the RoughCast System for Steel Castings, Lecture Notes in Computer Science, in: N. Nguyen, C.G. Kim, A. Janiak (Eds.), Intelligent Information and Database Systems, ACIIDS, Pt II**, 6592**, 52-61(2011).
[13] S. Kluska-Nawarecka, B. Śnieżyński, W. Parada, M. Lustofin, D. Wilk-Kołodziejczyk, The use of LPR (logic of plausible reasoning) to obtain information on innovative casting technologies, Archives of Civil and Mechanical Engineering **14**, 25-31 (2014).
[14] J. David, Z. Jancikova, R. Frischer, M. Vrozina, Crystallizer's Desks Surface Diagnostics with Usage of Robotic System, Archives Of Metallurgy And Materials **58** (3) 907-910 (2013).
[15] A. Glowacz, Diagnostics of DC and Induction Motors Based on the Analysis of Acoustic Signals, Measurement Science Review **14** (5), 257-262 (2014).
[16] S. Kluska-Nawarecka, K. Regulski, M. Krzyżak, G. Leśniak, M. Gurda, System of semantic integration of non-structuralized documents in natural language in the domain of metallurgy, Archives of Metallurgy and Materials **58** (3), 927–930 (2013).
[17] E. Nawarecki, S. Kluska-Nawarecka, K. Regulski K., Multi-aspect character of the man-computer relationship in a diagnostic-advisory system, in: Z.S. Hippe, J.L. Kulikowski, T. Mroczek (Eds.), Human – computer systems interaction: backgrounds and applications, Springer-Verlag, Berlin Heidelberg, 85-102, 2012.
[18] B. Mrzygłód, I. Olejarczyk-Wożeńska, A. Henryk**,** Studies of Phase Transformations in Ductile Iron with Additions of Ni, Cu, Mo, 24th International Conference on Metallurgy and Materials METAL Brno, Czech Republic, pp. 798-803, 2015.
[19] M. Gollapalli, X. Li, I. Wood, G. Governatori, Ontology Guided Data Linkage Framework for Discovering Meaningful Data Facts, in: Advanced Data Mining and Applications, Lecture Notes in Computer Science **7121**, 252-265 (2011).
[20] J. Euzenat, P. Shvaiko, Ontology Matching, 2007, Berlin Heidelberg Springer, New York.
[21] K. Regulski, D. Szeliga, J. Kusiak, Data Exploration Approach Versus Sensitivity Analysis for Optimization of Metal Forming Processes, Key Engineering Materials **611–612,** 1390–1395 (2014).
[22] A. Opalinski, W. Turek, K. Cetnarowicz, Scalable web monitoring system, Federated Conference on Computer Science and Information Systems (FedCSIS), 1261–1267, Kraków 2013.
[23] V. Gopalkrishnan, D. Steier, H. Lewis, J. Guszcza, Big Data, Big Business: Bridging the Gap, In Proc. of the 1st Intl. Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications, 7-11, New York 2012.
[24] J. Fong, J. Indulska, R. Robinson, A Preference Modelling Approach to Support Intelligibility in Pervasive Applications, 8th IEEE Workshop on Context Modeling and Reasoning (CoMoRea'11) Proc. of the 2011 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), 409-414, Seattle 2011.