A R C H I V E S O F M E T A L L U R G Y A N D M A T E R I A L S
Volume 55 2010 Issue 3

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DIAGNOSIS OF CASTING DEFECTS USING UNCERTAIN AND INCOMPLETE KNOWLEDGE

DIAGNOSTYKA WAD ODLEWÓW PRZY ZASTOSOWANIU WIEDZY NIEPEWNEJ I NIEPEŁNEJ

Diagnosis of the causes of casting defects is a difficult task. Many of the premises for defect diagnosis are intuitive, and therefore creation of systems for defect diagnosis must be supported by tools that can collect and use incomplete and uncertain knowledge. The aim of this article was to create a perspective in the formation of systems operating knowledge of this class. The problem that remains open is creating a knowledge base, adapted to particular casting technologies, and improvement of an interface oriented at the specific user needs. The article presents two methods selected for the construction of models of reasoning, i.e. the method based on fuzzy logic and the method based on the logic of plausible reasoning. While solutions based on the use of fuzzy logic have already found some approval in a number of practical applications and can be used as a point of reference, the logic of plausible reasoning still remains in this area a formalism quite innovative. In this study, apart from formal discussions, examples of fragments of the knowledge about the defects in castings and related algorithmic solutions and tools were presented.
Keywords: diagnosis of casting defects, identification of defect causes, fuzzy logic, logic of plausible reasoning

Diagnostyka przyczyn powstawania wad odlewniczych jest trudnym zadaniem. Wiele przesłanek dotyczących diagnostyki wad jest intuicyjnych, dlatego tworzenie systemów wspomagających diagnostykę wad musi być wsparte narzędziami, które potrafią gromadzić i następnie wykorzystywać wiedzę niepełna i niepewną. Zamierzaniem artykułu było stworzenie pewnej perspektywy odnośnie stworzenia systemów operujących tej klasy wiedzą. Problemem pozostaje tu stworzenie bazy wiedzy, dostosowanej do konkretnych technologii odlewniczych, a także doskonalenie interfejsu zorientowanego na specyficzne potrzeby użytkownika. Artykuł prezentuje dwie wybrane metody budowy modeli wnioskowania: w oparciu o logikę rozmytą oraz logikę wiarygodnego rozumowania. O ile rozwiązania oparte na zastosowaniu logiki rozmytej uzyskały już pewne potwierdzenie w szeregu zastosowaniach praktycznych i może stanowić pewien punkt odniesienia, o tyle logika wiarygodnego rozumowania jest w tym zakresie formalizmem całkiem innowacyjnym. W pracy obok rozważań formalnych przedstawiono przykłady fragmentów wiedzy o wadach odlewów oraz odnośne rozwiązania algorytmiczne i narzędziowe.

1. Introduction

An important factor in improvement of the casting production process is preventing the formation of casting defects. Identification of the causes of casting defects is one of the essential steps in foundry operation, and it usually takes place at the following stages of technological process:

– after knocking out of casting from mould,
– after removal of risers and fettling of casting,
– after finishing of casting (heat treatment included),
– after necessary tests carried out on the randomly chosen products (castings),
– during practical use of product (casting) by the customer [5],

The identification of the cause of defect can be based on a visual inspection of casting, or on the results of examinations carried out on the whole casting or on samples cast-on or cut out from this casting. The identification can also take place when the product (casting) is not able to perform the tasks declared by the manufacturer despite its proper use.

Identification of the defect cause is the process which, on one hand, involves the measurable parameters, like temperature, time, etc., while – on the other – it can also involve a number of operations performed in the course of the casting process, e.g. casting knocking out, pouring of mould, etc. Some parameters can be determined by measurement, while other can be defined in an approximate manner only, for example, basing on the visual inspection of ready product. Yet, in each case, the

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cause of the defects is indicated using our knowledge of the defects acquired from standards, catalogues, and experts' experience. With computer-assisted diagnostic process, this knowledge must be represented in a formalised way. The incomplete nature of the available knowledge requires application of appropriate formal methods. This study presents the possibility of defect identification based on the use of fuzzy logic and the logic of plausible reasoning.

2. Fuzzy logic

Fuzzy logic is a well recognised formalism, which has already found a number of practical applications, although its application in the field of foundry knowledge is still under development.

The remarks presented in this article were illustrated with examples of the reasoning procedures performed on a Fuzzy Logic module available in the Matlab packet. Input and output data for the package were developed along with the rules of inference and experimentally selected membership functions.

The need for a formalism that would take into account both the lack of precise knowledge of parameters that cause the occurrence of defects, as well as the approximate nature of the information about the parameters of the technological process, is a characteristic feature of casting technologies.

2.1. Basic concepts

In the classical theory of distributive sets, the key role is played by a characteristic function, which takes values from a two-element set {0,1}. In the definition of a fuzzy set [5], an analogical role is played by the function which determines the degree of membership of element x from space X to fuzzy set A. This function performs the mapping:

$$\mu_A: X \to [0,1] \tag{1}$$

where:

X – is the space of the Universe,

μ_A – is the membership function,

such that:

$$\begin{aligned}&\mu_A(x) = 1 \Leftrightarrow x \in A \text{(expresses full membership)}\\&\mu_A(x) = 0 \Leftrightarrow x \notin A \text{(expresses absence of membership)}\\&0 < \mu_A(x) < 1 \Leftrightarrow x \in A \text{(expresses partial membership).}\end{aligned} \tag{2}$$

Fuzzy set A in a (non-empty) space X is the set of pairs:

$$A = \{(x, \mu_A(x))\};\ x \in X. \tag{3}$$

Function μ_A, called *membership function*, is a generalisation (extension) of the concept of a characteristic function. As we can see, in classical approach, the characteristic function of the set satisfies the conditions (a) and (b), while condition (c) extends the concept of an element membership to a set by the, so called, *partial membership*.

Different types of membership function are applied, and usually they are selected in an arbitrary manner. The operations performed on fuzzy sets are from the conceptual point of view similar to the operations made on traditional sets. As most important for further discussion, the following operations are to be mentioned:

– determination of the common part (intersection) of fuzzy sets A∩B,
– determination of the sum (composition) of fuzzy sets AUB.

Compared with classical sets, the difference consists in this that the said operations are defined with T and S Norms, and each of them can be defined in several ways. For further considerations it is enough to determine the most commonly used interpretation of these *norms*, where min operator corresponds to norm T, while *max* operator corresponds to norm S. In this approach:

$$A \cap B = \{x, \mu_{A\cap B}(x) = \min[\mu_A(x), \mu_B(x)]\},\quad A, B \subseteq X, x \in X \tag{4}$$

where:

$\mu_{A\cap B}(x)$ – the function of membership to common part of fuzzy sets A, B;

$\mu_A(x)$ – the function of membership to fuzzy set A,

$\mu_B(x)$ – the function of membership to fuzzy set B

and:

$$AUB = \{x, \mu_{AUB}(x) = \max[\mu_A(x), \mu_B(x)]\},\quad A, B \subseteq X, x \in X \tag{5}$$

Graphical interpretation of these operations is shown in Figure 1.

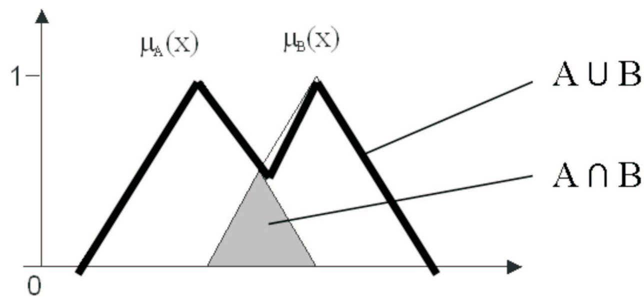

Fig. 1. Intersection and sum of fuzzy sets A,B

2.2. Fuzzy reasoning

As in classical logic, fuzzy reasoning is reduced to the use of implications, where both premises and conclusions are given in the form of fuzzy sets.

So, a fuzzy implication is written down as a rule:

$$\textbf{IF } [(x_1 \textbf{ is } A_1) \textbf{ AND } (x_2 \textbf{ is } A_2) \ldots\ \ldots \textbf{ AND } (x_n \textbf{ is } A_n)] \textbf{ THEN } (y \textbf{ is } B). \tag{6}$$

where:

$x_1 \ldots x_n$ – the premises ascribed to the corresponding fuzzy sets $A_1 \ldots A_n$;

y – the conclusion ascribed to fuzzy set B.

The operation of ascribing the variables (expressed in numerical or linguistic form) to fuzzy sets is called *fuzzification*.

The conclusion from a rule is, in turn, subjected to a reverse operation of *defuzzification* (sharpening), which consists in assigning to it a numerical (or linguistic) value.

It should be noted that the quantities hardly measurable (or non-measurable) are defined in the fuzzy rules in a linguistic form (large, small, high, low, etc.).

A set of fuzzy rules describing the decision-making process makes a fuzzy knowledge base.

Reasoning with fuzzy knowledge base is the same as in classical expert systems; what is most characteristic here is the mere technique of construction of the rules. This operation will be illustrated in detail when discussing the procedure used for identification of the causes of casting defects.

2.3. Methodology to design the module of reasoning

Literature [6,7] identifies the formal rules for the application of fuzzy logic in representation of incomplete and uncertain knowledge. Yet, these rules do not specify the methodology used in designing of solutions tailored to practical needs. The proposal of such a methodology for the diagnosis of defects in metal products, and more strictly, for the determination of the causes of occurrence of defects of a given type, will be presented in further course of this study, using the cases analysed below.

The design and implementation of a decision-making module based on the use of fuzzy logic includes the following steps which form a methodology proposed for the construction of this module:

1. Choose input and output variables operating as premises and conclusions of the rules, respectively;
2. Determine the rules of the fuzzification of these variables, i.e. define the fuzzy sets representing these quantities by:
3. selection of the number and names of fuzzy sets that characterise a given variable,
4. determination of membership functions describing each of the featured sets;
5. Determine conclusions of the rules of reasoning, that is, the fuzzy sets representing the output variable, and so:
6. the number and names of the sets and of the corresponding membership functions,
7. Using the results obtained under items 1,2,3, design the decision rules corresponding to a specific situation in technology (type of defect: premises, causes of occurrence).
8. Determine the procedure of defuzzification, i.e define the result of reasoning (in numerical or linguistic form).

From the above it follows that practical implementation of this procedure is not a trivial matter, as it requires deep technical knowledge acquired not only from standards and catalogues, but also from experts with a lot of practical experience.

In the course of the research it has become clear that acquisition of such knowledge, particularly in the practical part, is difficult and time-consuming, as it requires extensive discussions with numerous process engineers, remembering that their opinions can vary in most of the cases.

As a result of numerous contacts with industrial plants, it has been possible to specify elements of the knowledge indispensable for the creation and implementation of a fuzzy base of rules, which includes several characteristic defects.

These results, which both complement and illustrate the above methodology, will be presented in the sub-sections below.

2.4. Identification of the causes of defects

In the applied module, the procedures assisting the diagnosis of the causes of defects have been implemented, depending on the values that the casting process parameters are expected to assume. The result of the reasoning is estimation of the possibility of occurrence of a specific defect. In this case, the measurement data from several casting cycles have been used.

As input variables for the component, the following parameters have been adopted:

– Metal temperature on pouring;
– Interruptions in pouring;
– Metal castability.

These variables are parameters that can be determined or measured during casting process. Their value affects the possibility of defect occurrence in a cast product.

As output variables, the functions of membership to a given type of defect have been adopted:

– W-102 ***Misrun***, (according to Polish Standard PN-85/H-83105);

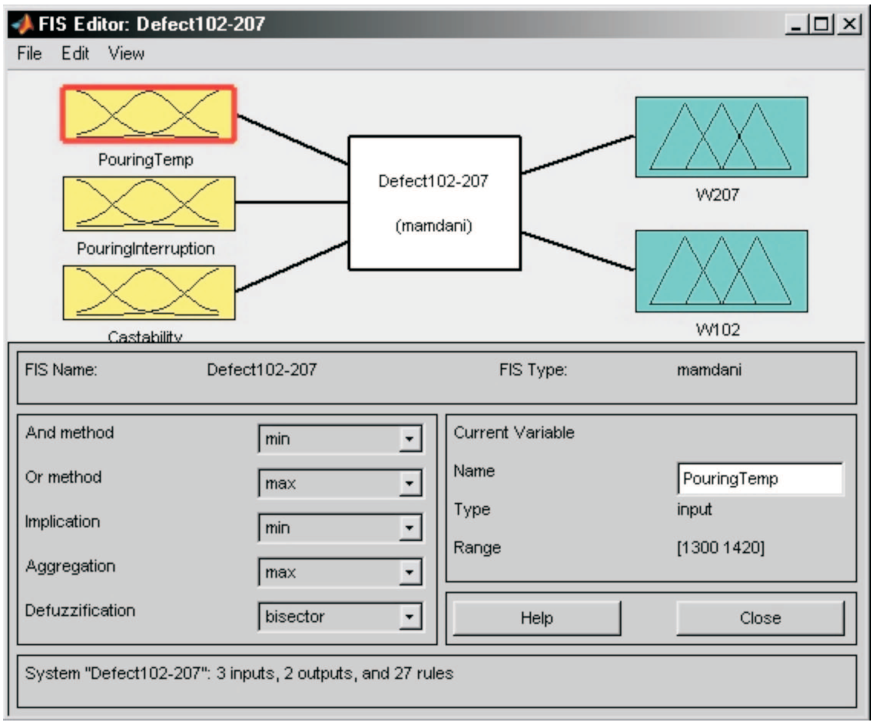

Fig. 2. Simplified schematic representation of knowledge component

– W-207 ***Fold***, (according to Polish Standard PN-85/H-83105);

A simplified diagram of this component is shown in Figure 2.

The ranges of parameters used in this reasoning have been defined basing on data given in literature and collected in actual production. Because for each of the materials, the input data may take different values in respective fields, it has been assumed that reasoning will be conducted for a specific product and related production data [1)].

It has also been assumed that the full range of *metal temperatures* that can occur during pouring of casting is comprised in an interval from 1300 to 1400°C. The range of 1360-1370°C was considered *Correct*, i.e. such within which the defects should not occur and the membership function value should equal 1. The temperature below 1346°C was considered definitely *too low*, while the temperature of 1390°C was considered *too high*. Within these ranges, appropriate membership functions assume the value of 1. Consequently, the fuzzy representation of the variable *Temperature* has three fuzzy sets, i.e. *Low, Correct and High*, Output variables

For both types of the examined defects, i.e. W-102 (*misrun*) and W207 (*fold*), the output variables of the component are represented by four fuzzy sets of the same names.

– WWZ – negligible risk of defect occurrence (in practice, the risk of defect occurrence can be disregarded),
– WWM – low risk of defect occurrence,
– WWS – medium risk of defect occurrence,
– WWW – high risk of defect occurrence.

The functions of membership to these sets were adopted arbitrarily. The knowledge about the represented defects was expressed in the form of fuzzy rules describing relationships between the input and output variables. The structure of the relationships described with these rules was schematically presented in Figure 3.

If we assume that the temperature of pouring is 1360°C, which is the range corresponding to the statement that the temperature of pouring is "*correct*", and the interruption in pouring is 0.5, which is corresponding to the statement that it is "*insignificant*", and castability is 25, which means membership to both sets denominated as "sufficient" and "insufficient" (which in practice may correspond to the statement "hard to say"), then, according to the form of the rule, the value of its left side (the premise) will be determined with MIN-yes operator, and hence, active will be only those rules for which the values of the membership function of all the variables are greater than 0. In this example, the following rules have been launched:

[1)] The author of this study has not been authorised to publish the data from the cooperating production plant.

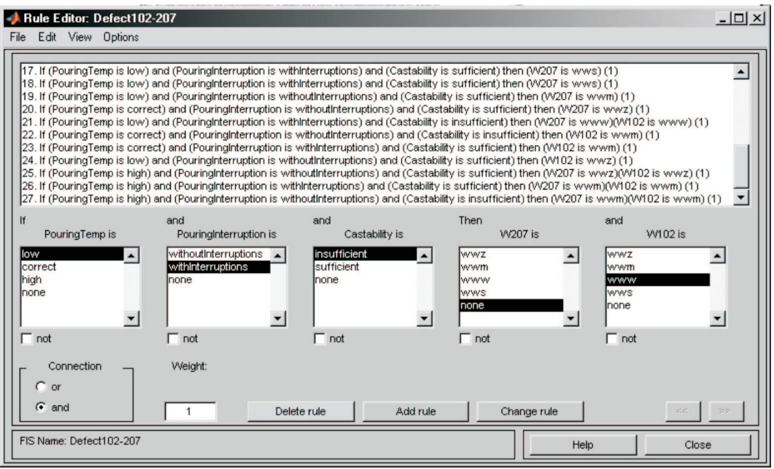

Fig. 3. The structure of relationships described with the rules

(PouringTemp==Low) & (Pouring==withoutInterruptions) & (castability==insufficient) => (W102=wwm) (1) (rule 6).

If (PouringTemp **is** Low) **and** (Pouring **is** withInterruptions) **and** (castability **is** sufficient) **then** (W207 **is** wwm) (1) (rule 12)

If (PouringTemp **is** correct) **and** (Pouring **is** withoutInterruptions) **and** (castability **is** sufficient) **then** (W207 **is** wwz) (1) (rule 13)

If (PouringTemp **is** correct) **and** (Pouring **is** withInterruptions) **and** (castability **is** insufficient) **then** (W207 **is** wws) (1) (rule 14)

If (PouringTemp **is** correct) **and** (Pouring **is** withInterruptions) **and** (castability **is** sufficient) **then** (W207 **is** wwm) (1) (rule 15)

If (PouringTemp **is** Low) **and** (Pouring **is** withoutInterruptions) **and** (castability **is** sufficient) **then** (W207 **is** wwm) (1) (rule 20)

If (PouringTemp **is** correct) **and** (Pouring **is** withoutInterruptions) **and** (castability **is** sufficient) **then** (W207 **is** wwz) (1) (rule 21)

If (PouringTemp **is** Low) **and** (Pouring **is** withInterruptions) **and** (castability **is** insufficient) **then** (W207 **is** www)(W102 **is** www) (1) (rule 22)

(PouringTemp==correct) & (Pouring==withoutInterruptions) & (PouringTime==correct) & (castability==sufficient) => (W207=wwz) (1) (rule 24)

According to the values obtained on the left side of the active rules, the values of the membership function of the output variable (conclusion) are determined. These results are integrated using MAX operator (multiple sum).

The final result is subject to defuzzification (sharpening) by application of the *Centroid* operator, equivalent to the determination of a coordinate of the centre of gravity, obtained by integration of a solid. The *final step* in creation of a knowledge component (sharpening) is carried out automatically by the software package used. Figure 4 shows the result obtained for W207; the final value is marked by red line.

The output function is 0 for both W207 (Fig. 4) and W102. This state corresponds to the situation when one or more parameters can cause the defect.

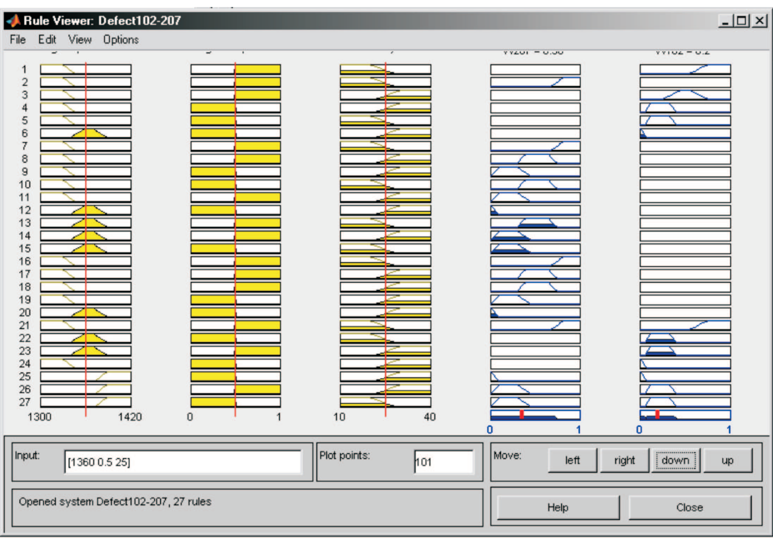

Fig. 4. Mapping of final result for the defects W-207 and W102

3. The Logic of Plausible Reasoning

An alternative approach refers to the situation in which it is not possible to estimate even in great approximation the parameters of the process. Then, an inquiry into the causes of defects is based on interrelations that exist between different premises. A formalism proposed here is the logic of plausible reasoning [1,2].

The fundamentals of the logic of plausible reasoning (LPR in abbreviation) are an interesting formalism, which until now has not found any wider practical application. The article presents the potential applications of this formalism in the representation of incomplete and uncertain knowledge in areas where human intuition is of great importance. Using this formalism and the knowledge derived from standards, catalogues, and books, a knowledge base has been created that enables identification of the causes of defect occurrence and detecting interrelations between the defects included in different systems of classification.

3.1. Basic concepts of LPR

3.1.1. Similarity

Similarity (with transformation of arguments in statements)

$$\frac{\begin{array}{l} A(o)=R:\ \gamma 1,\ \varphi,\ \mu a \\ o'\ SIM\ o\ in\ CX(O,D(O)):\ \gamma 2,\ \sigma \\ D(O)\leftrightarrow A(O):\ \gamma 3,\ \alpha \quad o\ SPEC\ O:\ \gamma 4 \\ o'\ SPEC\ O:\ \gamma 5 \end{array}}{A(o')=R:\gamma=f(\gamma 1, \varphi, \mu a, \gamma 2, \sigma, \gamma 3, \alpha, \gamma 4, \gamma 5)} \tag{7}$$

Similarity is a type of reasoning based on analogy. It allows replacing an argument in a statement with similar notion. The occurrence of a context limits the use of this type of reasoning to the relevant descriptors. The following notation describes this situation:
`castingDefects(causeMechanical)=damage-Mechanical` γ_1`=high,` φ`=low,` μ_a`=low`
`damageMechanical SPEC damageType in CX (castingDefects, defects(castingDefects));` γ_2`=,` ι`=high,` δ`=low`
`Defects(castingDefects)`$\leftrightarrow$`Causes(casting);` γ_3`=high,` α`=low`
`causeMechanical SPEC cause` γ_4`=very high`
`castingDefects(causeMechanical)=damage-Type` γ`=high`

Similarity (with transformation of values in statements)

$$\frac{\begin{array}{l} d(a)=\{R,\ldots\}:\ \gamma 1,\ \varphi,\ \mu r \\ R'\ SIM\ R\ in\ CX\ (d,\ D(d)):\ \gamma 2,\ \sigma \\ D(d)\leftrightarrow A(d):\ \gamma 3,\ \alpha \\ a\ SPEC\ A:\ \gamma 4 \end{array}}{d(a)=R',\ldots:\ \gamma=f(\gamma_1, \varphi, \mu_r, \gamma_2, \sigma, \gamma_3, \alpha, \gamma_4)} \tag{8}$$

As mentioned previously, this is a transformation based on analogy, but here the exchange takes place between objects.
`CauseOfDefectOccurrence (break off)=too-StrongImpactDuringCastingKnockingOutFrom-Mould` γ_1`=high,` φ`=low,` μ_a`=low`
`damageMechanical SIM tooStrongImpactDuringCastingKnockingOut-FromMould In CX (CauseOfDefectOccurrence, cause(CauseOfDefectOccurrence))` γ_2`=high,` σ`;`
`cause(CauseOfDefectOccurrence)`$\leftrightarrow$`defect(Ca-useOfDefectOccurrence)` γ_3`=high,` α`=high`
`break off SPEC Defect` γ_4`=high`
`causeOfDefectOccurrence (break off)= damageMechanical` γ`=high`

3.1.2. Positive transformation (derivation) based on implications

$$\frac{\begin{array}{l} D_1\ (A) = R_1 \Leftrightarrow D_2\ (A){:}\gamma_1, \alpha \\ D(a) = R_1\ {:}\gamma_2, \varphi \\ a\ SPECA{:}\gamma_3 \end{array}}{D_2\ (a) = R_2\ {:}\gamma = f(\gamma_1, \alpha, \gamma_2, \varphi, \gamma_3)} \tag{9}$$

This type of reasoning is based on the, well-known from classical logic, *modus ponens* rule. The LPR has been further enriched with the possibility of reasoning about objects occupying a lower position in the hierarchy and, classically in logic of this type, with the parameters of uncertainty. The following notation can be formulated here:
`defect(casting)=misrun`
`causeOfDefectOccurrence (casting)=tooLow-MetalPourTemp:` γ_1`=high,` α`=medium`
`defect(castMetal)=misrun:` γ_2`=high,` φ`=high`
`castMetal SPEC Casting:` γ_3`=high`
`causeOfDefectOccurrence (castMetal)= tooLowMetalPourTemp:` γ`=medium`

3.1.3. Transformation (derivation) based on positive dependence

$$\frac{\begin{array}{l} D_1\ (A)\overset{+}{\leftrightarrow} D_2\ (A){:}\gamma_1, \alpha \\ D(a)\neq R_k\ {:}\gamma_2, \varphi;\ where\ k \in \{\ 1,2,\ldots,n\} \\ a\ SPECA{:}\gamma_3 \end{array}}{D_2\ (a) = R_k\ {:}\gamma = f(\gamma_1, \alpha, \gamma_2, \varphi, \gamma_3)} \tag{10}$$

In this dependence, the descriptors that are on both sides take values from the same, linearly ordered, set. In positive dependence, the small values of the first descriptor are corresponding to analogical values of the second descriptor. The following example describes this situation:

`lowMetalTemperature(casting)`$\overset{+}{\leftrightarrow}$`misrunOccurrence (casting)` γ_1=`high`, α=`high`
`lowMetalTemperature (casting)=occurrence` γ_2=`high`, φ=`high`
`castMetal SPEC casting` γ_3=`high`
`misrunOccurrence (castMetal)= occurrence` γ=`high`

3.1.4. Transformation (derivation) based on negative dependence

$$\frac{\begin{array}{l} D_1\ (A) \overset{-}{\leftrightarrow} D_2\ (A){:}\gamma_1,\alpha \\ D(a) = R_k\ {:}\gamma_2,\varphi;\ \text{where } k \in \{\ 1,2,...,n\} \\ a\ SPEC A{:}\gamma_3 \end{array}}{D_2\ (a) = R_{n-k+1} : \gamma = f(\gamma_1,\alpha,\gamma_2,\varphi,\gamma_3)} \qquad (11)$$

This dependence is very similar to the positive transformation, the difference lies in the fact that to small values of the first descriptor are corresponding large values of the second descriptor.

`design(casting)`$\leftrightarrow$`defectOccurrence (casting)` γ_1=`high`, α=`high`
`design(casting)=good` γ_2=`high`, φ=`high`
`castMetal SPEC casting` γ_3=`high`
`defectOccurrence (castMetal)=low` γ=`high`

3.1.5. Transformations based on the law of transitivity Mutual transformation of implications

$$\frac{\begin{array}{l} D_1\ (A) = R_1 \Leftrightarrow D_2\ (A) = R_2\ {:}\gamma_1,\alpha_1,\beta_1 \\ D_2\ (A) = R_2 \Leftrightarrow D_3\ (A) = R_3\ {:}\gamma_2,\alpha_2,\beta_2 \end{array}}{\begin{array}{c} D_1(A) = R_1 \Leftrightarrow D_3(A) = R_3 : \gamma = f(\gamma_1,\gamma_2), \\ \alpha = f(\alpha_1,\alpha_2), \beta = f(\beta_1,\beta_2) \end{array}} \qquad (12)$$

And, correspondingly, the following can be written down:

`defect(casting)=misrun` $\Leftrightarrow$ `causeOfDefectOccurrence(casting)= tooLowMetalPourTemp:` γ_1=`high`, α_1=`medium`, β_1=`high`
`causeOfDefectOccurrence casting)=tooLowMetalPourTemp` $\Leftrightarrow$ `pouringTime(casting)=tooLong` γ_1=`high`, α_1=`high`, β_1=`high`
`causeOfDefectOccurrence(castMetal)`$\Leftrightarrow$`pouringTime(casting)=tooLong` γ=`high`

Transformation of dependences

$$\frac{\begin{array}{l} D_1\ (A) = R_1 \leftrightarrow D_2\ (A) = R_2 : \gamma_1,\alpha_1,\beta_1 \\ D_2\ (A) = R_2 \leftrightarrow D_3\ (A) = R_3 : \gamma_2,\alpha_2,\beta_2 \end{array}}{\begin{array}{c} D_1(A) = R_1 \leftrightarrow D_3(A) = R_3 : \gamma = f(\gamma_1,\gamma_2), \\ \alpha = f(\alpha_1,\alpha_2), \beta = f(\beta_1,\beta_2) \end{array}} \qquad (13)$$

The following notation describes this situation:

`defect(casting)`$\leftrightarrow$`causeOfDefectOccurrence(casting):` $\gamma 1$=`high`, $\alpha 1$=`medium`, $\beta 1$=`high`
`causeOfDefectOccurrence(casting)t`$\leftrightarrow$`pouringTime(casting):` $\gamma 1$=`high`, $\alpha 1$=`high`, $\beta 1$=`high`
`causeOfDefectOccurrence(castMetal)`$\leftrightarrow$`pouringTime(casting)` γ=`high`

The knowledge base has been based on the logic of plausible reasoning (LPR). The subsection sets out the individual elements of a knowledge base.

All elements necessary for the process of reasoning were entered to the programme in the form of objects.

3.2. Design of knowledge base

For the needs of defect diagnosis, a knowledge base was designed. Its use enables inference in the logic of plausible reasoning. Below a description of the database designed for a selected group of defects was given. The following is an example of how to enter objects to the base:

`obj(defect, "ParametersIndicatingDegreeMaterialDamage", "").`

This is the method of entering an object called *defect* to the knowledge base. This notation gives information that the word "defect" is an object for the system, while for the user it is the parameter defining the degree of material damage. Below, on the example of defect called *Mechanical Damage* (defined according to Polish terminology) and defect called *Impression Bruising Indentation* (classified according to Czech terminology), it will be demonstrated how different types of defects belonging to different categories are entered into the system.

`obj(w101DamageMechanical, "IdentificationOfDefectDescribedInPolishStandard", "").`

`obj(c116ImpressionBruisingIndentation, "Identification of defect described in Czech Standard", "").`

The following examples illustrate how individual parameters defining (in a descriptive manner) the individual characteristics and the causes of defects are entered into the system. The mechanical causes of defects are the parameter that determines the occurrence of defects for mechanical reasons. On the other hand, carelessTransport, incorrectCastingStorage, damageDuringKnockingOut, carelesslyRemoved Gates,...., are selected examples of attributes that belong to the category of "*mechanical causes of defects*". The following example illustrates this situation:

obj(mechanicalCausesOfDefect, "ParametersDeterminingMaterialDamageByMechanicalCauses", "").

obj(carelessTransport, "mechanicalCausesOfDefect", "").

obj(incorrectCastingStorage, "mechanicalCausesOfDefect", "").

obj(damageDuringKnockingOut, "mechanicalCausesOfDefect", "").

obj(carelesslyRemovedGates, "mechanicalCausesOfDefect" "").

obj(removedCastingPart, "mechanicalCausesOfDefect", "").

The next stage of entering the data into a system is based on the incorporation of a hierarchy indispensable for the process of reasoning. Below an example is given of the entered hierarchy where the top is “mechanical cause of defects,” and the sub-concept is “careless transport”, ..., and where the top of the hierarchy is “casting process as cause of defect,” and the sub-concepts are “metal cooling too quickly” and “metal cooling in uneven mode”

kb(h(carelessTransport, mechanicalCausesOfDefect, allProperties), hPL(1, 1), jd, "").

kb(h(metalCoolingTooQuickly, castingProcessAsCauseOfDefect, allProperties), hPL(1, 1), jd , "").

kb(h(unevenMetalCooling castingProcessAsCauseOfDefect, allProperties), hPL(1, 1), jd, "").

Further elements of the knowledge base are triples: *object-attribute-value*; they make the tools with which the parameters enabling identification of defects are determined. An example shows how to the defect W101 MechanicalDamage, the parameter *carelessTransport* belonging to the category: *mechanical causes of defect* has been ascribed. The following examples are similar in nature. In parenthesis, parameter determining the certainty of the formula has been specified.

kb(v(W101MechanicalDamage, mechanicalCausesOfDefect, carelessTransport), vPL(0.9), "").

Next, a formula has been presented which describes relationships occurring between the entered defects. The first formula indicates that both defects, i.e. *Mechanical damage W101* according to Polish classification and *Cold crack C111* according to French classification, have the cause of occurrence rooted in the “damage during knocking out of casting”. The successive examples were formed according to the same rule.

kb(e(w101MechanicalDamage, DamageDuringKnockingOutOfCasting, fr_C111ColdCrack, mechanicalCauseOfDefect), ePL(1),"","").

The following formulas illustrate the operation of the rules using similarity relationships between objects in the database. The notation shows that defect C111 *ColdCrack* and defect *W101 Mechanical Damage* are similar to each other in the category “damage during knocking out of casting”.

kb(s(fr_C111ColdCrack, w101MechanicalDamage, mechanicalcausesOfDefect), sPL(0.9), "").

The knowledge base has defined a series of queries about the values of the attributes of objects, which enable determination of the causes of defect formation, based on the information received from the user. To each query, a list of answers is given, from which the user can choose the right one. There is also an opportunity to answer “hard to say.” If this answer is given to the posed query, the system using other answers will define the result. It is also possible to enter with each answer a parameter defining the uncertainty of the entered information. Below, an example of the formulation of a query concerning the causes of defect is given.

quest(v(o, r mechanicalCausesOfDefect, v), [carelessTransport, incorrectCastingStorage, damageDuringKnockingOut,
carelesslyRemovedGates, ..., v),
"What can be the cause of defect occurrence?", "", many).

The most important knowledge leading directly to the identification of the name of defect is found in implications. The technique of the construction of implications shown below indicates that the defect *W101 Mechanical damage* will be defined basing on the values of attributes.

kb(impl(v(o,defect, W101MechanicalDamage), [v(o, mechanicalCausesOfDefect, carelessTransport),
v(o, mechanicalCausesOfDefect, incorrectCastingStorage),v(o,mechanicalCausesOfDefect, damageDuringKnockingOut),
v(. . . , v[]), iPL(1), jd, " Polish defect Mechanical Damage ").

The user of the system answers the queries raised by the system. The system, basing on the answers, is concluding which of the defects best fits the description. First, it indicates the most adequate one, which has been reasoned out. If user wants to know further results he may have it, or quit the system at any arbitrary stage.

Fig. 5. Example of dialogue with user in LPR implementation

3.3. Notes on implementation

The aim of the created application[2)] is finding causes of the defect basing on a dialogue with the user (Fig. 5), as a result of which the knowledge is acquired of the process run, of some of its parameters, and of the casting appearance. The application as a whole performs the basic tasks of an expert system, aiding the user's (process engineer) decision-making process carried out in a dialogue mode. As soon as the system is started by the user, specific queries are posed, and the user gives answers which start up the system of inference. Then the user obtains either the next query or final decision. Additionally, until the very end, the application is explaining to the user the applied course of reasoning.

In the created application, LPR is the basis for operation of the reasoning module and knowledge base. Here, the knowledge which the application is using is incomplete and uncertain. There is also possibility of introducing coefficients of reliability (uncertainty) for individual knowledge components.

Not less important task here is to enable the user to gather knowledge and continuously expand and update it, and therefore it is possible to transfer and store the system in the successive expanded versions of a knowledge base.

4. Final conclusions

The diagnosis of the causes of casting defects is a difficult task. Many of the premises used for this diagnosis are of an intuitive character, and this is why creating systems aiding the diagnosis of defects must be supported by tools that can collect and use later the incomplete and uncertain knowledge. The aim of the article was to create certain perspective regarding the creation of systems operating this class of knowledge.

Solutions based on the use of fuzzy logic have already received some support in a number of practical applications. What remains here is the problem of creating a knowledge base, tailored to specific casting technologies, and improvement of interface oriented at the specific user needs. Certain limitation in the fuzzy approach is the need to provide current access to the technological process in full run. Fully open is, on the other hand, the problem regarding application of the logic of plausible reasoning. Here it is still difficult to determine whether difficulties in intuitive formulation of rules, and particularly complex procedures of inference, do not constitute a barrier limiting the effectiveness of this approach. It seems, therefore, well justified to present even the preliminary results of the work in this area, since it can open new perspectives in the field of the creation of diagnostic knowledge.

REFERENCES

[1] A. Collins, Fragments of a theory of human plausible reasoning, [in:] D. Waltz (ed.), Theoretical Issues in Natural Language Processing II, 194-201, Universyty of Illinoi (1978).

[2] A. Collins, R.S. Michalski, The logic of plausible reasoning: A core theory, Cognitive Science, **13** 1-49, (1989).

[3] A. Macioł, R. Wrona, A. Stawowy, P. Macioł, An attempt at formulation of ontology

[2)] Implementation was done on SOWA software designed by Paweł Gurgul in his MSc. Thesis under Jarosław Durak, PhD. guidance

for technological knowledge comprised in technical Archives of Metallurgy and Materials, **52**, 3, 381-388 (2007).

[4] A. G r z e g o r c z y k, The system of Leśniewski inrelation to contemporary logical research, Studia Logica, **III**, 77-97 (1955).

[5] B. K a l a n d y k, R. Z a p a ł a, A. R a k o w s k a, Characteristics of defects present in industrial steel castings due to metal-mould reactions, Archives of Metallurgy and Materials **54**, 2 (2009).

[6] J. D u r a k, M. W o j t a s z e k, B. M r z y g ł ó d, Application of Matlab's Fuzzy Toolbox in didactics of material science, Computer supports for didactics : Łódź, 25-27 June 2008, ed. Edward Kącki, Joanna Stempczyńska; WSI, 2008. – ISBN 978-83-60282-07-6.

[7] S. K l u s k a - N a w a r e c k a, Z. G ó r n y, B. M r z y g ł ó d, D. W i l k - K o ł o d z i e j c z y k, K. R e g u l s k i, Methods of development fuzzy logic driven decision-support models in copper alloys processing. Archieves of Foundry, Polish Academy of Sciences, 2010, ISSN 1897-3310.

[8] S. K l u s k a - N a w a r e c k a, A. S m o l a r e k - - G r z y b, D. W i l k - K o ł o d z i e j c z y k, A. A d r i a n, Knowledge representation of casting metal defects by means of ontology, Archives of Foundry Engineering, Polish Academy of Sciences. Commission of Foundry Engineering ; ISSN 1897-3310. **7**, 3, 75-78 (2007).

[9] S. K l u s k a - N a w a r e c k a, R. M a r c j a n, A. A d r i a n, The role of knowledge engineering in modernisation of new metal processing technologies, Archives of Foundry Engineering, Polish Academy of Sciences. Commission of Foundry Engineering ; ISSN 1897-3310. **7**, 2, 169-172 (2007).

[10] S. K l u s k a - N a w a r e c k a, H. P o ł c i k, J. T y b u l c z y k, Evolution of computer programming in production processes control, Archives of Foundry Engineering Polish Academy of Sciences. Commission of Foundry Engineering 2, 5, 80-86 (2002).

[11] A. M a c i o ł, R. W r o n a, A. S t a w o w y, P. M a c i o ł, An attempt at formulation of ontology for technological knowledge comprised in technical Archives of Metallurgy and Materials **52**, 3, 381-388 (2007).

[12] A. M a c i o ł, R. W r o n a, A. S t a w o w y, An application of advanced information technology in foundry engineering, Archives of Foundry Engineering, Polish Academy of Sciences. Commission of Foundry Engineering; ISSN 1897-33102010. **10**, 2, 83-88.

[13] R. W r o n a, A. S t a w o w y, A. M a c i o ł, A formalised description of foundry production program, Archives of Foundry Engineering, Polish Academy of Sciences. Commission of Foundry Engineering; ISSN 1897-3310. **7**, 3, 179-182 (2007).

[14] J. D u r a k, M. W o j t a s z e k, B. M r z y g ł ó d, Application of Matlab's Fuzzy Toolbox in didactics of material science, Computer supports for didactics: Łódź, 25-27 June 2008, ed. Edward Kącki, Joanna Stempczyńska; WSI, 2008. - ISBN 978-83-60282-07-6.

Received: 10 February 2010.