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THE HEURISTIC MODEL BASED ON LPR IN THE CONTEXT OF MATERIAL CONVERSION

High complexity of the physical and chemical processes occurring in liquid metal is the reason why it is so difficult, impossible even sometimes, to make analytical models of these phenomena. In this situation, the use of heuristic models based on the experimental data and experience of technicians is fully justified since, in an approximate manner at least, they allow predicting the mechanical properties of the metal manufactured under given process conditions. The study presents a methodology applicable in the design of a heuristic model based on the formalism of the logic of plausible reasoning (LPR).

The problem under consideration consists in finding a technological variant of the process that will give the desired product parameters while minimizing the cost of production.

The conducted tests have shown the effectiveness of the proposed approach.

Keywords: conversion of a technology, ductile iron, ADI, logic of plausible reasoning

1. Introduction

Finding innovative ways to improve the physical properties of material conversion is mainly based on experimental studies. This situation leads to a lack of mathematical models that would describe changes. As a result of this situation, of great importance is to develop a methodology for the construction of heuristic models that would allow, be it even in a very approximate way, finding, a relationship. It should be noted that the main difficulty in creating this class of models results from some limitations associated with the physical experiments which involve costs, and also with the complexity of the conducted studies. The consequence is that, on the one hand, the aim is to test as large number of the variants of the toughening treatment as possible, while, on the other, the idea is to reduce the number of samples tested. Therefore, it seems reasonable to seek opportunities for the construction of heuristic models, which by their very nature are of an approximate character, but owing to this can base on a very limited experimental material [1-5,9-10]. The paper proposes this type of an approach using logic of plausible reasoning (LPR).

2. Heuristics and heuristic models

The term "heuristic" means certain orbitally (intuitively) selected quantity, which can characterise the tested process (phenomenon) under the conditions when creating its precise description is not possible due to the lack of sufficient knowledge, or it is too difficult (e.g. on account of the excessive computational complexity). Currently, the use of heuristics is becoming increasingly common in various areas of research.

Interesting use of heuristics to create models of different processes can be found, among others, in [6], where the heuristics were used for traffic modelling, or in [7] which presents a heuristic approach to the semantic classification of text documents. With the use of the adopted heuristics it is possible to construct a model of a process, bearing in mind the fact that dependencies (relationships) obtained in this way can describe this model in an approximate way only. Therefore, whenever possible, the heuristic model should be verified for a reliability of its performance. Both the selection of heuristics as well as the interpretation of the results of the model application are the tasks of the knowledge engineer / user.

From a formal point of view, the operation of a heuristic model can be interpreted as a sequence of mappings:

$$H:X\rightarrow U;M:U\rightarrow V;G:V\rightarrow Y$$

where:

- H – operator mapping the space of physical parameters into the space of heuristics,
- M – operator mapping the input heuristics of a model into the output heuristics,
- G – operator mapping the output heuristics of a model into the space of real parameters (physical). It should be

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noted that operators H, M, G do not always take the standard form of functional dependencies, but may involve complex calculation procedures. In fact, the freedom of choice of the used transformations is an important feature of this class of models. Below two variants of models used for the interpretation of the results of the experimental studies described in the previous section will be presented. In both cases, the discussion has been limited to selected fragments of the data only to illustrate the same methodology of studies.

3. Linguistic knowledge of foundry and metallurgical problems

3.1. The processing of linguistic information

Acquisition, representation, and use of knowledge expressed in linguistic form differs significantly from the situation where data and knowledge are acquired through physical experiment and have a numeric form.

In recent years, the problems of obtaining and processing information and knowledge expressed in natural language are the subject of research of many scientific centres and companies. One of the main reasons for this interest is constantly growing role of the Internet, especially the WEB, where most of the emerging information has a linguistic form.

Existing algorithms for the semantic text analysis are characterized by high computational complexity, which makes them unsuitable for industrial conditions, when it comes to making decisions in a short time and with limited expenditure on computer hardware.

In this situation it is necessary to search for possible simple solutions, focused on a limited area of applications that with the relatively modest expenditures can provide the required functionality. One of such solutions is, proposed in this paper, model of linguistic knowledge, tailored to the needs of the diagnosis of material conversion.

Schematic diagram illustrating the process of the creation of linguistic knowledge is presented in Fig. 1.

Information is obtained from the scattered and heterogeneous sources, among which the most important are:

– catalogues, standards and publications used to create solid knowledge resources;
– expert knowledge, expressed mostly in a descriptive manner;
– databases regarding patents, new technologies, research projects and companies;
– WEB network, from which the information is acquired in the form of WEB pages that contain the most up to date, but at the same time dynamically changing.

It should be noted that in the case of the knowledge of the casting processes, in particular innovations as shown in [25,26], of great importance is the fact that this knowledge is often incomplete and unreliable.

Well-known formalisms of representation of this type of knowledge are: fuzzy logic, rough sets, decision trees, logic of plausible reasoning.[23,24].

The model of knowledge in the form of an attribute table is the connection between the first two of the above mentioned formalisms.

4. Knowledge base

The model was tested before on two small domains. To show advantages of the proposed solution in a larger scale, a decision support system was developed in a domain, which is complex enough, contain hierarchies of objects, and is characterized by a number of parameters of an intuitive nature, difficult to measure. The system supports the choice of metal products manufacturing technology, casting technology included. Knowledge base consists of more than 700 formulas.

Often the choice of technology for the manufacture of metal item and of the material from which this item is to be produced stems from the experience and knowledge of the engineer designing this item. These human aspects are difficult to represent using formal languages. When the task of designing machine parts is undertaken, parameters that the item should have and the related operational and utility functions must be taken into account. This also applies to the case of the conversion of

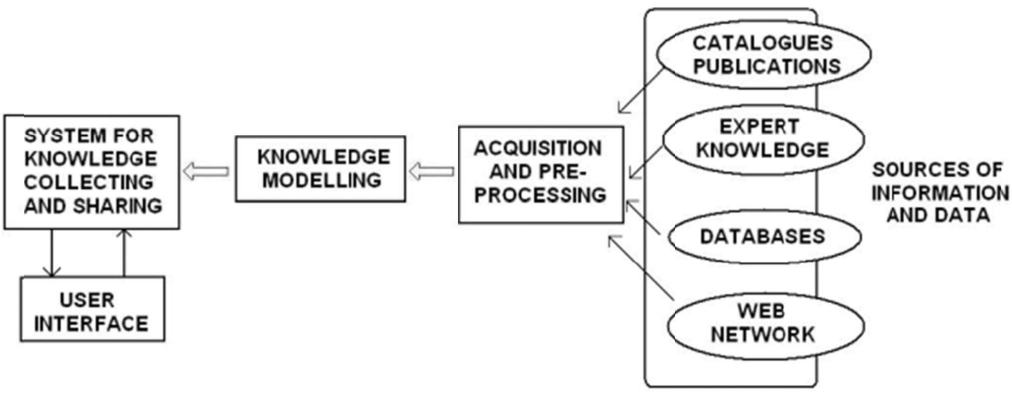

Fig. 1. Schematic diagram of the process of knowledge creation in linguistic form

material. A new type of material must provide at least the same mechanical properties and reliability as the original one. The choice of the method of manufacture is affected by the batch size, dimensional accuracy, dimensions, complexity, the type of the necessary machining and heat treatment, etc. All these factors also create costs. In this situation, the problem which the designer of a particular product (machine part) has to face and solve consists in selecting the material and the technology of its manufacture, which will ensure that the specific technical requirements are satisfied, while allowing the maximum reduction of production costs. In the application of LIIS system considered here it is very important to indicate the appropriate material, which could replace the traditional materials (forged steel, cast steel). This material can be Austempered Ductile Iron (ADI), which has a favorable relationship between the tensile strength (Rm) and elongation (A), offering at the same time significantly lower manufacturing costs (savings of approx. 20%). The decision about the possible use of ADI must be based, however, on more detailed analysis of requirements imposed on a particular product and its characteristics, to mention as an example the damping capacity, corrosion resistance, dimensions, the batch size, and the weight of a single item.

It is accepted that the low-volume production includes up to 50 pieces of castings weighing between 0 and 25 kg. Low-volume production also comprises up to 10 cast pieces if the casting weight is 25-500 kg. If the casting weight exceeds 500 kg, the small-volume production comprises 1 cast piece. Medium volume production covers 50-5000 pieces for the weight range between 0 and 25 kg, 10-100 pieces for the weight range of 25-500 kg, and 2-10 pieces for the total weight of more than 500 kg. All values above this level stand for the large-lot production.

The batch size (production volume) is dependent on the weight of product for each of the three type ranges. This helps to better understand the comparison of prices for the same product made from ADI and carburized steel for different batch sizes and product weights.

Core of the knowledge base are hierarchies. They were defined during consultations with experts. They represent facts that ADI is a kind of cast iron adenine its 63 subtypes (ADI GSJ-1400-1, ADI 1, ADI 2, ..., ADI 31, ..., ADI 34, ADI 41, ..., ADI 44, ADI 51, ..., ADI 68, ...). Context is related to cost, production volume, application and mechanical properties. The first label value (typicality) is high (often equal to 1.0), which means that certainty of specialization of objects and values (SPECo and SPECv) will be also high. The second label (dominance) is low.

1. H(adi, cast iron, cost): 0.8: 0.1
2. H(adi, cast iron, volume production):0.8:0.1
3. H(adi gsj-1400-1,adi, application):1.0:0.1
4. H(adi_4, adi, application):1.0:0.1
5. H(adi_42, adi, application):1.0:0.1

In statements minimum elongation and tensile strength of selected steel grades are expressed. Labels representing certainty have high values. Similar statements are prepared for other types of ADI (like ADI 4, ADI 42, ADI 52 etc.). Some parameters are not known and corresponding statements are missing.

1. V(adi, application, rake):1.0
2. V(adi gsj-1400-1, minimal elongation A, 1):1.0
3. V(adi gsj-1400-1, tensile strength Rm, 1400):1.0
4. V(engjs 14001, chemical composition c, 3.462-3.524):1.0
5. V(adi gsj-1400-1, austenization time, 105-inf):1.0
6. V(adi gsj-1400-1, austenization temp, 867.5-895):1.0
7. V(adi gsj-1400-1, hardening time, 187.5-inf):1.0

The rest of formulas have form of implication. Four of them allow to recommend a material for production (see below). They have conclusion V(casting, material alternative, X). The more parameters are checked (and more premises the rule has), the more certain the answer is. The first implication checks application, costs, tensile strength and minimal elongation and it has certainty 1.0. Fourth rule checks only application, therefore its certainty is equal to 0.25 Other rules allow to predict the production costs assuming a particular batch size and product weight.

1. V(casting,application required,A) ^ V(X, application, A) ^ V(casting,cost required, COST MAX) ^ V(X,cost,COST CALCULATED) ^ P(COST CALCULATED, COST MAX) ^ V(casting,tensile strength Rm required,STRENGTH MIN) ^ V(X, tensile strength Rm, C) ^ P(STRENGTH MIN,C) ^ V(casting,minimal elongation A required,ELONG MIN) ^ V(X,minimal elongation A,E) ^ P(ELONG MIN,E)]→V(casting,material alternative,X):1.0
4. V(casting, application required, A) ^ V(X, application, A)] _V(casting, material alternative,X):0.25

Scenario 1

The first scenario illustrates a simple case, in which all the knowledge necessary for reasoning is given explicitly in knowledge base. Application of the material is a rake3, the maximum cost limit is equal to 15, product weight is heavy, the batch size is large, minimal tensile strength Rm is equal to 1100 and hardness is high. As a result, the system recommends ADI 4 with confidence 1.0.

The proof was obtained by double application of the Modus Ponens (MP) rule and double object specialization (SPECo) rule. It is presented in Fig. 2. In the first step, the MP rule was applied to implication no. 1, which means that if the required application of casting under consideration is equal to A (premise 1) and is the same as the application allowed for an alternative material in the rule marked by variable X (premise 2), the required maximum cost is equal to COST MAX (premise 3), and the cost calculated for an alternative material is equal to COST CALCULATED (premise 4) and is lower than the maximum cost (premise 5), the required minimum tensile strength Rm is STRENGTH MIN (premise 6), and for an alternative material it is C (premise 7) and is higher than STRENGTH MIN (premise 8), and required hardness described as HARDNESS (premise 9) is the same as for alternative material (premise 10), then the alternative material (X) should be used with confidence 1.0.

Premises 1 and 3 can be adapted to the knowledge base elements or answers to questions. Premise 2 (application accept-

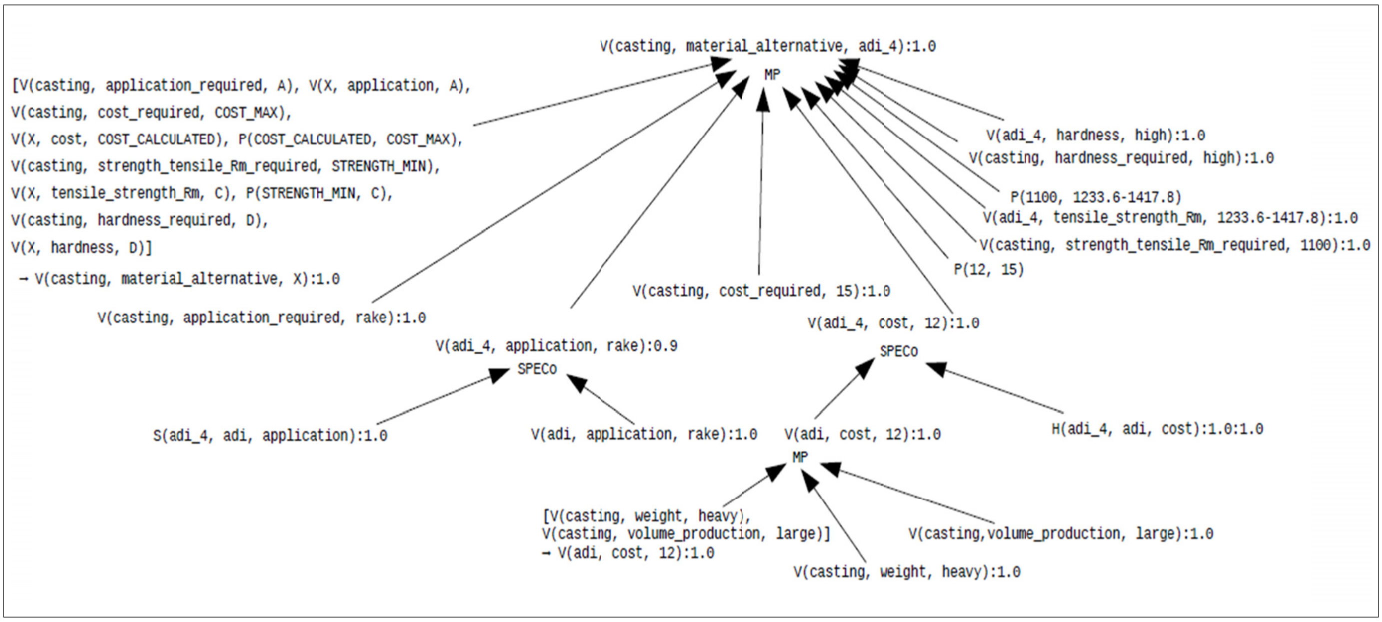

Fig. 2. Graphical presentation of the proof found in scenario 1

able for ADI 4) was inferred using SPECo object specialization rule because ADI 4 is a typical ADI in terms of application, and it is known that ADI may be used to produce rakes. Similarly, premise 4 was derived using SPECo specialization rule and knowing that ADI 4 is a typical ADI in terms of the cost of obtaining it and calculating this cost for ADI based on the mass of the casting and using the implication no. 13 as above. Premises 5-10 can be unified with the knowledge base elements or answers to questions.

5. Conclusions

This study compares the methodology of constructing heuristic knowledge models in the use of experimental data in embodiment models of knowledge expressed in linguistic form. Model presented in the study has an innovative character.

This types of model of the knowledge had as a main aim the identification of differences in the methods used for construction of such models, depending on the acquisition mode and nature of the data and knowledge on which the proposed solution has been based. The use of LPR formalism seems justified because of its intuitive nature and the ability to assess the degree of certainty of the results. The idea of creating a meta knowledge to facilitate material conversion is completely original, since in the literature on the LPR no references were found on the use of hierarchical structures, while application of this approach in relation to the technological knowledge is a complete novelty

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