Publishing House
AKAPIT

COMPUTER METHODS IN MATERIALS SCIENCE

Informatyka w Technologii Materiałów

Vol. 12, 2012, No. 2

ASPECTS OF KNOWLEDGE INTEGRATION USING ONTOLOGICAL MODEL IN ISSUES OF DECISION SUPPORT IN THE PROCESS OF DIE FORGING

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Abstract

This article presents an outline of the concept of development of a knowledge base applied to inference systems based on an ontological model and example of appliocation SWRL rule language. Application of ontologies is motivated by a distributed information environment, as well as an input structure of the databases, which prevents reproduction of the data model in the very structure of relations. Ontology also enables the use of an SWRL language in rule base construction, which greatly facilitates further work on the stored data sets.

Key words: knowledge integration, ontological model, decision support, die forging

1. CHARACTERISTICS OF THE TECHNOLOGICAL PROCESS

Making forgings in the die forging process involves a combination of upsetting, punching and extrusion. The process should be designed in such a way as to provide for the technological allowances in final product, determined by appropriately designed and milled impressions in both top and bottom die.

Despite the apparently simple shape, axisymmetrical forgings may have varying degrees of shape complexity, mainly due to the position of the die parting plane or web and the depth of the individual impression cavities relative to the parting plane.

The selection of the stock for forging depends on how deformable the forged material is and what geometry the forging has, all this to ensure proper positioning of the stock in die impression, smooth filling of die impression cavities without the resulting defects, and ensuring a uniform deformation on the entire forging cross-section. When flat rings are forged, the degree of processing provided by the technological process is relatively large, owing to which the cut stock of a cast structure can be used. Quite often, in forging of rings, there is no need to apply upsetting before the main process, unless cleaning of stock or the need for ensuring an adequate flow of material in the die impression require this operation.

Die forging involves a number of technological operations which include among others: making slug, reheating of slug, blocking, forging, finishing of final product.

ISSN 1641-8581

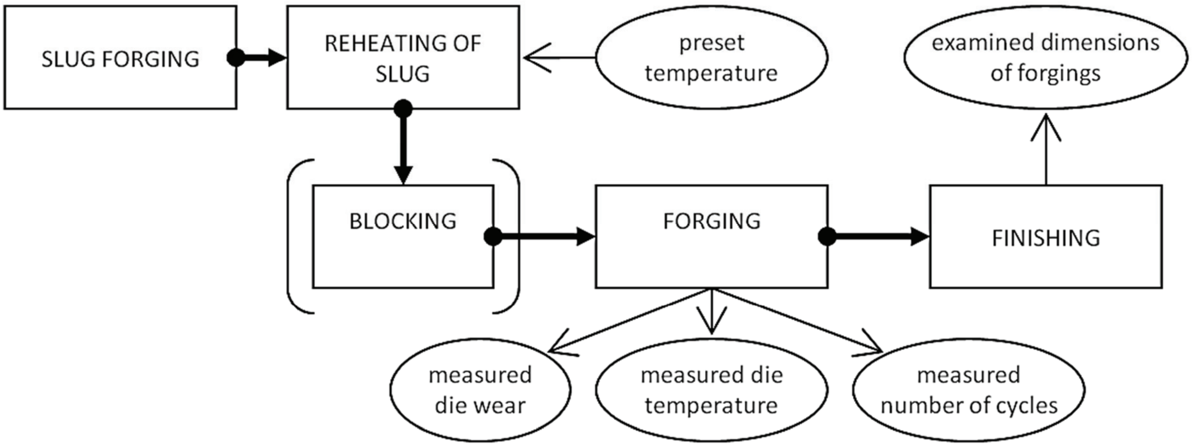

Fig. 1. *Die forging process with specification of the main parameters used by an inference system.*

The problem that the inference system must solve is related with an optimisation of the tool temperature (die, punch) in terms of the die life on performance, determined by its wear and tear. The starting point are the data on the type of surface, surface draft, the quantity of forgings made by the device and the results of fracture tests.

2. DEFINING RESEARCH PROBLEM

Optimising the metal processing technology is currently the modelling domain using finite element method (FEM). Simulation and modelling enable developing a set of parameters which will ensure the best possible configuration of the future process. Additionally, knowledge gained in this way can be successfully used also in the development of other products, tools and processes. For the purpose of FEM modelling, data are collected on various characteristics of materials (e.g. the stress-strain curves), on the experimental conditions and features of individual samples (test objects) and, finally, on the results of the experiments. When creating a simulation programme, very often we use the distributed data – material bases, internal databases, simulation programmes, and literature data on process conditions. In addition, the results of simulation are usually stored in separate files, or are disclosed in the form of tables using tools such as spreadsheets. Using data sources collected in this way in further process of reasoning based on the obtained results may be difficult. For this reason it was decided to propose an algorithm which would support the creation of an integrated knowledge base, giving in future the opportunity of assisting the reasoning in the range of issues similar to the test case, namely an optimisation model of the die forging process parameters to extend the die failure-free operation time, with particular regard to the forging temperature control.

As a tool for knowledge integration, ontology has been selected. It provides an opportunity to create a model of knowledge machine-interpretable in an OWL language (Web Ontology Language) which, in turn, enables creating on this basis the inference rules in an SWRL language (Semantic Web Rule Language). There are, of course, many ways to formalise the scientific and technological knowledge. One of the oldest is the creation of mathematical models, and it consists in the description of processes, events, or objects using mathematical expressions. However, there are numerous problems for which this classical approach is inadequate. An important advantage of mathematical models is the ease of their implementation in computer systems, but mathematical description of the real world has a limited range of applicability for, while it is easy to describe in this convention the heat exchange or a diffusion process, it would be quite difficult to express, by means of mathematical expressions, the procedure of temperature control for tools, forging temperature, cooling of dies by feeding grease or uneven spraying of lubricant (Kluska-Nawarecka et al., 2004). Such knowledge is in many respects a typical procedural knowledge, capable of being approached with logical rules. There are many formalisms that allow writing such rules, ranging from the rules in industrial systems in the form of IF .. THEN, and going through multivalued logics such as the fuzzy logic and rough sets theorem (Kluska-Nawarecka et al., 2010a; Górny et al., 2010; Wilk-Kołodziejczyk et al., 2008; Staab & Studer, 2004; Kluska-Nawarecka et al., 2011). It has been decided to write the rules in an SWRL language, mainly due to the possibility of integrating thus written rules with the ontology which, in turn, will allow an integration of the distributed sources of knowledge (Kluska-Nawarecka et al., 2010b) by defining the context of material or its parameter. Ontological models are one of the established formalisms, rapidly developing in recent times, perfectly reflecting the character of the described area. Literature gives many definitions and examples of applications of this formalism (Gruber, 1993; Ciszewski & Kluska-Nawarecka, 2004; Regulski, 2011). Ontology is a logical representation of certain field of knowledge and relationships between objects occurring in it. Yet, it differs from other ways of representing knowledge in that it does not only provide a diagram or description of a given field, but using the tools of logic (axioms, definitions, rules) can strictly define the hierarchy of its components and criteria for their classification.

created for a comprehensive expert system. This database has a lexical structure, determined by a specific character of the data modification system, namely during the work related to modelling and simulation, knowledge is collected iteratively - after each round of experiments, test results are archived. Teams of researchers responsible for simulation and databases modelling, respectively, are working in parallel, hence at the stage of creating a database model it is not possible to predict what attributes will ultimately be stored in the database. For this reason, the model database in the form of an ER diagram does not reflect the knowledge model of the objects studied. The studied properties are stored in the database in the form of records containing also the name of the parameter. This structure results in the fact that the knowledge of the base structure does not provide knowledge about the contents included therein. The next databases contain information on,

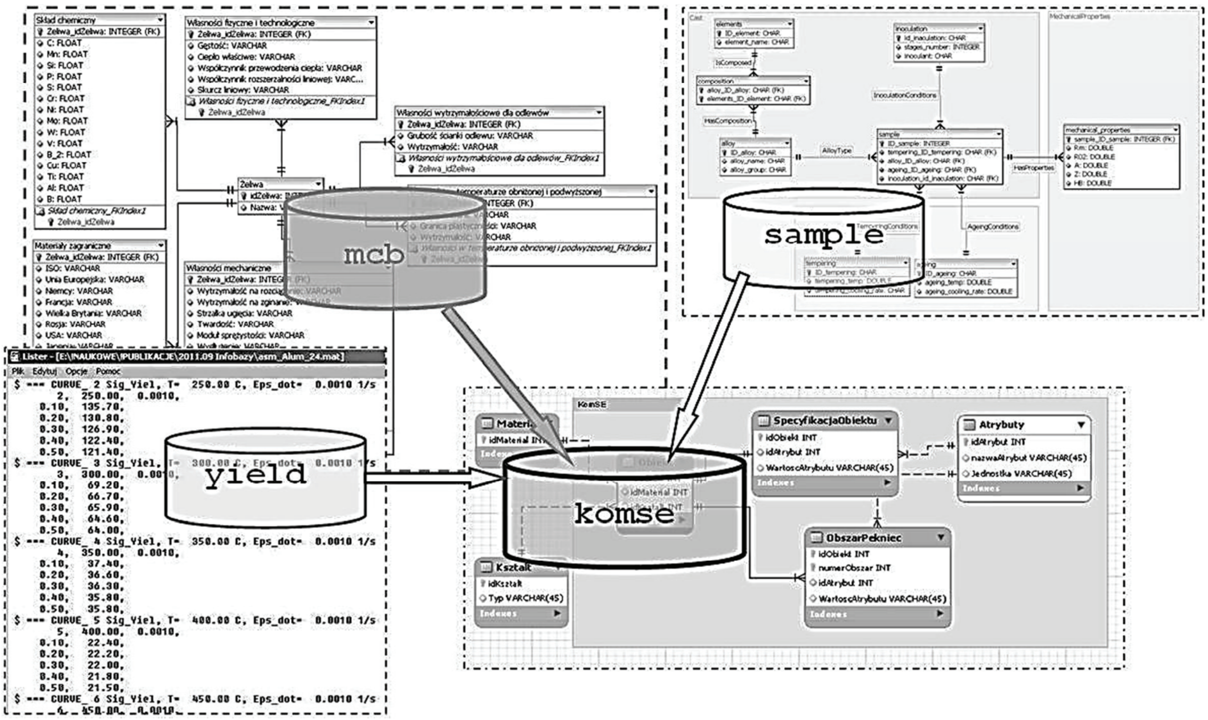

Fig. 2. Databases included in an inference system.

3. DATA SOURCES

In the case under discussion, as input data to the system, four databases will be integrated. Each of them has a specific structure and has been designed to serve another purpose. The mcb base (materials characteristics base) is a set of information on materials taken from the literature and standards; it includes physical and mechanical properties, chemical compositions, etc. Another base is a komse base

respectively, how to prepare samples for testing - the type of heat treatment and the type of alloy, as well as the chemical composition of alloy and characteristics of its stress-strain curve - the yield strength, the elastic limit, etc. (figure 2).

As we can see, the data model is highly fragmented and has a diversified structure. Additionally, it does not store the metadata which enable describing the structure of knowledge stored in this model. To effectively process such non-homogeneous data, an ontological description has been used. This model has also another important advantage, which determines a practical aspect of this solution. The ontologies written in an OWL language allow for an easy integration with the database of rules stored in an SWLR language. Rules are created based on the classes and their dependencies (object properties). Thus saved rules form an abstract knowledge which enables further reasoning.

4. ONTOLOGY

Mapping the knowledge model contained in databases requires the use of a transformation algorithm. In this case, the knowledge model is determined by the data obtained from research. The possibility of embedding it in the context of the domain knowledge is provided by an ontological model.

The first step is to save all the tables and individual fields in a graphic form. Most tables will reflect the future classes. The linking tables, which are the implementation of many-to-many relationships (*n:m*), are the basis of future relationships in the ontology (*object properties*). Also, the fields which are foreign keys will form a relationship in the ontology (figure 3). In this way one can limit the number of attributes in a diagram, thus making the basis for future ontology.

cracks, plastic deformation, the depth and thickness of cracks.

Furthermore, the ontology should reflect the largest possible number of relationships detected between the objects in a database. The knowledge often trivial for the researcher becomes a precious tool determining the quality of acting by inference. And so, what seems obvious to the technologist is knowledge unknown to the designer of a database, e.g. the fact that the sample may be subjected to aging or quenching (in H1, H2, H3, H4 variants), and for a given experiment, the temperature (which is parameter of these processes) can take appropriate values of S1, S2, S3, S4. A reflection of these relationships will be object properties and class instances.

Currently there are already known methods for semi-automatic transformation of database schemas into ontologies stored in the OWL language (Kluska-Nawarecka et al., 2010b). Most of them, however, requires interaction with the ontology designer on one of the stages of transformation. Especially in addition to possibility of occurrence different terms used in databases designating the same concepts. It turns out that for simple databases, such a transformation can be successfully carried out manually, using tools for ontologies creation, and using the basic rules of transformation.

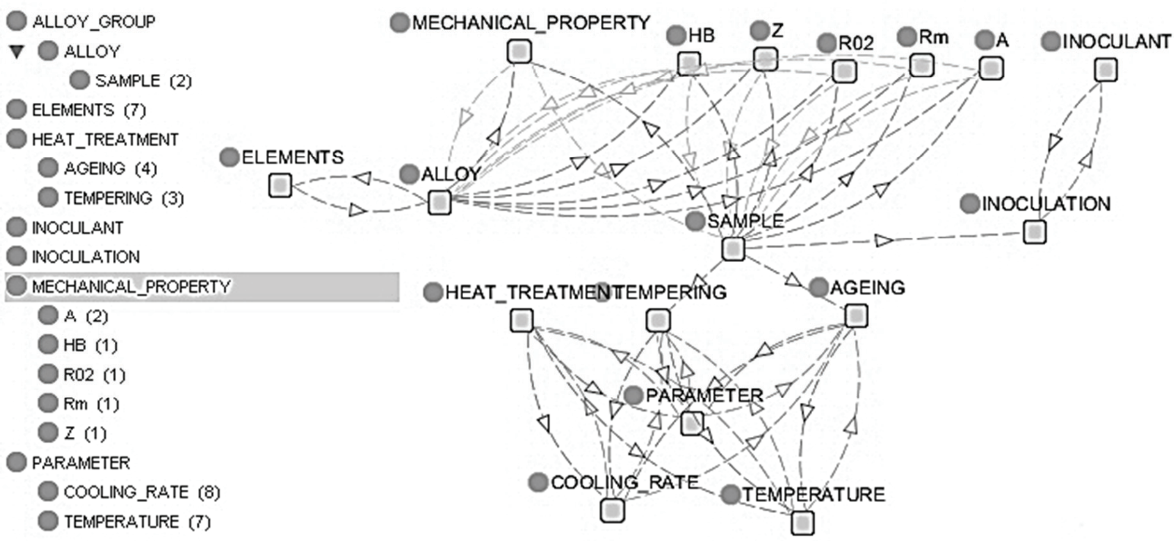

***Fig. 3.** Excerpt of ontology for a database of material samples.*

Additionally, the model is enriched with attributes that are not directly represented in the database model dictionary. These attributes are stored in the database as individual records. This could be, for example, the results of studies regarding the individual areas with cracks, including the secondary

5. RULES

The purpose of the system is to create a mechanism for reasoning about the operating conditions of the die in a forging press, the forging temperature – in particular. This requires the implementation of a number of inference rules to enable detection of the risk of die failure based on the die performance data and on the die material data, including the treatment processes to which it has been subjected and the results of measurements of forgings leaving the press. As an example may serve a simple rule which enables us to determine when the die is classified as suffering a failure. We measure the material drawn back from the die surface. With the assumption that 2 mm is the boundary value, when this value is exceeded, the die is considered worn out. In the SWRL language this can be written as follows:

```
(wearOfSurface >= ?heavy)(?x) ^
  swrlb:heavierThan(?heavy,2)
     → dieWornout(?x,true)
```

An analysis of the above notation (the question mark in SWRL is a variable) gives the following conclusion: objects that are instances of OWL classes with the associated restriction that the property wear of Surface is determined at the minimum `?heavy`, when the variable `?heavy` assumes values greater than 2, such objects can be classified as dies worn out with the property `dieWornout(?x, true)`.

From the viewpoint of system architecture, the best situation would be if the rules operated only on classes, properties and instances of ontology, while values of these objects would be stored in a database. For the above example, the value of 2 mm adopted as a limit of destruction is inserted into the rule base as a "stiff" value. Much more preferred situation would happen if this parameter could easily be manipulated by the user, and in the rule base remained only a symbolic notation in the form of properties `heavyWear(?x,true)`.

This structure leads to the conclusion that ontology should be only representation of an abstract knowledge about a given domain, in a like way as the rules of inference, whereas the fact base should be rooted in a database, with the assumed values of the variables specified by the investigator. Thus, we reach the conclusion that (keeping in mind the lexical structure) some queries should be established and addressed to the database with clearly defined criteria to make the results of these queries form a fact base. Databases provide us with a tool for such actions - these are views.

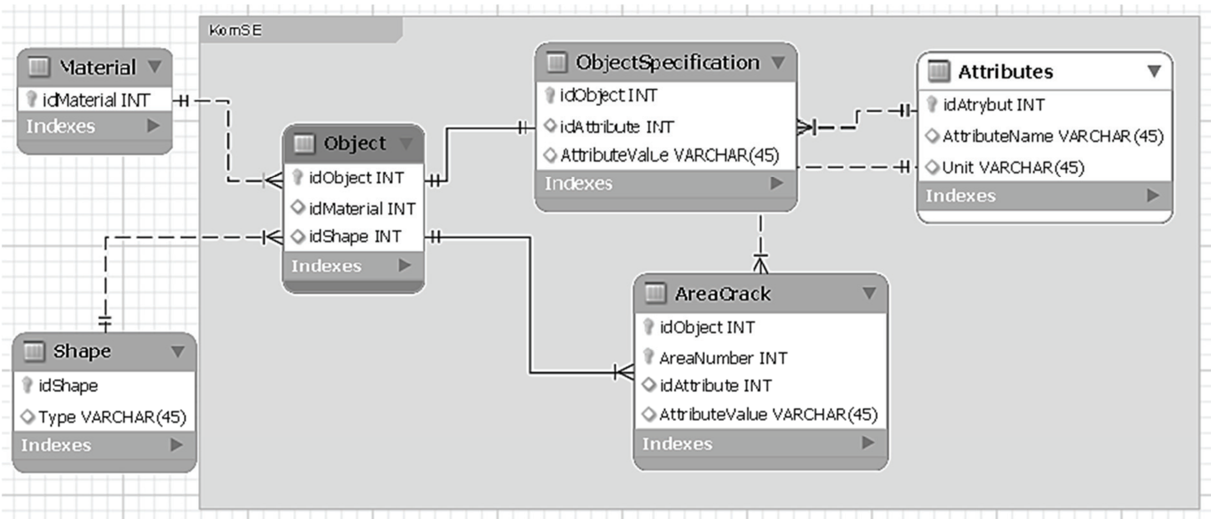

***Fig. 4.** An ER model of the `komse` database.*

The basic tool in the creation of ontologies is Protégé editor. Starting with version 3.4 it provides support for the SWRL language.

Let us note that thus created rule operates on two properties of objects: `wearOfSurface` and `dieWornout`. In addition, we are dealing with a variable `?x` and `?heavy`, and also with literals: `2` and `true`. The variables in this case may be objects belonging to the ontology classes, or may have an assigned value.

6. FACT BASE

Let us assume that operating on the `komse` base with ER model as shown in figure 4, we want to gather facts about the objects that in certain areas show the wear rate well above the fixed value of z_l = 2. Let us observe that this will be equal to searching for objects with the satisfied property `heavyWear(?x,true)`, with the lower limit established at z_l.

For the user who does not know the domain model, the creation of such query will be difficult.

However, with the ontology at hand, the knowledge engineer is able to create for such a database a view called `heavyWear`.

```
CREATE VIEW heavyWear
AS SELECT Object.idObject FROM
Object,AreaCrack,Attributes
WHERE Object.idObject= Ar-
eaCrack.idObject
AND AreaCrack.idAttribute=
Attributes.idAttribute
AND Attributes.nameAttribute LIKE
'WearValue'
AND AreaCrack.ValueAttribute >= 2
ORDER BY Object.idObject;
```

This way, a predefined query has been created that is based on the ontology, because it requires knowledge of the attribute named `WearValue`, which is stored in the table Attributes, while its value is placed in the table `AreaCrack`. For future user of the system, this process is completely transparent. He will be provided with the set of facts in a tabular form that satisfy the requirements. At the same time it will be possible to run an inference process on these objects, because they are, in some way, an instance of the rules. The fact base is always valid, because views offer the possibility to perform queries on current data, without the redundancy - the server stores the view definitions and the associated metadata (among others, permissions and information on relationships between views and other database objects), but not copies of data returned by the views.

7. SUMMARY AND CONCLUSIONS

In this article, a concept of data integration using an ontological model has been proposed. Ontology in this case is the basis for a database of rules – the rules are formed basing on *objectProperties* from ontology. Using the same *objectProperties* to design predictive views in a lexical database enables the retrieval of relevant attributes from the database in such a way as to create a database of facts required. In this way, the database becomes a repository of instances for the ontology. This allows avoiding the redundancy in a database, and at the same time allows creating a domain model for the lexical database. In the course of further work on the project, the SWRL rule base will be developed to enable effective inference about the process parameters. The possibility of using the same database to store the ontology in the form of RDF is also anticipated.

Scientific work financed from funds for the scientific research as an international project. Decision No. 820/N-Czechy/2010/0.

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ASPEKTY INTEGRACJI WIEDZY Z UŻYCIEM MODELU ONTOLOGICZNEGO W ZAGADNIENIACH WSPOMAGANIA DECYZJI W PROCESIE ODKUWANIA MATRYCOWEGO

Streszczenie

Artykuł przedstawia zagadnienia związane z metodyką budowy bazy wiedzy z użyciem modelu ontologicznego na potrzeby systemów wnioskowania. Przedstawiono przykład zastosowania języka wnioskowania SWRL. Omawiana baza została zaprojektowana dla systemu ekspertowego na potrzeby wspomagania decyzji w procesach przemysłowych związanych

z przetwórstwem metali. Zastosowanie ontologii zostało podyktowane rozproszonym środowiskiem informacyjnym, a także słownikową strukturą baz danych, co uniemożliwia odwzorowanie modelu danych w samej strukturze relacji. Ontologia ponadto umożliwi zastosowanie języka SWRL do konstrukcji bazy reguł, co w dużym stopniu ułatwi dalszą pracę na przechowywanych zbiorach danych.

Received: November 11, 2011
Received in a revised form: February 20, 2012
Accepted: June 25, 2012