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Adhesive selection via an interactive, user-friendly system based on Symbolic AI

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Abstract

Adhesive joints are increasingly used in industry for a wide variety of applications because of their favorable characteristics such as high strength-to-weight ratio, design flexibility, limited stress concentrations, planar force transfer, good damage tolerance and fatigue resistance. Selection of a proper adhesive for a particular application depends on many often conflicting product and manufacturing process requirements and is therefore a cumbersome task. Traditionally, adhesive selection is done by an adhesive expert based on experience, prior knowledge and trial and error. Adequate tooling to support adhesive bonding experts in the design processes is lacking, generally yielding suboptimal results.
This research presents an interactive adhesive selector tool, aimed at supporting the design of adhesive joints. Knowledge on the gluing process and its associated constraints is captured from adhesive experts and represented formally in a Knowledge Base (KB). The knowledge inside the KB is then processed using the Imperative Declarative Programming (IDP) reasoning engine in order to support the adhesive selection.
Through an intelligible, interactive, interface the application requirements (such as use conditions, materials, process requirements, etc.) are entered, based on which the IDP system reduces the search space of potential adhesives.
The selector tool has been tested on an industrially relevant case in which an adhesive had to be selected for bonding a composite panel to a steel frame for an automotive application. Using the selector tool, an adhesive expert was able to select an appropriate adhesive 10 times faster than without.

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1. Introduction

Adhesives are widely used in industry because of their favorable characteristics such as high strength-to-weight ratio, design flexibility, limited stress concentrations, planar force transfer, good damage tolerance and fatigue resistance [1–3]. There does not exist one adhesive suitable for all applications. Selecting the right adhesive is therefore a critical step in the design process to ensure reliable, high quality joints [1,4]. However, this selection process is a very labor and knowledge intensive task because of the wide variety of commercial available adhesives, the large number of variables which should be taken into account and the complex relations between the variables [1,3,5,6]. For example, for a 2-component epoxy adhesives, increasing the curing temperature will decrease the required curing time but also increase the final strength while lowering the flexibility. So changing one parameter in the production process, will not only impact the behavior in the production process, but also the final performance of the bond. All these variables should be taken into account during adhesive selection.

The adhesive selection process consists typically out of two steps. First an initial list of possible adhesives is created by an adhesive expert based on personal experience and expert

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knowledge. Second, this list of candidates is reduced via practical testing and trials. Although final selection occurs after the second step, this first selection process is of high importance. Once practical trials begin, timescales and resources start to increase rapidly. Hence the selection of unsuitable adhesives can become very costly in the long run [1]. So, there is a need for tooling which supports adhesive experts in making a proper initial selection of suitable adhesives.

1.1. Available support tools for adhesive selection

Informative websites, such as adhesives.org or adhesivestoolkot.com, provide neutral and useful background information which can support adhesive selection [7]. However, experts still need to look up and process this information themselves.

Several companies offer personal assistance in selecting the right adhesive, after filling in a requirements form. This form is sent to a technical team which will typically answer the request in a couple of days. The answer is, however, often company product biased so that the end user will have to make calls to a range of adhesive suppliers to get a full market assessment [7].

Expert systems to support adhesive selection were developed in [3–6,8,9]. The approaches of [3–6] are based on simple decision trees or selection tables where adhesive selection is done by eliminating unsuitable adhesives after each question. Meyler and Brescia developed an expert system for adhesive selection which allows to combine information and rules, and can make decisions itself. [5]. Finally, there are also rule-based expert systems, which gather expert knowledge in the form of procedural rules [4,8,9]. These rules can then be reasoned upon by performing either *forward chaining* to select a suitable adhesive, or by performing *backward chaining* to generate explanations. The advantages of these systems compared to the prior ones is that expert knowledge is formally captured in the form of facts and rules.

However, these expert systems all have some shortcomings, which can be categorized in four groups:

1. Low maintainability and interpretability of the system,
2. Give rise to sub-optimal solutions because complex relationships are not taken into account,
3. Not user friendly to make modifications,
4. Limited number of adhesives and/or substrates.

First of all, all knowledge is expressed in imperative IF-THEN rules. These rules by itself are *not* a correct representation of the knowledge. Indeed, while they are capable of producing the right output (i.e. they can select a suitable adhesive), they do not represent the rules domain experts would use to select a proper adhesive. As a consequence, this reduces the maintainability and interpretability of the system. Moreover, some knowledge is often either not included, or is represented in an inelegant manner (further reducing the interpretability of the rules). Secondly, another downside is that these expert systems only allow two reasoning modes: either they perform adhesive selection (*forward chaining*), or they perform explanation generation (*backward chaining*). However, there are situations in which other usages might be interesting instead, such as when attempting to find a suitable substrate. Thirdly, most systems are rigid for the domain experts: only the AI experts are capable of making modification (such as adding glues, substrates, …) to the knowledge of the system. The one exception is the system by Su *et al.* [4], which allows a "knowledge update" in the form of adding/deleting adhesives, changing the values of adhesive attributes, modifying the boundary values used in the rules, and other operations. However, they do not allow directly adding/removing rules. Finally, the systems typically only contain a limited number of adhesives and/or substrates, possibly due to performance limitations.

1.2. Knowledge Representation and Reasoning

The artificial intelligence research field of Knowledge Representation and Reasoning (KRR) focuses on representing domain knowledge in a formal language, so that computer systems can reason about them. It is not limited to knowledge about adhesive selection, but can be used for all kinds of design problems. Early examples of work in this area include expert systems of the kind discussed in the previous section. This work uses a different, more declarative approach: the Knowledge Base Paradigm.

1.2.1. Knowledge Base Paradigm & IDP

The core idea in the Knowledge Base Paradigm (KBP), as described by Denecker and Vennekens [10], is to separate domain knowledge from its use to solve specific problems. More concretely, knowledge is stored in a so-called Knowledge Base (KB), using a formal representation. Afterwards, a multi-purpose reasoning engine is then used to reason on this knowledge. This approach offers multiple advantages. To begin, the KBP facilitates knowledge reuse: once the KB is created, the knowledge can be (re)used for many different purposes. Indeed, instead of describing *how* to solve a specific problem, a KB describes the specific problem itself. In other words, the KB contains the required knowledge of a problem domain, but does not dictate how to actually solve it. Furthermore, the representation of knowledge inside the KB is purely declarative, leading to the extra advantage of being more readable and interpretable for non-IT experts. Finally, as the KB contains a formal description of all required knowledge in a domain, this knowledge becomes *explicit*. The KB effectively *stores* the knowledge of a domain expert, meaning that it will not be lost if the domain expert e.g. leaves the company.

A practical implementation of the KBP is the IDP system [11]. Here, the knowledge in the KB is encoded using an extended version of First Order logic, called FO($\cdot$). FO($\cdot$) allows us to define the symbols needed to describe a domain (such as *strength*, *minimum elongation*, …) and the laws/constraints that are applicable. Examples of such laws are shown below. Formula (1) represents the formula for calculating the maximum stress given the load and the adhesive bonding area. Formula (2) expresses that an adhesive's strength should be higher or equal to than a minimum value. Finally, Formula (3) expresses a constraint on the usage of radiation curing acrylates: at least one of the two substrates should be UV transparent, to ensure proper curing.

$$MaxAllowedStress = Load/BondingArea \quad (1)$$

$$MinBondStrength \leq BondStrength \quad (2)$$

$$AdhesiveFamily \in \{RadiationCuringAcrylates\} \Rightarrow SAUVTransparent \lor SBUVTransparent \quad (3)$$

After creating such a KB, we can use the IDP system's powerful inference tasks to solve concrete problems. For example, by using the *model expansion* inference task, we can have the IDP system generate a value assignment for every variable in the system, conform to the knowledge in the KB (also known as a *model*). Using *propagation*, the system will derive (in)equalities that always need to be satisfied. This is particularly useful to see the effect of a symbol's value on the rest of the symbols, as will be demonstrated later. It is also possible to generate specific models with the highest or lowest value for a symbol by using the *optimization* inference. Other inference tasks besides these also exist, but are not used in this work and will not be discussed further. More information on the IDP system can be found on the website (www.IDP-Z3.be).

1.2.2. Interactive Consultant

The Interactive Consultant is an IDP-based web-interface, allowing for user-friendly interaction with KBs [12]. It serves as a layer between end-users and the IDP system, to facilitate the latter's usage. The interface is completely generic, in the sense that it is capable of generating a view for any FO(·) KB. Concretely, the interface consists of *tiles*, which each represent a specific symbol. The tool's usage is intuitive: each time the user enters a choice (such as setting the value of *BondStrength*), the system performs IDP's *propagation* to derive all consequences of this assignment. This propagation step ensures that an infeasible combination of values can never be reached – in this way, a user is *guided* in finding a correct solution, by assigning values and having their effects propagated.

In addition to automatically deriving values for symbols, the interface is also capable of explaining *why* a certain value was derived. To ask for such an explanation, the user clicks on the symbol's assigned value. This opens an explanation overlay, consisting of two parts: (1) the list of user-made choices that led to this decision and (2) the list of constraints that, together with the user-made choices, imply the symbol's value. In other words, it shows the values a user has entered, and why those values influence the system's decision.

Once a user has finished entering all their information, they can have the interface perform model expansion or model optimization to end up with one or more final solutions.

2. Methodology

The creation of the tool can be divided in two parts: the creation of the knowledge base, and its subsequent integration in the Interactive Consultant tool.

The knowledge base was created by performing *knowledge acquisition*. Typically, in knowledge acquisition a domain expert and AI expert sit together, to discuss and formalize domain knowledge. More specifically, this work employed the *knowledge elicitation* method [13], in which the Decision Model and Notation standard (DMN) [14] is used as a common notation between domain expert and modeler, to directly involve the domain expert in the formalization. Throughout the project, three *knowledge articulation workshops* have been held, with each time one AI expert and 4-6 domain experts present. The main goal of having multiple domain experts was to stimulate conversation between them, as a form of knowledge validation. In the first workshop a high-level overview of all required knowledge and the connections between it was modeled using DMN's Decision Requirements Diagram. During the two subsequent workshops, these interconnections were fleshed out by adding actual knowledge, typically in the form of formulas or constraints. Afterwards, adhesive parameter data was added, such as strength, flexibility and temperature resistances. Similarly, parameter data was added for the substrates as well. In total, 21 adhesive parameters and 11 substrate parameters were added to the KB, as listed in Table 1 and Table 2 respectively.

Table 1. List of adhesive parameters.

Adhesive parameters available in the system		
Bond Strength	Elongation at Break	Lowest/Highest Performance Temp.
Lowest/Highest Application Temp.	Humidity Resistance	Lowest/Highest Humidity
Color	Potlife	Time Until Handling Strength
Adhesion	Viscosity	Water Resistance
UV Resistance	Chemical Resistance	Polymer Type
Min/Max Gap Filling Capability	Adhesive Family	

Table 2. List of substrate parameters

Substrate parameters available in the system	
Substrate Family	Max Temperature
Water Absorption	Water Vapor Absorption
Max Elongation	Base Material
Strong Acid Resistance	Organic Solvent Resistance
Magnetic Type	Transparency
Electrical Conductivity	

One caveat is that often not all parameters are known for each adhesive. For example, it might be possible that a data sheet does not mention an adhesive's resistance to chemicals or UV light. In such a case, the domain experts consider this parameter's value to be equal to that of the generic family to which the adhesive belongs. For an adhesive's chemical resistance, for instance, this is expressed in the KB as:

$$\neg KnownAdhesive(chemres) \Rightarrow ChemRes = FamilyChemRes \quad (4)$$

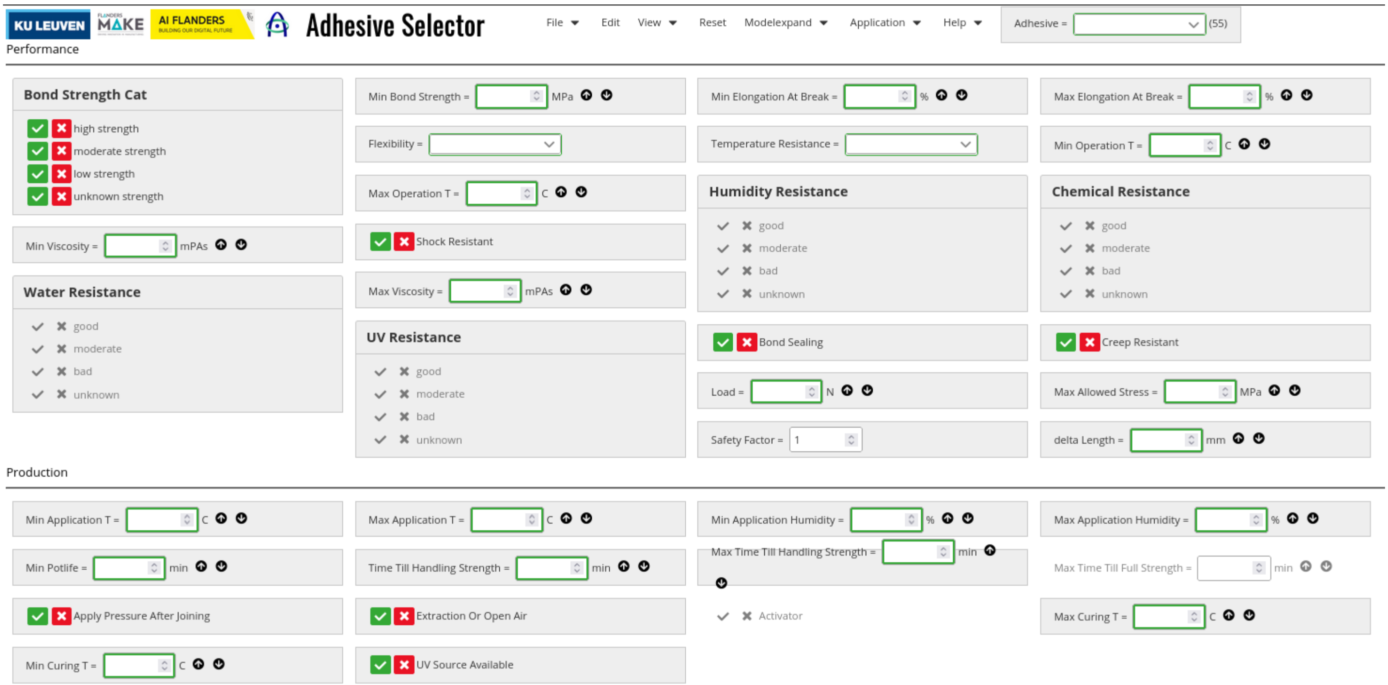

Fig. 1. Screenshot of KB presenting tiles.

In the rare case where a parameter value is also unknown for the adhesive family, the system is set up to err on the side of caution and will not apply constraints on that parameter. The idea is that in such a case, the expert should try to find out the parameter's value and, based on that, decide for themselves whether the adhesive is suitable. Alternatively, they can choose to ignore adhesives with unknown parameters in favor of those that are fully known.

For example, in the KB, Formula (2) is expressed as shown below in Formula (5) to enable this behavior.

$$Known(bondstrength) \Rightarrow MinBondStrength \leq BondStrength \quad (5)$$

After finalizing the KB, the Interactive Consultant is used to interact with it. Here, each symbol of the KB is represented using a "tile", as demonstrated in the screenshot shown in Fig. 1. The tiles are ordered based on their category, which can be "Performance", "Production", "Bond", "Substrate A" or "Substrate B". At the top-right of the screen a dropdown list of all adhesives is visible, together the number of suitable adhesives, as shown in Fig.2. When first opening the interface, all 55 adhesives are still available. The adhesive experts can then start entering values into the system; after each entry, IDP's propagation inference is performed by the Interactive Consultant in order to derive the consequences. As a result, each time a value is entered or an assignment is made, the number of suitable adhesives will go down and the list will shrink. For example, after clicking on ShockResistant, only 27 adhesives remain.

Fig. 3. shows a closer look at some of the tiles in the system. Here, an expert has already entered two requirements: the adhesive should be shock resistant, and it should be able to withstand an operation temperature of up to 80 degrees Celsius. This reduces the number of remaining suitable adhesives to 20. Note that the assignment of $Flexibility = very\ flexible$ was not made by the expert, but instead was automatically derived by the system (thus shown with grey outline). In such a case, the Interactive Consultant has a feature to explain a choice made by the system, by clicking on the derived value.

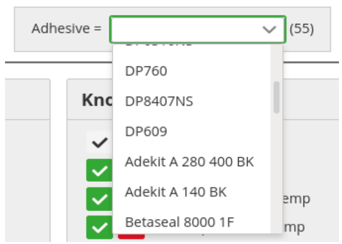

Fig. 2. Dropdown displaying suitable adhesives.

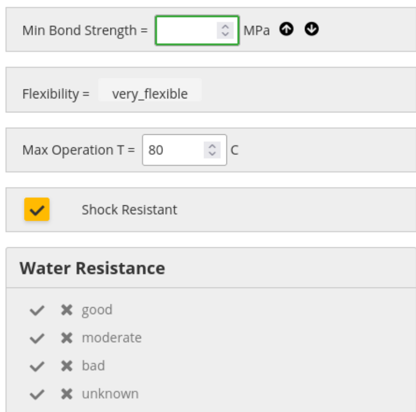

Fig. 3. Close-up screenshot of some variables in the interface.

This explanation feature ensures that the tool is explainable, which increases trust in the system. Furthermore, it also serves as an excellent tool for performing validation: if an error in the KB leads to an incorrect value for a variable, the explanation can help to pinpoint the location of this error.

One advantage of our knowledge-based approach is that the knowledge in the system can be used for more than just finding suitable adhesives. Indeed, the same knowledge can be reused to e.g. find a suitable second substrate, given that the first substrate and the adhesive have already been decided. When selecting, for example, radiation curing acrylates as the preferred adhesive family and steel as substrate A; the tool will indicate that Substrate B must be transparent to UV radiation. This is indicated by a "✓" symbol before SB Transparent To UV, as demonstrated in Fig.4. On the other hand, the "×" symbol before SA Transparent To UV indicates that steel is not transparent to UV light. In addition, the list of possible substrates will be reduced to only those substrates which are transparent to UV or for which the transparency is unknown. The KB does not need to be modified in any way in order to support other tasks, as it contains no procedural information. Other examples of reusing the knowledge include finding an optimal adhesive (e.g. the strongest/cheapest/most flexible suitable adhesive) or verifying if a pre-owned adhesive can be reused for a new gluing task.

3. Benchmarking of the adhesive selector tool

The adhesive selector was tested on a typical case from the automotive industry. The goal was to find a suitable adhesive to join a large composite panel (glass fibre reinforced polymer) to a high-strength low-alloy steel frame with the following additional requirements:

- Min. shear strength: 11 MPa at room temperature
- Dimensions bondline: 4842 mm x 202 mm
- Good shock + impact resistance
- Desired bondline thickness: 5 mm
- Temperature resistance in operation: -40°C till +80°C
- Range of allowable application temperatures: 18°C to 30°C
- Min. potlife of 60 min
- Max. time till handling strength 12h
- No oven curing possible

This case was first solved by an adhesive expert without guidance of any adhesive selection tools. First, the adhesive expert reasons on possible adhesive families which would be suitable based on the requirements and constraints. Only 2C-Polyurethane, 2C- epoxy and MMA are still identified as possible adhesive families after this first selection round. Next, one supplier of industrial adhesives, from different adhesive families, was contacted to gather technical datasheets of different adhesives belonging to these adhesive families. The exact specifications of the different adhesives are compared to the required ones to make a final selection. Finally, the adhesive expert selected an MMA-based adhesive (Plexus MA 560-1). The whole process took about 3 h to find a suitable adhesive. It should be noted, that the whole process would take much longer if a full market study would be performed instead of contacting only one supplier of industrial adhesives.

This whole selection process was repeated by another adhesive expert with guidance of the adhesive selector developed in this research. The selector tool could reason on a database of 55 adhesives. In the end, the same MMA-based adhesive (Plexus MA 560-1) was suggested by the adhesive selector but the whole process now took only 5 min. In other words, the time to find a suitable adhesive could be reduced by a factor 36 by using the adhesive selector.

In literature, significant reductions in time to suggest suitable adhesives are also reported. Moseley and Cartwright developed an expert system for the selection of Industrial adhesives and tested it in a large industrial company for suggesting suitable adhesive tapes for a specific application [8]. Prior to the development of this tool, it took the sales representatives on average 10 days to suggest suitable adhesive tapes. This was reduced to max. 36h with the guidance of their adhesive selector tool. So here the time to find a suitable adhesive was reduced with at least a factor 6. The research of Moseley and Cartwright together with the one reported here indicate that adhesive selector tools can generate significant reductions in the time to find a suitable adhesive.

The time needed by an adhesive expert to find a suitable adhesive can differ greatly based on their experience and knowledge.

The time needed to select an adhesive for a completely new application will be significantly higher than for a well-known case. Consequently, the time savings reported in this research provide only rough estimates. One can conclude that, although this benchmarking was only performed for one case, it shows the potential of the adhesive selector tool for reducing the time to find a suitable adhesive significantly.

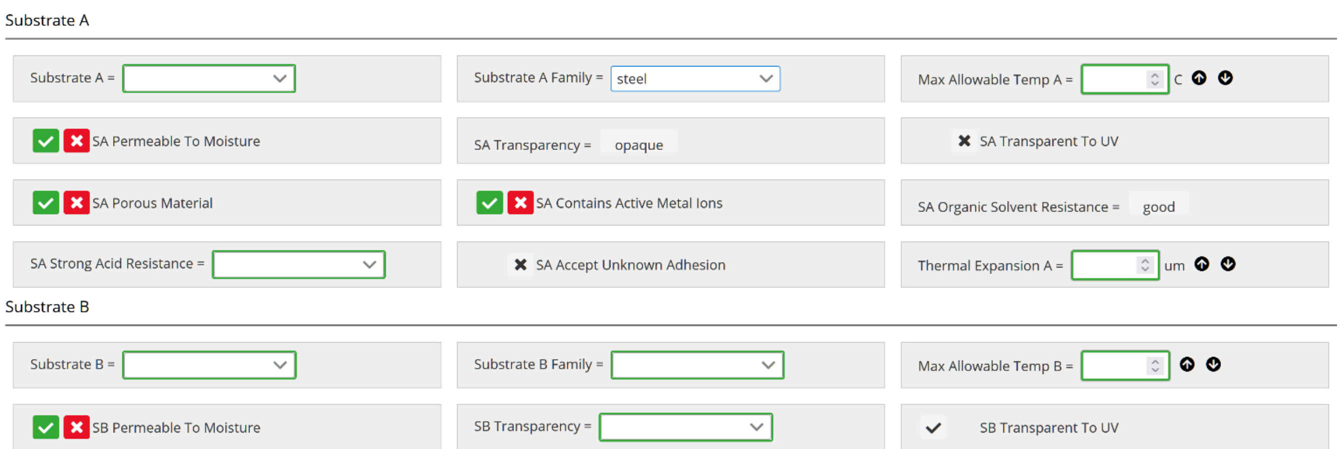

Fig. 4. Indication of constraints for Substrate B when selecting an adhesive family and Substrate A.

4. Maintenance and evolution of the system

One of the advantages of representing knowledge in a purely declarative KB, as performed in this work, is the *robustness* of the knowledge [15,16]. Indeed, if the selection process is changed in any way, we only update the relevant parts of the KB to reflect this, as most knowledge will still remain the same. The knowledge inserted in this adhesive selector tool originates from different adhesive experts which acquired their knowledge via official European Adhesive Bonder and Specialist courses, besides practical experience and literature. Therefore, it is expected that this knowledge will not change drastically over time and maintenance will remain limited. Moreover, because of the Knowledge Base Paradigm, this change to the KB is all that is required to update the tool in its entirety. Indeed, the way in which the knowledge is applied (e.g., performing the selection of a suitable adhesive) does not change. Similarly, because of the Interactive Consultant's generic nature, the interaction with the knowledge also requires no modifications. Because of the combination of these properties, our tool is easier to maintain than typical imperative tools on several levels.

One additional goal of the tool is that the knowledge is maintainable by the adhesive experts themselves, without requiring constant assistance from a knowledge engineer. While FO(·) is readable for most experts, there is a steep learning curve necessary to write it. To make editing the knowledge more accessible, the KB could be represented in Constraint Decision Model and Notation (cDMN) [17] instead. cDMN, as an extension of DMN, aims to retain the user-friendliness and intuitiveness of the original, while increasing the expressiveness to allow for more complex expressions. cDMN is automatically translatable in FO(·), and can thus serve as an alternative representation.

5. Conclusion and future work

We have presented an adhesive selector tool based on a knowledge-based approach, in which knowledge of the problem domain is represented formally, independent of its use. The knowledge of the adhesive selection process was captured via several interactive workshops with adhesive experts to build a Knowledge Base. Together with the Interactive Consultant interface and the IDP system, this forms a user-friendly and interactive tool to support adhesive selection. The tool is multi-purpose: besides adhesive selection, it can verify suitability of glues, find suitable substrates, generate explanations and more. It was tested on an industrially relevant case for automotive industry, where one expert was given access to the tool, whilst another used the manual approach. Here, both experts selected the same glue, but the time needed to select it was reduced by a factor of 36 when using the adhesive selector.

Future work on this tool is threefold. Firstly, the KB will be extended with additional adhesives and substrates. Secondly, the knowledge in the KB will be validated during real-life usage by the experts. Finally, the representation used for the KB will be converted from FO(·) to cDMN [17], to increase the readability of KB, to give the domain experts themselves more control over the knowledge.

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