DREAM: Design Rules Extractor for Additive Manufacturability

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Abstract: This paper presents a computer-aided design tool that supports creative designers to rapidly prototype ideas using additive manufacturing. DREAM (Design Rules Extractor for Additive Manufacturability) processes textual description (300-700words) of the idea and distills a set of applicable design rules related to its rapid prototyping. Everything we propose is intended to be included in a PLM approach of knowledge management associated with the product from the idea to its industrialization. On the one hand the idea sheet is processed with the Python NLP toolkit Stanza before being enriched with lexically and semantically related terms. On the other hand, we use a design for additive manufacturing ontology developed with Protégé to structure the design rules for additive manufacturing. Knowledge structures (thesaurus, ontologies, word embeddings, etc) also serve to expand design rules vocabulary for increasing similarity matching. The matching of design rules with the idea sheet relies on the cosine similarity measure between two vectors: 1) a vector corresponding to a chunk expanded text of the idea sheet, and 2) a vector of the expanded text of a design rule. The design rules with the highest similarity score are considered to be potentially applicable and consequently recommended to the creative designer in form of a report. The experimental use of DREAM on a case study leaded to the identification of 6 design rules among which two were false positives. False positives are due to short sentences containing non-discriminant terms making the measure of similarities challenging. To improve the quality of the results, in the future we will concentrate on the automatic textual description and analysis of sketches provided by designers to illustrate their idea.

Keywords: Design Rules, Natural Language Processing (NLP), Ontology, Knowledge-management, Design for Additive Manufacturing.

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1 Introduction

When developing a product, the more time passes, the costlier and more inefficient it becomes to make any changes to the product(Blanchard and Fabrycky, 1981; Herzog, 2004). Moreover, during the early design phase, the decisions taken will represent more than 80% of the total expenses, whereas this phase costs less than 10% of the total costs (Laverne *et al.*, 2015). Therefore, it is necessary to carry out the design phase in a meticulous way. It is important to multiply the models and the tests before presenting a product that can be manufactured in series (Blanchard and Fabrycky, 1981; Herzog, 2004) . The early stages of design are not very well-equipped with IT tools, so there is an interest in digitizing these phases to include them in a PLM environment especially with technologies like AM (Segonds *et al.*, 2017). Nevertheless, before producing any final part available on the marketplace, we should focus on the design phase, which involves the rapid manufacture of many prototypes, mainly for conceptual and functional assessment (Rocheton *et al.*, 2021). Rapid manufacturing and more specifically additive manufacturing have become an essential part of the design phase. The arrival of new processes and theories all as diverse as each other makes a voluminous documentation of design rules associated with additive manufacturing. Design engineers often looked for solutions in previous design cases to solve their design problems where they spent 20-30% of their time retrieving and communicating design information (Court, Ullman and Culley, 1998) and finding the right knowledge is not always easy, especially because unstructured documents are still widespread in the industry (Kassner *et al.*, 2015) (Huet, Pinquie, *et al.*, 2021). Many companies still store knowledge of design rules in simple PDFs that can exceed tens or hundreds of pages. It is then essential to facilitate the retrieval of additive manufacturing knowledge, so that everyone can quickly find the guidelines and design rules relevant to their project. Because knowledge results from the encounter of an information with an individual there must be appropriation and interpretation of the information by an individual to be able to speak of knowledge (Laverne and Industriel, 2017). Designers and manufacturing engineers have two different points of view, the designer will be interested in the utility and mechanisms of the product while the manufacturing engineer will focus on its manufacturability. Two different objectives and therefore two different standards, guidelines, and languages. Some knowledge for a manufacturing engineer is not necessarily the same for a designer (Enrique *et al.*, 2011). That is why the innovation strategy of a company is part of the knowledge management domain, it is essential that all existing knowledge be organized and made available to the different actors of the design process (Laverne and Industriel, 2017). The last decade has seen the explosion of text mining technologies that enable everyone to process and work with a large amount of knowledge. Knowledge representation models like ontologies have been developed to help designers find the data they are looking for. Such tools are an opportunity to develop design tools, especially for rapid prototyping using additive manufacturing.

The tool will have to extract the right knowledge according to the description of a product idea. In our application the knowledge is design rules for prototyping using AM. The product concepts that will be used to test the tool during its development are in the form of idea cards. Each idea card has two parts: a textual part and a diagram to describe the idea as precisely as possible Fig 1. During a preliminary study we found that the relevant data to be extracted to test the different design rules are half in the text and half in the diagram. We reached this conclusion with the help of 10 idea cards and a criterion list of about 30 design rules. This makes 300 rules to test in total that can be checked with the text, the diagram, or both at the same time. Not all design rules could be evaluated due to lack of information, 12% of the rules were not evaluated. Out of 300 verified design rules, 46% were partially verified by text and 51% were partially verified by diagram. We decided to concentrate on the text and not to analyze the diagram. We are aware that we are losing half of the relevant data. A method to analyze the data of the diagram will be addressed in a future work.

Cooking aid for rice bag

The utensil allows to handle the rice bags (fast cooking), it has the advantage to protect the user from the boiling water, to help him to control the trajectory of the bag as well as its draining. It also protects the user from sources of dirt (on the hands, on the work surface). It also helps the user to open the bag and to serve the rice.

Take the utensil with one hand by the handle and the bag in the other hand, place the handle of the bag around the hook of the utensil. Press the button that opens the clamp of the utensil and place the bottom of the bag in it, release the button to close the clamp on the bottom of the bag: the bag is then fixed on the utensil. Place the utensil/bag in the boiling water. The hand that holds the handle of the utensil stays outside the pan (at a sufficient distance from any heat source). Grab the handle, drip over the pan (or sink) using the "drip guide" (see diagram), the bag being attached to the utensil, its trajectory is controlled (no swinging, no projections). Using a pair of scissors, cut the edge of the bag, then open one side of the rice bag. The other side of the bag is held by the handle. Rotate the utensil/bag assembly to empty the rice directly into the plate (see diagram). Throw the bag into the garbage by releasing it from the utensil by pressing the button (without getting dirty). Wash the dirty parts of the utensil (possible without getting your hands wet). To allow the handling of a bag of rice (fast cooking or not) in safety (without burning oneself) and without dirtying the environment (projection, drops). To allow the serving of rice with the utensil without getting dirty or burned. To be washable with a simple passage under a jet of water and in machine. To be easily stored (foldable axis). To allow the installation of a lid on the pan. Do not disturb the quality of cooking, or even improve it. Be adapted to the working environment. Pleasant handling (touch, sound...). Control the flow and dripping of the bag. Protect the user from heat sources.

Words on the picture : Button, Rice, Flat, Nylon wire, Break drops, Pivots Push button

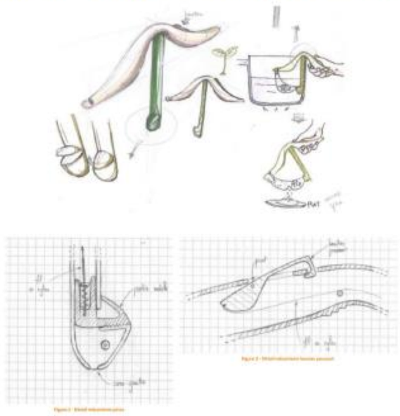

Fig 1 Example of idea card

DREAM will analyze textual data from idea card to recommend the right design rules from a set of rules to prototype concept with additive manufacturing.

2 Literature review

Before developing our solution DREAM, we conduct reviewed the literature on related topics including DFAM, rapid prototyping defects, ontologies, and NLP.

DFAM

DFAM (Design for Additive Manufacturing) is a set of methods and tools that help designers consider the specificities of AM (technological, geometrical, etc.) during the design stage (Laverne *et al.*, 2015). The principle of DFAM comes from DFX (Design for X) and is part from DFM (Design for Manufacture and assembly). Although the methodologies and tools of DFM will focus on manufacturing in general, DFAM will focus on the constraints and opportunities that additive manufacturing offers. DFM typically means that designers must adapt their designs to eliminate manufacturing difficulties and minimize the manufacturing, assembly, and logistics costs. However, the capabilities of additive manufacturing technologies offer an opportunity to rethink DFM to take advantage of the unique capabilities of these technologies (Gibson, Rosen and Stucker, 2010). The DFAM tools will focus on defining design theories, processes, methods, tools, and techniques developed to address the inherent coupling between material, geometry, and quality in these systems (Thompson *et al.*, 2016). The DFAM will be separated in two parts depending on the use of the AM process. Either we use AM for prototyping “manufacturing-driven design strategy”, or we use AM to produce parts “function-driven design strategy” (Klahn, Leutenecker and Meboldt, 2015).

We adopt the “manufacturing-driven design strategy” focusing on prototyping. Fig 2 shows that the DFAM tool will be used for design and innovation in the second phase of production of innovative solutions (Laverne and Industriel, 2017). DREAM will focus on the manufacturability of the concept using AM (AManufacturability).

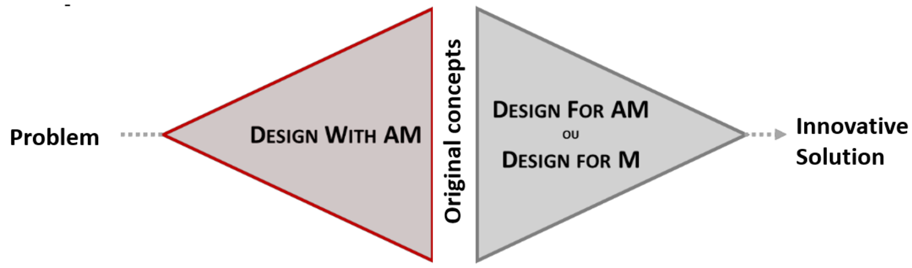

Fig 2 Place of the DFAM in an innovative design approach (Laverne and Industriel, 2017)

Through the literature, other DFAM tools examine the AManufacturability of parts. The DFAM worksheet (Booth *et al.*, 2017) will study the AManufacturability of a part using a criteria grid. The criteria grid will provide a numerical evaluation to determine if the part should be redesigned or not. The worksheet helps designers assess the potential quality of a part made using most AM processes and indirectly suggests ways to redesign it. The immediate benefit of the worksheet is to filter out bad designs before they are printed (Booth *et al.*, 2017) The advantage of this approach is that it offers an analysis even before the CAD (Computer Aided Design) model is built, which saves time. The analysis is not automatic as the designer must fill in the criteria grid, unlike CAD models which have tools to automatically redesign a part beginning with the useful surfaces (Thompson *et al.*, 2016). Although having the CAD model has advantages for designing the part, it also has some disadvantages. Indeed, apart from the long construction of the CAD model, AM CAD models must be higher quality and contain more complete information than has been traditionally needed for other process technology since the transition from the CAD model to the finished prototype will be done automatically through the machine (Thompson *et al.*, 2016). The study of manufacturability is equivalent to a check of the different design rules, (Floriane *et al.*, 2017) states that it is essential to provide the knowledge (AM design rules here) just as necessary to improve the design phase with AM. This methodology uses a tailored AM knowledge, it means **a knowledge** delivered to the right user at the right time and in the right format to be useful and usable during the creative stages of the design process. This method concerns the creative stage and not the prototyping stage, but even for prototyping, AM knowledge should be retrieve just as needed. However, implementing a DFX implies the management of knowledge as well as the management of various product abstractions and the use of tools for integration of design constraints (Kuo, Huang and Zhang, 2001; Laverne *et al.*, 2015). Without the use of CAD model, the DFAM requires intermediate representations of the part, its different design features, AM knowledge and AM guidelines (Bouchard, Camous and Aoussat, 2005).

RAPID PROTOTYPING DEFECT

To determine the manufacturability of the different concepts we will study the opportunities and especially the constraints imposed by additive manufacturing. We focus on the Fused Deposition Modeling (FDM) process because it is widely used during the prototyping phase. There are many studies that provide criteria and guidelines for each process. The evaluation of the AManufacturability of a part will be based on:

- Factors including build volume, minimum feature size, volume of support material, build time, estimation of surface roughness, build orientation (Lynn *et al.*, 2016).
- Constraints and opportunities of additive manufacturing (Gibson *et al.*, 2014).
- Geometric and mechanical criteria of the DFAM worksheet (Booth *et al.*, 2017).
- Numerical values for different geometric features (holes, thin wall, horizontal bridges…) (Cheung and Moultrie, 2013).
- Tolerances that may be expected from a certain manufacturing process (Lieneke *et al.*, 2015).
- Benchmarking model for additive manufacturing [9], [10].
- List of relevant geometric features (Alafaghani, Qattawi and Ablat, 2017).
- Produced surface roughness that may be expected from a certain manufacturing process (Rahmati and Vahabli, 2015).

ONTOLOGIES

The management of design information and knowledge has become a critical issue worth investigating (Liu and Lim, 2011) . Artificial intelligence (AI) and the knowledge that engineering offers allow designers to produce symbolic reasoning on computers. These techniques enable designers to model intuitive knowledge, judgment, and experiences that expert designer use, and to integrate them into available quantitative tools (Kuo, Huang and Zhang, 2001).

In terms of knowledge management, one of the most popular knowledge representations are ontologies. “An ontology is an explicit representation of concepts of some domain of interest, with their characteristics and their relationships.” (Bedini and Nguyen, 2007) . During the design process, ontologies can enable automatic feature recognition (AFR) to bridge the gap between design and manufacturing (Enrique *et al.*, 2011) or information retrieval trough documents (Li and Ramani, 2007). Li et al uses ontologies to perform search operations, this representation of the data enables to adapt the search paths according to the user of the request, because meanings depend on the domain, rib does not mean the same thing in anatomy and aerospace (Li and Ramani, 2007). (Liu and Lim, 2011) highlights 3 types of applications for ontologies in design engineering: (1) design information annotation, sharing and retrieval; (2) interoperability; (3) product design configuration. Ontologies enable to find links between the keywords of design rules and abstract principles that a classical database could not find. This database is based on the relationships between the different attributes of a domain. When working with ontologies, two choices are offered to us: working with existing ontologies or creating our own ontology from scratch or by combining them. There are methods and guidelines for developing an ontology for a chosen domain (Pinto and Martins, 2004; Zhou *et al.*, 2004), (Ahmed, Kim and Wallace, 2007). These methods will ensure a coherence to the ontology and will facilitate its development when the amount of knowledge will grow. A poorly designed ontology will not only be inefficient but also sometimes be wrong. If the axioms are poorly defined the inference system will not be correct. For some applications it is also interesting to create its ontology automatically from external data such as text or CAD model and detect relationships directly through the data (Bedini and Nguyen, 2007), (Cheong *et al.*, 2017) .

To create ontologies or work with ontologies, the main language is OWL (Sean *et al.*, 2004) and different software enables to work with this language, we preferred Protégé (*protégé*, no date) and the Python library owlready2 (Lamy, no date) because they are widely used, wwell-document, and free.

NATURAL LANGAGE PROCESSING (NLP)

NLP techniques are central to the development of our tool since the data to be processed is found in the textual part of the idea form. The explosion of automation and machine learning has allowed great progress in terms of NLP techniques (Ali, Jamal and Tehmina Amjad, 2016), (Ni *et al.*, 2021). Previous research studies shown in the field of PLM, demonstrated the NLP and text mining techniques facilitate the management of product requirements (Véron, Segonds and Croué, 2016) from large specification documents, especially by their automatic extraction to feed PLM software (Véron, Segonds and Croué, 2016) and their automatic classification into domain-specific categories (Véron, Segonds and Croué, 2016). NLP and text mining techniques were also successfully applied to ubiquitously recommend design rules in a context-aware CAD environment with a proof of concept in the aerospace domain(Huet, Pinquié, *et al.*, 2021).

The first phase of NLP is the pre-processing of the text (Kannan *et al.*, 2015). We split chunks of text into sentences and words called tokens, this is the tokenization stage, then comes the lemmatization or stemming which will reduce the different words to their roots. Another step to reduce the number of words is to remove the "stop-words" that do not give any meaning to the text, these are the words common to all-natural language texts ("the", "a", "this"...). It is also possible to do parsing and to identify the co-references, that means to do a syntactic analysis of the text to linked two tokens which reference the same entity. For instance, “he” might reference to “Steve”. Algorithms exist to identify the different types of entities named with NER (Named Entity Recognition) (Shelar *et al.*, 2020), it recognizes Los Angeles as a LOCATION and Coca-Cola as an ORGANISATION. All these steps of pre-processing a text or annotating tokens (NER and syntactic analysis) are concentrated in a single tool called a pipeline, the pipeline will extract the pre-processed textual data. There are a lot of customizable pipelines, for our project we will use Stanza a Python NLP toolkit (Qi *et al.*, 2020).

Once the text is pre-processed, a semantic analysis can be performed. Semantics is the part of linguistics that deals with the meaning of words and the relations between words. The semantic analysis will enable us to make connections between sentences with different tokens, but which speak about the same subject. An aircraft and an airplane are different tokens but are semantically very close. To perform semantic matching, databases were created such as WordNet (Miller *et al.*, 2009) (manually created) or ConceptNet (Speer and Havasi, 2013) (automatically created), and toolkits such as Word2Vec (Dhariyal and Ravi, 2020) allow to create word embedding models from any text source, whether it is Wikipedia pages or scientific papers on AM. A Word embedding model is a vector space that can transform tokens into vectors, in this space the aircraft and airplane tokens are very close.

The classification techniques are the ones we are interested in. Indeed, we want to associate design rules and descriptive texts. For text classification it is sometimes more interesting to train the word2vec model (Cheong *et al.*, 2017) on a specific textual database such as for example biomedical. Indeed, on a word embedding model that considers too many single words, it is more complex to play on nuances which can be problematic for the interpretation of the most technical design rules. Moreover, since the design rules will be detected only through short passages of the text, the number of words to be interpreted will be limited. It is often useful to use similarity functions that will determine with the help of a lexical database the semantic proximity between two words or two sentences (Romain, 2016), (Yih and Meek, 2007) .To study the similarity between two sentences (Yih and Meek, 2007), we found three main categories of methods:

-Surface matching, which will expand each sentence with synonyms of the different keywords and transform both expanded sentences into vectors and look at the cosines between them.

-Corpus-based methods, one method looks at the volume of documents where the two sentences co-occur, the longer the sentences are the lower this method is efficient. Another corpus-based method is to find documents where the different keywords of the sentences appear and use the documents as expanded representations of the sentences, then we compare the two expanded representations of each sentence.

-Query-log methods, consists of a dataset of couple of sentences that we know similar then we train a linear regression algorithm to predict new sentences, the relevant features are : surface characteristics such as number of characters or words of the sentences, syntactic difference between the two sentences such as Levenshtein edit distance (Yujian and Bo, 2007) or size of prefix overlapping, and substitution statistics such as the log-likelihood ratio or the mutual information between the sentences using their keyword in the dataset.

Often NLP works with ontologies for instance NLP techniques are used to extract design rules from unstructured text and the design rules are stored and represented in an ontology (Kang *et al.*, 2015).

3 Research positioning and goals

We plan to develop a computer-aided tool that analyses the textual description of an idea sheet to facilitate the manufacturability of the prototype concept when using additive manufacturing. The tool will output an AManufacturability analysis report with the list of potentially applicable design rules, whether they are satisfied or not. Additionally, there is an overall evaluation of the AManufacturability status of the depicted ide. The goal of the DREAM tool is illustrated in Fig 3.

The literature review presented previously enable us to place ourselves in relation to the different scientific advancements in DFAM, AM, NLP, and in the use of ontologies. Our tool aims to assist the designer during the prototyping phase using AM. Thus, our proposal is a tool for DFAM, focusing on the prototyping part of AM (Klahn, Leutenecker and Meboldt, 2015).

One of the challenges will be to manage the domain knowledge associated with AM, especially the specific vocabulary. Ontologies will serve as a good representation of AM knowledge. Two options are open to us: develop an ontology from scratch or start from an already developed ontology. We will use an existing ontology of additive manufacturing (Kim *et al.*, 2019) and interact with it using Protégé (*protégé*, no date) and owlready2 the Python library (Lamy, no date).

As mentioned in the introduction, to analyze the product concepts we will use a description in the form of idea cards. For this study only the text will be analyzed on the idea card, which means no diagram or CAD model will be analyzed. Studying the diagram and CAD model would be relevant for a complementary study to our work.

The texts to be analyzed will first be preprocessed with the Python NLP toolkit Stanza (Qi *et al.*, 2020) and the development of the tool will be done on Python 3.8. The model used to represent our concept description text will be the Bag of Words model, there will be one bag of words by sentence. In this model the structure of the text is lost, and we will only be concerned by the different words present in each sentence.

To semantically match sentences and design rules for prototyping with AM, we will use the surface matching method (Yih and Meek, 2007). To carry out this method we will use the WordNet thesaurus (Miller *et al.*, 2009) and the ConceptNet general ontology (Speer and Havasi, 2013)

.Finally, we will use the Word2Vec toolkit (Dhariyal and Ravi, 2020) to work with the words in the text. Working with word2vec enables us to train word embedding models on a specific AM corpus.

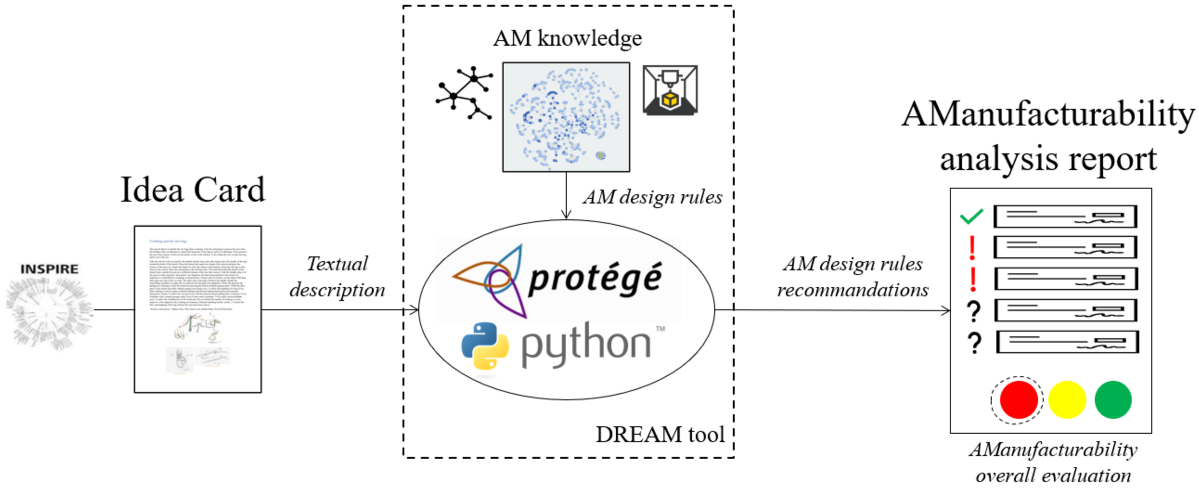

Fig 3 The DREAM tool

4 Design rules set

To study the AManufacturability of the idea concepts to be prototyped, we have drawn up a list of 30 design rules in the form of a closed questions. This list was made thanks to the literature review, made on the manufacturing defects with AM (Booth *et al.*, 2017), (Lynn *et al.*, 2016). This list, Fig 4, is accompanied by quantitative criteria that are associated with the FDM process which is one of the processes used for prototyping.

Questions	Quantitative criterion
Is the part completly 2D?	
Is the part mainly 2D and can be made in a mill or lathe without repositionning the clamp?	
Is the part can be made in a mill or lathe, but only after repositionning it in the clamp at leats once?	
Does the part has complex splines or arcs for a machine operations such as a mill or lathe?	
Does the part has interior features or surfaces curvature are to complex to be machined?	
Does mating surfaces are bearing surfaces or are expected to endure for 1000+ of cycles?	
Does Mating surfaces move significantly, experience large forces or must endure 100-1000 cycles?	40 Mpa flexion / 20 Mpa in traction
Does mating surfaces move somewhat, experience moderate forces , or are expected to last 10-100cycles?	Less than 5MPa overall
Does surfaces are purely non-fonctional or experience virtually no cycles?	
Does the part is smaller than or the same size as the required support structure ?	
Will there be small gaps that will require strutures?	
Will it be difficult to remove unwanted materials from the internal geometries?	
Will there be any internal cavities or channels or holes on the part?	
Will there be long unsupported features?	5-10mm
Will there be short unsupported features?	1-5mm
Will Overhang features have a slopped support or a 45deg support?	
Will there be small holes?	2mm of diameter
Will the part be lightly embossed or chamfered?	
Will the part be strongly embossed or chamfered?	
Will the parts have to fit together perfectly?	More or less of 0,5% / [2] : xy : Entre 11et 13 z: 11 et 14 (ISO 286-1)
Does Hole or lentgh tolerances are adjusted for shrinkage or fit?	
Is there no tolerance in terms of the dimensions of the part?	At leat 0,5 mm between two parts meant to fit together
Does the part will have large flat surfaces? Does it needs an exact flatness?	
Will there be any flat surfaces that need to have almost exact flatness?	
Does the part need to have a low surface rougness ?	Lowest 20 microns for a plane end 40microns for a 45° surface
Are the thinner planes too thin?	0,8mm
Will there be any engraving or work on the surface which will be to precise?	0,6mm width and 2mm high
Are the rectangular or circular bars too thin?	2mm (circular) 3mm (rectangular)
Will the part be prototyped out of plastic?	
Will the part can be prototyped out of metal or ceramic ?	

Fig 4 Design rules set.

It is now a question of structuring this design rules set so that it can be analyzed by our python program and exploited during the phase that matches the relevant design rules with an idea card.

5 Ontologies

We have chosen to represent our design rules using an ontology. According to (Rangarajan *et al.*, 2013), to represent DFM design rules (DFAM in our case) in an ontology it must have three key elements: 1) A formal representation of the domain (an ontology) that includes design and manufacturing process-related concepts (features, material data, welding, laser cutting, etc.), relationships (bend has a radius), etc. 2) Instances from the domain – a 22-gage stainless steel part with 2 bends of specified radius and a louver with specific width and height. 3) Rules such as the manufacturability rules that are applied to a design. To represent our rules, we will use the DFAM ontology (Kim *et al.*, 2019), which has many useful concepts to fill the point 1) and to develop the point 2) and 3) in our different cases according to our idea cards and our design rules set.

The DFAM ontology (Kim *et al.*, 2019) has eight main classes: AM_Capability, AM_Process, Failure, Feature, Machine, Parameter, Part, PostProcessing. The tool should be able to identify the different features of the concept such as a cylinder, a hole, or a type of shape. Once the features are identified and associated to a class or a subclass. It will be necessary to use rules implemented in the ontology to identify were there could be design problems of the concept. Then the tool will have to present the rule that causes problems and need to be checked by the designer.

To integrate the rules, we will add an additional class to the 8 already present classes. The rules will be stored in a class named "Design_Rules", a subclass of the design rules (DR) class will be the "Current_design_rules_SET" class, which will store the DR that match with the studied idea card. Once a DR is added to this class, we will link the DR to the other classes of the ontology according to the nature of the DR. For example, the DR associated with the question "Are the thinner planes too thin? (0.8mm for FDM)" is a DR that deals with walls that depend on a minimum thickness which depend on the process used to prototype. Fig 5 illustrate the integration of "Thin_wall_rule" in the DFAM ontology (Kim *et al.*, 2019).

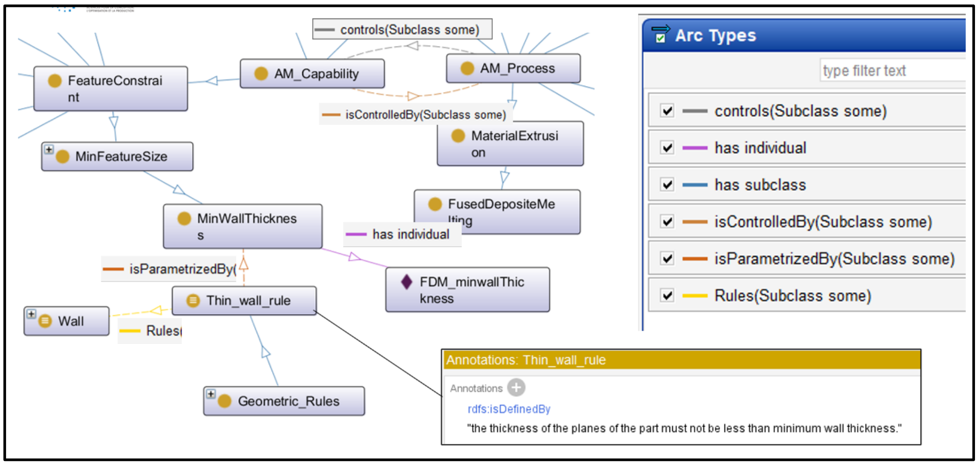

Fig 5 Thin_wall_rule in the DFAM ontology (Kim *et al.*, 2019).

It is important to mention the annotation of the DR with the rule written in natural language. This annotation will be used during the text analysis stage to link the words of the descriptive card with the words of the DR which are integrated with the concepts of the ontology.

6 NLP and expanded representation of sentences.

The process for determining the similarity between a sentence and a DR is illustrated with Fig 6.

After preprocessing the text using the Python NLP toolkit Stanza, we will have a text in the form of "bag of words", one bag of word per sentence. In the bag of words, the stop words will be removed, and the words will be lemmatized. To associate the right DRs with the different sentences, we will use an expanded representation of each sentence of the idea card since we use the surface matching method (Yih and Meek, 2007). To do so we will use the WordNet (Miller *et al.*, 2009) and ConceptNet (Speer and Havasi, 2013) thesaurus so that the sentence is associated with its synonyms and semantically close concept.

To attach more AM-specific words to the expanded representation, we will use the terms present in the ontology according to the match between the words of the sentence and the words present in the annotations of the concepts in the ontology.

Word2vec trained on a scientific AM data will serve to collect related AM concepts (Dhariyal and Ravi, 2020).

Once the knowledge of the ontology and the word2vec model is exploited we will transform our sentences into vectors. For that we will also create the expanded form of our DR. Once the sentences and the DR are in expanded form, we will use the method (Romain, 2016) to build vectors and to determine their similarity using the cosine function. With the different similarities between DR and sentences, we will determine which DR are the most relevant for each sentence and more overall for our idea card.

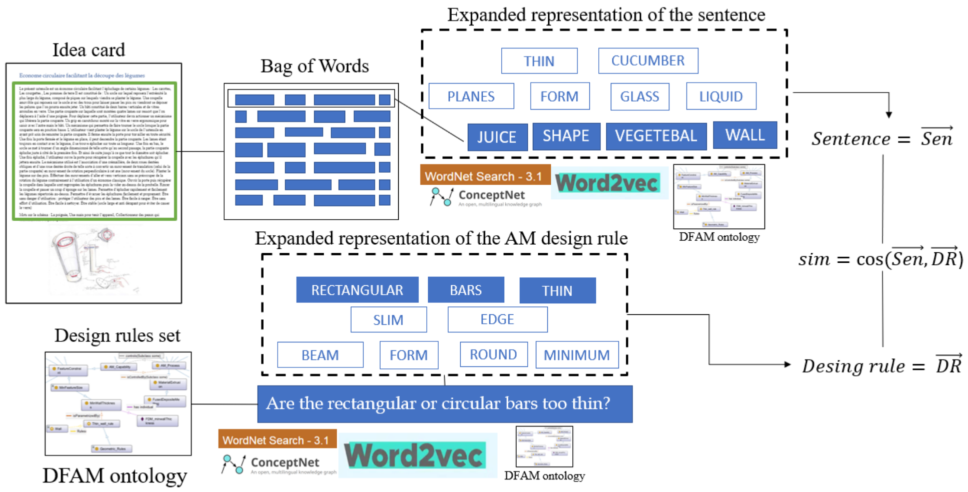

Fig 6 Process to determine similarities between sentences and DR.

7 Overall architecture

Once the similarity index has enabled us to determine the rules that are relevant, we must check if these rules are respected or not. In some cases, checking if the rule is respected can be done with the text, for example in the case where the prototype must absolutely be in metal (prototype of knife) the DR on the material used could be automatically qualified of not respected. However, most of the rules require exact geometrical precision, which is why it is rarely possible to automatically conclude whether the rule is respected or not. Therefore, the DREAM tool will mainly support creators without AM expertise to imagine rapid prototypes that meets the basic requirements of additive manufacturability. The rules will be completed by their quantitative criteria during the AManufacturability report which will enable the designer to conclude quickly without having to do documentation on the possibilities of AM. The overall architecture of the DREAM tool is illustrated with the Fig 7.

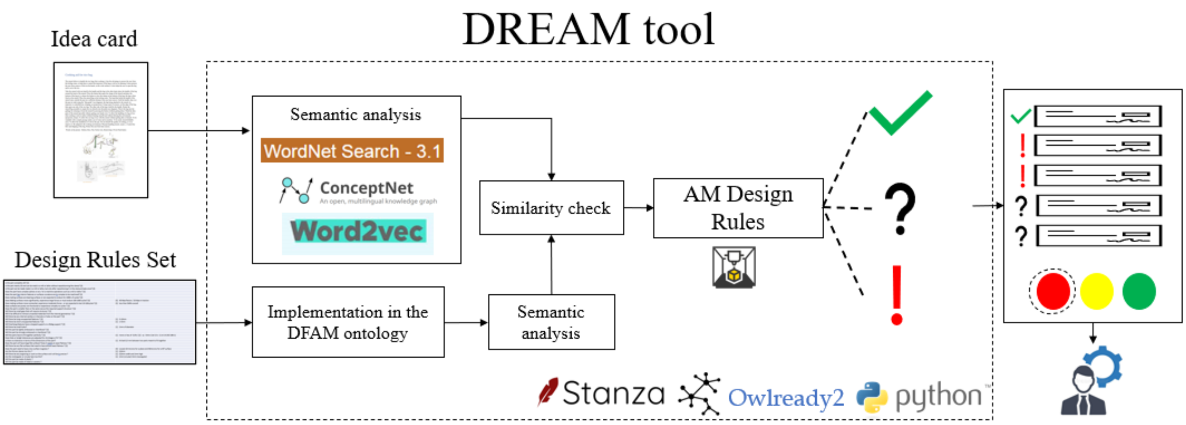

Fig 7 Overall architecture of the DREAM tool

8 First DREAM prototype

Although the final structure of the tool is well defined, we have developed a prototype of the tool that considers fewer knowledge sources Fig 8. The prototype has a GloVe (Global Vectors for word representation) word embedding model. This model 'glove-wiki-gigaword-300' is trained on Wikipedia pages where words are represented in a 300-dimensional space. The GloVe model will be for this prototype our only source to enrich the sentences. For each token we will use the model to have the surrounding tokens in the glove space. For the prototype, the set of AM design rules will be reduced to only 5 rules:

- Thin_wall_rule: The thickness of the walls of the part must not be less than 0.8.
- Max_part_size_rule: The overall length of the full size should be less than 1000.
- Min_bars_size_rule: A circular bar must be larger than 2 and a rectangular bar must be larger than 3.
- Materials_rule: The prototype should be functional with only plastic or polymer features, any other materials cannot be used.
- Small_holes_rule: Holes made on the part should not be too small, minimum 2 of diameter.

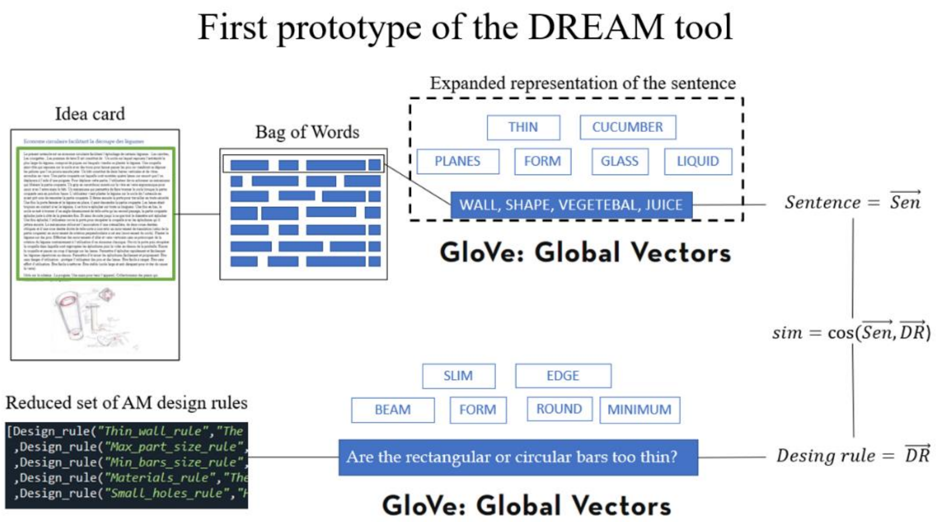

Fig 8 Architecture of the first prototype of the DREAM tool

For the prototype of the tool 3 parameters are useful to calibrate the tool:

Nsentbychunk: During the implementation we gave ourselves the freedom to compare several sentences at once to a single design rule. We will call these groups of sentences chunks. By default, the number of sentences per chunk is **1**.

Nsimwordsbytokens: This parameter regulates the size of the extended representation of each chunk. This number represents the volume of similar words that will be extracted from the Glove model. By default, its value is **5**.

Similarity-threshold: This number is the threshold value at which a design rule will be considered relevant compared to a chunk. Its default value is **0.35**.

9 Use case on a product idea card

The prototype of the DREAM tool will be tested on a product card. The product concept will be a circular peeler. This product idea comes from one of the LCPI product idea cards. As a reminder, only the textual description of the concept will be analyzed by the DREAM tool prototype.

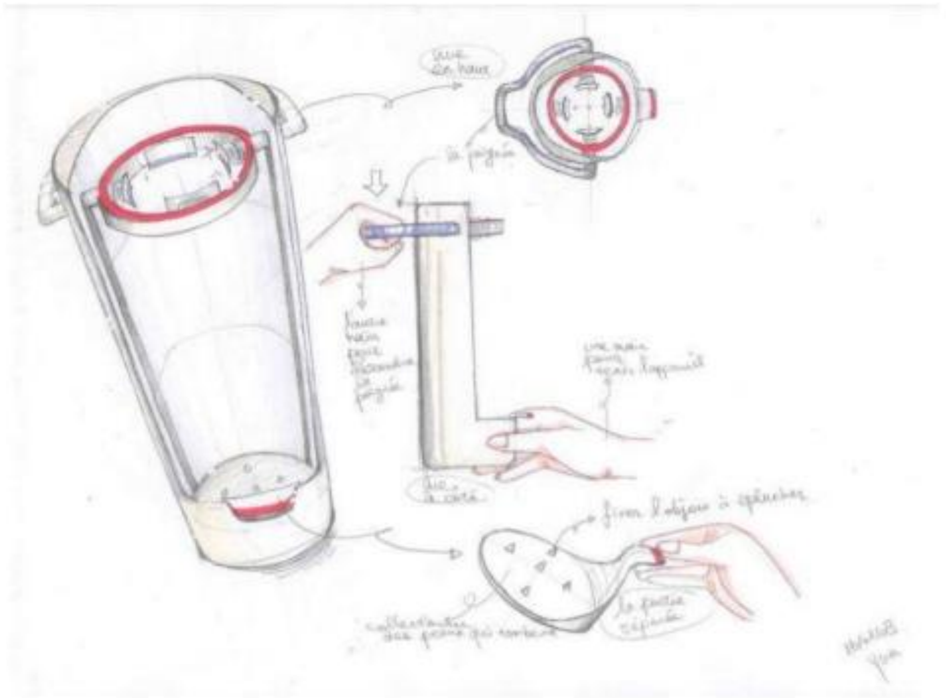

Fig 9 Circular peeler – LCPI

Textual description of Fig 9: *"This utensil is a circular peeler facilitating the peeling of certain vegetables: Carrots, cucumber, potatoes. The overall structure is cylindrical, the size is about 25 cm high, to allow the most classic vegetables to pass through. It consists of: A base on which will rest the widest end of the vegetable, composed of sharp spikes on which will be planted the vegetable. A removable cup which will rest on the base with small holes to let pass the spikes or will come to deposit the peels which one will be able to throw then. A frame made of two vertical cylindrical bars and rounded glass panes. A cutting part on which are mounted four spring-loaded steel blades that can be moved with a handle. To move this part, the user will have to activate a* *mechanism that will release the cutting part. A rubber grip mounted on the ergonomic glass window to grasp the frame with the other hand. A mechanism that will allow the base to rotate when the cutting part is in the down position. The user plants the vegetable on the base of the utensil having taken care to raise the cutting part. He then closes the door to work safely. Once the door is closed and the vegetable is in place, he can lower the cutting part. The steel blades being still in contact with the vegetable, it is peeled on all its length. Once at the bottom, the base starts to rotate at an angle so that on the second pass, the cutting part peels right next to the first. And so on until the entire diameter is peeled. Once peeled, the user opens the door to recover the cup with the peelings that he will then throw away. The mechanism used is the association of a rack, two oblique toothed wheels and a straight toothed wheel in such a way as to convert a translation movement (that of the cutting part) into a rotation movement perpendicular to this axis (movement of the base). Plant the vegetable on small vertical spikes. Move the vegetable back and forth vertically without worrying about the rotation of the vegetable as opposed to using a classic peeler. Open the door and retrieve the cup in which the peelings are grouped, then empty it over the garbage can. Rinse the cup and wipe the steel blades with a sponge. Allow for quick and easy peeling of the vegetables listed above. Allow for easy and clean disposal of peels. Be safe to use protect the user from spikes and steel blades. Easy to store. Effortless to use. Easy to clean. Be stable (wide base and anti-slip to avoid breaking the glass). Words on the picture: The handle, one hand to hold the device, collecting the falling skins, fixing the object to be peeled."*

Results and discussion:

Similarity :	Rule	Rule annotation	Triggered words	Tokens from the text
Number of sent by chunk = 1, Number of expanded words by token = 5, Similarity treshold = 0.35				
0,503986	Max_part_size_rule	The overall length of the full	['increased', 'more',	['overall', 'structure', 'cylindric
0,392915	Small_holes_rule	Holes made on the part shou	['par-5', 'birdie', 'put	['removable', 'cup', 'rest', 'ontl
0,486854	Min_bars_size_rule	A circular bar must be larger	['bars', 'rectangular',	['frame', 'make', 'vertical', 'cyli
0,43245	Small_holes_rule	Holes made on the part shou	['cm', 'circumferenc	['entire', 'diameter', 'peel']
0,370328	Small_holes_rule	Holes made on the part shou	['smaller', 'large', 'tir	['Plant', 'vegetable', 'small', 've
0,368605	Materials_rule	The prototype should be fun	['used', 'allow', 'use']	['effortless', 'use']

Fig 10 Raw results from the DREAM tool prototype

The prototype produces results in table form Fig 10. In these tables we find each design rule and text excerpt whose similarity score has exceeded the threshold 0.35. Fig 11 puts the results of the prototype in their context, to facilitate their analysis. Eventually, the tool should provide this type of report for each idea card analyzed.

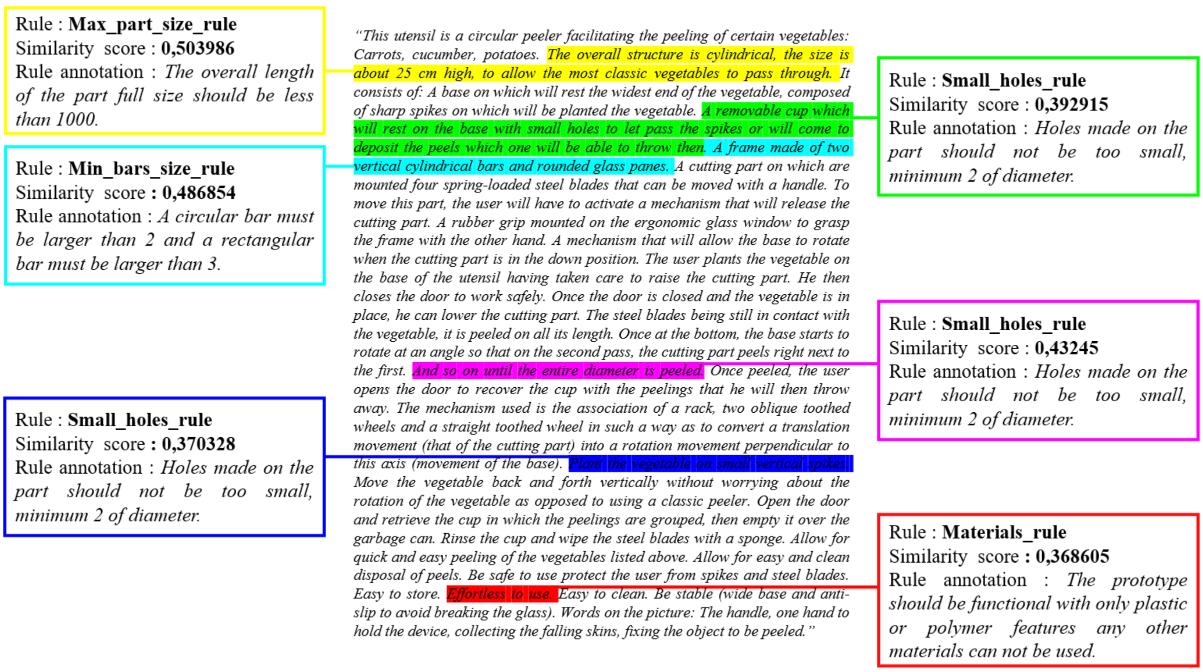

Fig 11 DREAM prototype results on the use case

On this idea card the prototype of the DREAM tool identified 6 extracts to associate with AM design rules. Among the 6 associations, 4 were considered successful and 2 unsuccessful. Each association comes with triggered words to explain the selection of the prototype. The more apparent the association is, the higher the similarity score should be. We analyzed each association:

Yellow association:

Rule: Max_part_size_rule
Similarity score: 0.503986
Triggered words: ['increased', 'more', 'smaller', 'sizes', 'third', 'large', 'improved', 'overall', 'increase', 'size', 'larger', 'diameter', 'sized', 'fourth']

The association had the highest score. The presence of common words in the annotation of the design rule and in the text, excerpt greatly helps the association. We can see that the expanded representation of "high" which gives a sense of limit in terms of dimensioning will be associated with the expanded representation of "length". This association rules-text is considered successful.

Green association:

Rule: Small_holes_rule
Similarity score: 0.392915
Triggered words: ['par-5', 'birdie', 'putt', 'holes', 'smaller', 'large', 'hole', 'tiny', 'par-4', 'few', 'larger', 'small']

This association has an average similarity score. This association is due to the presence of the two words “small” and “holes” on both the design rule association and the text excerpt.

Light blue association:

Rule: Min_bars_size_rule
Similarity score: 0,486854
Triggered words: ['bars', 'rectangular', 'cylindrical', 'lounge', 'cafe', 'pub', 'restaurant', 'diameter', 'bar']

This association as a high similarity score. This association is due to the presence of the expanded representations “bars” and ‘bar” but also due to the expanded representations of “circular” and “cylindrical”.

Pink association:

Rule: Small_holes_rule
Similarity score: 0,43245
Triggered words: ['cm', 'circumference', 'cylindrical', 'diameters', 'width', 'diameter']

This association has an average similarity score. This association is due to the presence of the word “diameter”. This example shows the limit of the prototype, with small sentences the prototype struggles the identify the context of the sentences.

Dark blue association:

Rule: Small_holes_rule
Similarity score**:** 0,370328
Triggered words: ['smaller', 'large', 'tiny', 'few', 'larger', 'small']

This association has a low-average similarity score. This association is due to the presence of the word “small” which let us think about a small feature which an AM machine struggle to do. However, there is no mention about holes in the sentence. This exposes the issue of a limited number of DR for the prototype a more general rule like a Minimum_feature_size_rule.

Red association:

Rule: Materials_rule
Similarity score**:** 0,368605
Triggered words: ['used', 'allow', 'use', 'using', 'uses']

This association has a low-average similarity score. This association is completely unsuccessful. The words “use” and “used” are both on the text on the DR annotation. Once again it exposes how much the DREAM prototype struggles with short sentences. The word “use” brings no technical and useful meaning. With 3 word sentences the cosine similarity score is not relevant. One solution is to increase the number of sentences by chunk.

The first three design rules (yellow, green, and light blue) to associate responds exactly to what is expected from the tool. The dark blue association is relevant although no hole is specified in the extract. Indeed, the fine geometries remain a challenge for the FA machine. We can criticize however the accuracy of detection associated with the small_hole_rule.

We can also find some missing associations. For example, an association between Material_rule and the extract "A *cutting part on which are mounted four spring-loaded steel blades that can be moved with a handle."* was expected.

Overall, this prototype shows the relevance of this study. However, it exposes some early weaknesses about short sentences and meaningless words take in consideration like "use" in the pink association. These problems should be solved with more semantic knowledge with Concept net and Wordnet, and more technical and geometrical knowledge with a relevant use of an AM ontology.

10 Conclusion

During the early stages of design, the prototyping stage implies to manufacture a first usable version of the product. For that the designer requires knowledge in rapid manufacturing. Designers new to the manufacturing process like additive manufacturing will make valuable mistakes and waste time and money, moreover they will not take advantage of the opportunities that additive manufacturing offers.

With the architecture for the DREAM tool presented in this study it is possible to develop a tool that extract the most relevant design rules by analyzing a textual description of the product. With the extracted rules designers will successfully prototype the product using AM process. The architecture proposes to use ontologies to represent the knowledge of additive manufacturing. The text analysis is done using thesaurus and ontologies, they are used to develop the surface matching method that allows to determine the rules that are the most relevant for the concept to be prototyped.

A prototype of the DREAM has been developed and applied to a use case. The prototype extracted 6 design rules from the textual description. Among them 4 have been considered satisfying and relevant according to our use case. For those 4 the prototype managed to identify the meaning of the sentences and linked them with AM design rules. 2 among the 6 design rules have been extracted after a miss interpretation of short sentences by the prototype, we consider those extraction not satisfying. The results also shown some missing design rules that could have been expected after a manual analysis of the textual description. Overall, the results validate our architecture and are encouraging for further improvement of the DREAM tool.

It will be possible to improve the prototype by testing it on a larger number of concepts. We will then be able to identify the rules that frequently cause problems and what information is regularly missing. Then we could adapt the format of the idea cards to ask the designer for precision to accelerate the analysis process with more accurate input data.

Our tool currently focuses a lot on the constraints of additive manufacturing and little on the opportunities. An improved version of the tool could propose an improvement of the concept by using the opportunities of materials and unique geometrical freedom that additive manufacturing offers.

Although the form of our tool is primarily designed for AM DR such an architecture can be adapted for other domains with an ontology associated to the domain. It would be for example possible with the right knowledge source to create a tool to promote eco-design during the early design stage.

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