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KNOWLEDGE DISCOVERY IN MANUFACTURING QUALITY DATA TO SUPPORT DESIGN DECISIONS

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ABSTRACT
Product design is knowledge-intensive process and involves large quantities of decisions. The efficiency and effectiveness of these decisions depends on the provision of many kinds of related knowledge to designers from different sources throughout the lifecycle. Knowledge on product quality is one of the most important knowledge sources. To provide quality related knowledge, this paper proposed one data mining based knowledge discovery approach. First, decision making during the engineering design process is analyzed and classified into two main categories, namely organizational and technical decisions. Second, this paper analyzed and classified product design knowledge into three categories such as product, process and product support knowledge. Then knowledge needs of design decisions are also analyzed. Third, a data mining based quality related knowledge discovery approach is proposed. This approach can extract quality related knowledge from large volume of manufacturing quality data. This approach is illustrated by an example adapted from literature. Finally, some conclusions and future works are discussed.

Keywords: Data mining, manufacturing, quality data, knowledge on quality, design decision

1 INTRODUCTION
The engineering design process can be seen as a series of interrelated operations that is driven by decisions [1]. In developing a large, complex product, there may be 10 million decisions and the most critical decisions may be roughly 1000 to 10,000 [2]. Engineering design is also a knowledge intensive activity. Thus there is an overwhelming need to provide knowledge support decision throughout the design process. The knowledge used comes from a variety of sources, from within the company as well as from outside, from work related as well as non-work related events [3]. The knowledge may exist in many areas including ergonomics, packaging, management, manufacturing processes and so on [4] (Figure 1). As products become more complex and competition intensifies, it is essential to make the maximum use of the available knowledge and to deliver that knowledge in the appropriate form at the right time in the product development process.

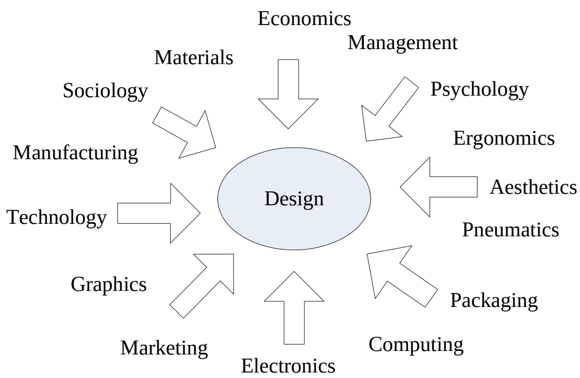

Figure 1. Knowledge areas for design

In the age of digital information, a large amount of quality data has been automatically or semi-automatically collected during the product manufacturing process. However, much of the industrial data are in fact not used, or at least, not used efficiently, which leads to an undesirable situation – data rich, but information poor. There are much research and applications of data mining (DM) in manufacturing data to improve the quality of the product. However, the patterns extracted from the raw data are only used by decision makers in manufacturing process. In fact, this knowledge may include useful ones for decision makers in product design process. Decision makers may potentially use the information buried in the raw data to assist their decisions through DM for possibly identifying the specific patterns of the data [5].

Most of the design engineers rely on their own domain knowledge and experience to determine the specific characteristics of products. However, such judgments are ineffective and limited by their own domain knowledge. Therefore, it has become an important topic to effectively transfer plethora and complex manufacturing quality data (MQD) into valuable information and knowledge for quality improvements and product design. The extracted information and knowledge can assist the designers as their reference and basis for similar product design.

This paper is organized as follows. Section 2 describes decision-making in product design and classifies these decisions. Section 3 classifies the product design knowledge into several categories and illustrates the knowledge needs of decisions. Section 4 illustrates the process of DM in MQD. Section 5 proposes a framework of knowledge support for design decisions. Section 6 concludes with discussion and further research directions.

2 DECISION-MAKING IN ENGINEERING DESIGN

It is difficult to overestimate the importance of design decisions. For example, it has been reported that upwards of 70% of a product’s manufacturing cost is dictated by decisions made during the product design stage [6]. Poor product design decisions causes many defects on the production floor [7].Thus, an effective design process relies heavily upon effective decision making [8].

2.1 Decision and Design Decision

According to Simon [9], the work of managers, of scientists, of engineers, of lawyers is work of choosing issues that require attention, setting goals, finding or designing suitable courses of action, and evaluating and choosing among alternative actions. The first three of these activities--fixing agendas, setting goals, and designing actions--are usually called *problem solving*; the last, evaluating and choosing, is usually called *decision making*. Mezher [10] describes decision as “a process which generates and evaluates alternatives and which makes choices among them”. Others see decision as one step in the complete problem solving process which including goal clarification, solution search, solution analysis, solution valuation, decision and control [11].

Any action involves decisions. Also, thus, with engineering design [12]. Design activities involve decision-making. However, we believe that not all design activities are decision activities. When the design task is extremely well-formulated, the design engineer’s decision-making process is the solution of an optimization problem. Here decision-making is problem-solving. In contrast, when the design task is ill-formulated, design engineers are less able to apply formulaic numerical techniques to “solve the design problem.” In these cases, the design engineer’s decision-making process is a collection of heuristics that generate and evaluate solutions until a satisfactory one is found [13]. According to Accreditation Board for Engineering and Technology (ABET) [14], decision-making defines engineering design. ABET says that design is "a decision-making process (often iterative), in which basic sciences, mathematics, and the engineering sciences are applied to convert resources optimally to meet stated needs." The natural conclusion is that to be good designers, engineers should be skilled decision-makers.

Much works have been done on decision-making in engineering design by both academy and industrial practice. In academia, there exist guidelines and analysis for decision-making in design methodology literature [15-18]. However, a survey carried out in British industry [19] indicates that design methods are sparsely adopted and used in industrial practice. An empirical study of engineering designers in industrial practice [20] has not found support for the generally believed approach. Ahmed’s study indicates that engineering designers follow a design strategy dependent on their perception of the current status of the design process rather than applying a decision method. Based upon a study of current state-of-the-art literature and methodologies, Hansen & Andreasen [21] propose a framework of design decision-making consisting of two models; the decision node is a generic model of the interrelated decision-making activities consisting of six subactivities: to *specify*,

to *evaluate* solution alternatives, to *validate* a design solution, to *navigate* through the solution/activity space, to *unify* the current decision into consistent wholes, and to *decide*. The decision map is a model of the object of decision-making during design. More works on this decision model are referred to [22-25]. Herrmann and Schmidt [13] view product development as a decision production system, they define a decision production system as an information flow governed by decision-makers who make both design decisions and development decisions under time and budget constraints.
The design engineering community has focused much effort on understanding design as a decision-making activity. This work has yielded Decision-Based Design (DBD), a perspective that views design as a decision-making process involving values, uncertainty, and risk. (Details on DBD can be found online in the Decision-Based Design Workshop at http://dbd.eng.buffalo.edu/, and the published book "Decision Making in Engineering Design" [26]).

2.2 Classification of Decisions in Design

Product development includes many different types of decision-making by engineers and managers. Herrmann and Schmidt [13] divided these decisions into design decisions and development decisions. *Design decisions* determine the product form and specify the manufacturing processes to be used. Design decisions generate information about the product design itself and the requirements that it must satisfy. *Development decisions*, however, control the progress of the design process. They affect the resources, time, and technologies available to perform development activities. They define which activities should happen, their sequence, and who should perform them.
Krishnan and Ulrich [27] make a literature review on product development decisions. They present a revision of a total amount of 200 references related to the design decisions and provide a long list of questions that follows the typical decomposition of product development. They observe that, while *how* products are developed differs not only across firms but within the same firm over time, *what* is being decided seems to remain fairly consistent at a certain level of abstraction. Some product development decisions include: *Which (printing) technology will be adopted in the product? Where will the (printer) product be assembled? Who will be on the product development team and who will lead the team? Which variants of the (printer) product will be developed as part of the product family?* Though most of them are development decisions, their list includes the following design decisions: *What is the product architecture? What will be the overall physical form and industrial design of the product? What are the values of the key design parameters? What is the configuration of the components? What is the detailed design of the components, including material and process selection?* While rigorous at a bibliographical level, the decision listed has not been empirically verified yet. An empirical study by García-Melón et al. [28] confirmed that the decisions identified in the literature do correspond to the decisions mostly made in innovative companies of the Valencia Region (Spain).

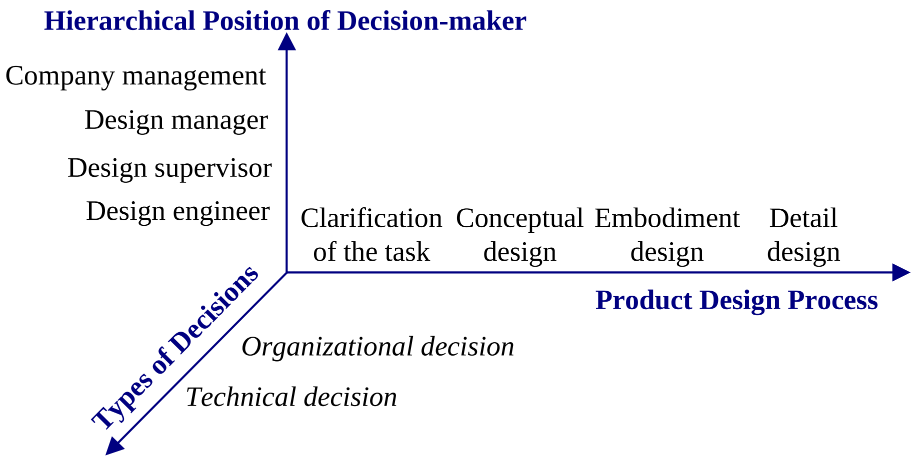

Figure 2. A characterization of decisions during the product design process

Corresponding to the two types of decision named design decisions and development decisions [13]. We divide the decisions during the product design process into two types: Technical decision and organizational decision. *Technical decisions* focus on the product itself and determine the parameters about the product. Most of technical decisions are made by product design engineers. *Organizational*

decisions, however, control the progress of the design process. They define what will be done, when it will be done, and who will do it. Most of organizational decisions are made by design managers or people in other company management levels (e.g. the project leader judges the results obtained so far compared to the resources spend, and determines what to do next, how to do it, and who has to do it, the company management at project milestones judges the results obtained compared to the expected business opportunity, and determines the future of design project in a go/no-go decision [23]).
Here we analyze design decisions in three dimensions as shown in Figure 2. Axes X indicates a design process consisting of four phases: Clarification of the task, conceptual design, embodiment design, and detail design [15]. Axes Y indicates different types of decision-makers including design engineer, design supervisor, design manager and company-level management. Axes Z indicates organizational decision and technical decision.

3 PRODUCT DESIGN KNOWLEDGE

Design knowledge can improve the quality of design decisions [29]. Increasing design knowledge and supporting designers to make right and intelligent decisions can achieve the improvement of the design efficiency. Many contemporary authors distinguish among data, information, and knowledge. The generally accepted view sees data as simple facts that become information as they are combined into meaningful structures, which subsequently become knowledge as meaningful information is put into a context and when it can be used to make predictions [30].
Unless specified otherwise, this paper uses “knowledge” interchangeably with “information”.

3.1 Classification of Design Knowledge

3.1.1 Related works

Engineering designers need many different types of information. Many proposed classifications of engineering design knowledge can be found in the literature [31-33]. The classification by Vincenti [31] includes six categories such as fundamental design concepts, criteria & specification, theoretical tools, quantitative data, practical considerations and design instrumentalities. But it does not include the ‘design process’. The classification shown in Figure 3 by Zhang [32] reflects this concern. Li et al. [34] categorised the design knowledge into five types as shown in Figure 4: Design Process; Customer requirements; Design definition/design history and past cases; Practical considerations; Fundamental design concept and principles.

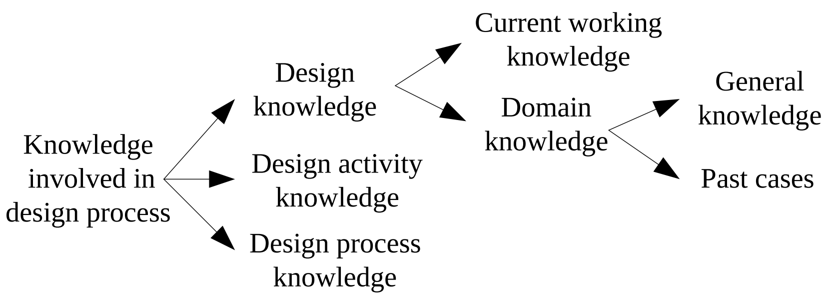

Figure 3. Design Knowledge by Zhang [32]

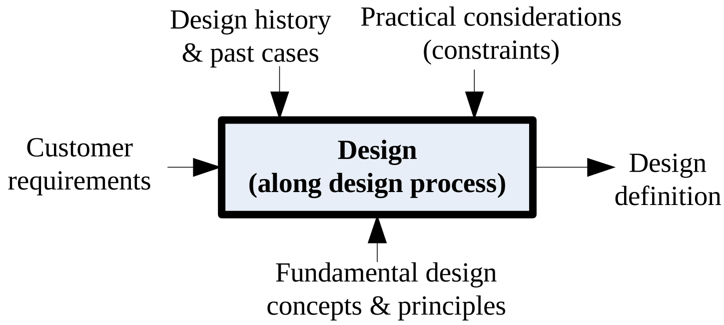

Figure 4. Design and Design Knowledge by Li [34]

Ahmed et al. [35] classified product design knowledge by two dimensions: In one dimension, the knowledge is divided into process-related and product-related knowledge. In another dimension, the knowledge are divided into Stored externally Information, Stored internally in human memory (including Explicit knowledge, Implicit knowledge, and Tacit knowledge). Li and Zhang [36] classified design knowledge into four categories: (a) artefact (product) structures, (b) artefact behaviours, (c) artefact functions and (d) causalities among structures, behaviours and functions.

Carstensen [37] explores the types of information needed by engineering designers including: Previous designs; Design rationales; Similar products; “Known problems” in products; Component specifications; Standards and norms; Working procedures; Production line characteristics; New materials and components; Literature and research results; Relevant persons; Project documentation.

In one project of Ullman [38], information was organized by the component or assembly being worked on. However, as work progressed, and new parts evolved and old ones disappeared from consideration, this structure broke down. A second effort [39] tried to organize the information by issue being addressed; where an issue could be about a part, a feature of a part, a function or the process being used. This too ran into difficulty as issues were worked on, left for a while, returned to and sometimes abandoned. Finally, it was realized that the best structure was to think in terms of the decisions made [40]. Since those initial studies, work has focused on the mantra: Design is the evolution of information punctuated by decision-making. It is important to put heavy emphasis on decision-making because: A decision is a commitment to use resources.

3.1.2 Classification of Product Design Knowledge

In this paper we group product design knowledge into three groups: Product Knowledge, Process Knowledge and Product Support Knowledge. The first two only refer to the knowledge generated and then utilised during the product design process.

Product knowledge is all knowledge related to the product itself. As in Aziz and Chassapis [41], any product related knowledge could be grouped into four categories: Knowledge about components; Knowledge about relations between components; Constraints on properties of materials involving part formation; Relations between components and user preferences. This part of knowledge is most for product design engineers who focus their efforts on the product itself.

Process knowledge is the knowledge about the design process. This part of knowledge is most for product design managers who focus their efforts on the product design process, and based on this knowledge, they have to decide what the work will be done, when it will be done, and who will do it. As in [42], Jung et al. defined process knowledge into three types of process knowledge such as process template knowledge, process instance knowledge, and process-related knowledge.

The latter one, Product Support Knowledge, refer to the knowledge coming from many different sources which locating outside the product design process, for example, knowledge from marketing, manufacturing, packaging etc.(see Figure 1).

3.2 Knowledge needs of Decisions

In engineering design process, design decision is knowledge intensive activity. The engineering design process can be described as a complex information processing activity, directed by the decisions made by the individuals in the design team [43]. Good decisions rely on relevant and accurate information. The importance of information is underlined by the fact that design activities both consume and create large amounts of information as they proceed. One study reported that designers spent in excess of 50% of their time handling information, e.g., retrieving, organizing, etc [44]. Thus, the efficiency and the quality of the design process may depend considerably on how well designers are able to handle large amounts of information. To understand how best to support product designers’ information needs, we face the difficulty of having to study the complexity of the activity itself, the complexity of the environment, and the hidden nature of the information needs of the product designers.

Different types of decisions need different types of knowledge. The most important information in design management are data describing the product itself, i.e. its geometry and direct properties (material, …). This information is most useful for product designer for technical decisions. The second major source for information is the product development process. This information is most useful for design managers or other people in company management levels. Design managers need to be able to keep an overview over multiple process steps, problems, decisions and schedules, e.g. for the design of sub-modules, product tests or the production of tools.

Li et al. [34] presents a list of knowledge support requirements elicited from engineering designers by interview. Eekels [12] indicates that, in order to decide, a decision-maker needs four kinds of information: publicly or privately accessible factual information concerning the alternatives; intuitively guessed factual information; normative information; methodic information.
Here we propose a three dimensional model to illustrate the knowledge existing during the product design process as shown in Figure 5.

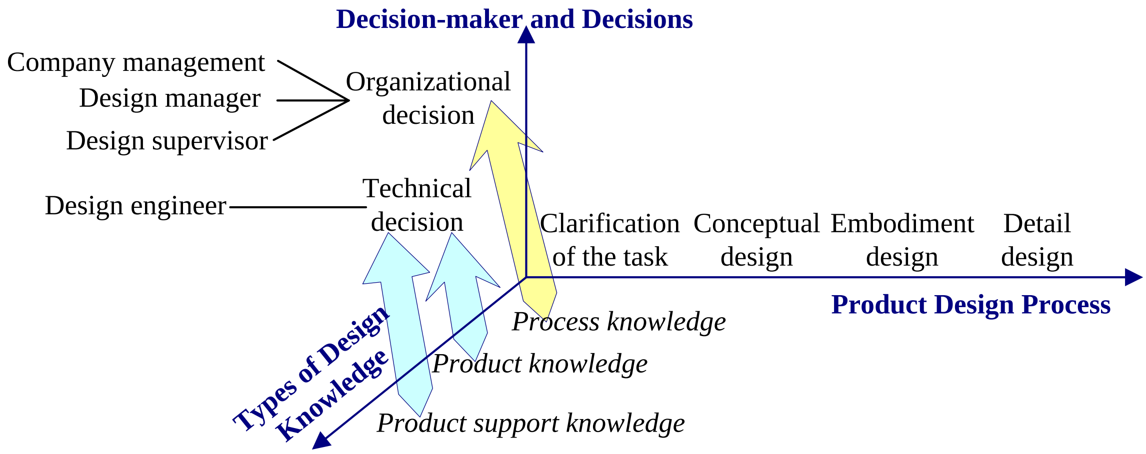

Figure 5. A three-dimensional characterisation of design knowledge

4 DATA MINING IN MQD

DM is at best a vaguely defined field; its definition largely depends on the background and views of the definer. In some literature, Knowledge Discovery in Database (KDD) refers to the overall process of discovering useful knowledge from data, and DM refers to a particular step in this process. DM is the application of specific algorithms for extracting patterns from data. Others see KDD interchangeable with DM. This paper adopts the latter point of view, i.e., DM is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data [45].
The growing volume of MQD is a challenge that needs research on tools that discover unique properties of the data. Some works on DM in quality has been emerged (e.g. [11, 46-50]), but most of them focus on finding patterns to solve manufacturing problems, without considering the possibility of problems related with product design stages. Using DM to find useful quality-related knowledge in MQD is an important approach to meet knowledge needs of product designers, and furthermore, to support technical decisions of similar products or the redesign or improvement of the current product.
This section proposes the quality-related knowledge discovery in MQD using DM approach.

4.1 Framework of DM in MQD

In practice, when the product has suffered the quality problem, engineers will examine whether there are causal relationships between the manufacturing process and product defects. However, there maybe some root causes existing in early product design stages. Many statistical methods are used to find quality problems in manufacturing processes. However, the quality problems are complicated and the results are usually hard to be interpreted. Thus, we can construct a DM framework with involved techniques to solve the complicated manufacturing problems through product design. Through accumulating DM experiences and transferring the extracted patterns into systematic rules and knowledge, similar problems can be identified efficiently and effectively through product design.
According to Fayyad et al. [45], we constructed a DM framework to explore the huge volumes of MQD for finding patterns to support technical decisions of designers. This framework includes five major steps (Figure 6): problem definition, target data selection, data cleaning, data transformation, data mining implementation, and evaluation and interpretation. In order to understand the complete process of DM process, the details of its basic steps and the applicability of the DM approach are illustrated in the following subsection through one example being adapted from [49].

4.2 Example of DM in MQD

The background of the example in [49] is illustrated as follows:

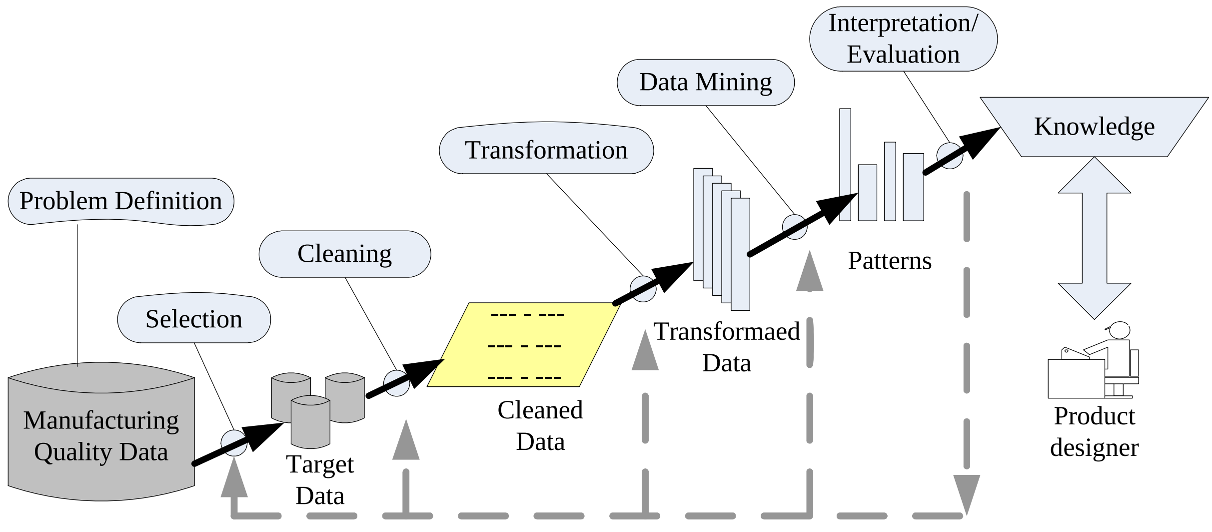

Figure 6. Framework of DM in MQD

Large volumes of the dimensional data are collected during the fan blade manufacture. There are many statistical methods used to control production and support the manufacture of products within design limits. However, these kinds of methods cannot identify the manufacturing limitations of the current set of production systems. A product's output dimensions are a good measure of the quality of the production cycle and can help in suggesting any alteration in the design or any dependency or relation between different dimensions resulting from the manufacturing process. It is very important for designers and production engineers to understand the interrelationships between different dimensions of the product, particularly when components have complex geometry and need to be manufactured to a high level of precision. This subsection will illustrate the complete steps of DM in MQD.

4.2.1 Problem definition
First we should develop an understanding of the application domain and the relevant prior knowledge and identifying the goal of DM. This research is to identify the interrelationships between different kinds of manufacturing quality characteristics of fan blade. During the fan blade manufacturing process, quality measurement and test are conducted to ensure the product quality. The product quality data, such as the width, height, thickness of fan blade, will be extracted to find some unknown patterns about the product. Data may be recorded during manufacturing, assembly, or testing to determine, for instance, how well products generally meet certain dimensional constraints. These kinds of transactional data can be analysed to study the effectiveness of a design in meeting the target strength, shape, and dimensionalities. Hence, transactional data can contain useful information that may enable designers to generate more efficient and optimal designs in the future.

4.2.2 Target data selection
There are many kinds of MQD generated and stored in different databases. In order to implement DM, we should create a target data set: selecting a data set, or focusing on a subset of variables or data samples, on which discovery is to be performed.

Many dimensional values were examined at more than 250 different sections for each fan blade. It is not possible to explain the proposed methodology clearly and concisely using the complex geometry of the wide-chord fan blade, and all the different variables. Therefore, to reduce the complexity and to explain the approach fully, a simplified example of a small section of the product will be demonstrated using different dimensions. Here 13 different sections are chosen corresponding to the three important dimension such as thickness, width and height. These 13 different sections are named as aa_Thickness, ab_Thickness,…af_Thickness, aa_Width,…, ad_Width, aa_Height, ab_Height, ac_Height. Then the data sets concerning to these 13 sections of fan blade are chosen as target data sets.

4.2.3 Data cleaning
Data cleaning is a very important stage in the process of DM and is very time-consuming. The inappropriate data may lead to departure of mining results. It is therefore crucial that MQD be cleaned

carefully and thoroughly to make them ready for the different types of transformations that may be necessary before particular data mining techniques can be applied.

Much of the data obtained from the manufacturing process of the fan blade were in the form of flat files, however, the collected data often include noisy, missing and inconsistent data, which should be cleaned to remove inconsistencies and discrepancies and then compiled into one workable table so that different data mining algorithms could be applied. In particular, deciding on strategies for handling missing data fields, replaced or deleted.

4.2.4 Data transformation

Different sections (such as aa_Thickness, ab_Thickness,…af_Thickness, aa_Width,…, ad_Width, aa_Height, ab_Height, ac_Height) for an output dimension of a fan blade are divided into 11 bands (such as Uout, Upper, H-Upper, S-Upper, Nominal, S-Lower, M-Lower, H-Lower, Lower, and Lout). The measured dimensional data value of different sections is then transformed into integer identifiers, which are easier to use as input for the association rule algorithm. This is then used to find the frequent itemsets and then the association rules. Then, each measure product has its integer identifier. Each integer identifier is a combination of two- and two-digit numbers (these numbers can be chosen according to the requirements). The first two digits show the dimensional band, they are numbered as 11, 12, 13… 20, 21. The last two digits show the section of the product, they are numbered as 01, 02, 03…12, 13. For example, if the 'ac' section of 'Width' (numbered as 09) has a measured value in the S-Lower band (numbered as 17), then that value will be translated as 1709.

Then, each fan blade has 13 sections and each section has its measured value categories in to 11 different bands. Therefore, each fan blade has 13 integer identifier, which should be considered as one record or item. Table 1 show 15 example data records which shows 15 different measured fan blades.

Table 1. Example data

ID	Data
1	1612, 1303, 1507, . . .
2	1703, 1303, 1703, . . .
3	1611, 1303, 1612, . . .
4	1612, 1303, 1507, . . .
5	1408, 1303, 1404, . . .
6	2106, 1303, 1703, . . .
7	1408, 1703, 1504, . . .
8	1603, 1303, 1609, . . .
9	1612, 1303, 1507, . . .
10	1312, 1303, 1803, . . .
11	1713, 1303, 1601, . . .
12	1612, 1404, 1507, . . .
13	1612, 1303, 1507, . . .
14	1401, 2006, 1507, . . .
15	1612, 1303, 1507, . . .

4.2.5 Data Mining Implementation

In implementation of DM task, first of all, matching the goals of the DM task to a particular data-mining method. For example, summarization, classification, regression, clustering, and so on. Then, choosing the DM algorithm(s) to execute the DM methods. Then, DM techniques are performed to identify problems and specific patterns such as specific relationships between quality characteristics by applying DM technology.

In the work of [49], association rule DM method and Apriori algorithm are used. Association rule mining can be used on historical data to find any relationships that may be present to improve designs. This can be illustrated with the example data shown in Table 1, which has been selected, cleaned, transformed. The data in Table 1 show 15 transactions or products, which have been carefully chosen for illustration purposes only and is just for showing the effectiveness of DM approach in MQD.

There are many valid rules extracted in these data. The two are illustrated as follows:

1. 1612-1507;
2. 1612-1303.

4.2.6 Interpretation and evaluation

All the results should be interpreted to be understood by people be of interest, and be evaluated by discussing with domain engineers and data experts.

For example, the two rules extracted in the above subsubsection named “1612-1507” and “1612-1303” can be interpreted as follows:

1. 1612-1507: IF ‘ab’ section of ‘Height’ is nominal THEN ‘aa’ section of ‘Width’ is S-Upper;
2. 1612-1303: IF ‘ab’ section of ‘Height’ is nominal THEN ‘ac’ section of ‘Thickness’ is H-Upper.

Confidence and support are the two most important indexes to evaluate the rule quality, which rules are one kind of knowledge represented in the form of “If …, Then …”. In this example, the first rule has 40 per cent support and 100 per cent confidence and the second rule also has support of 40 per cent and 83.3 per cent confidence. The first rule is a valid rule because 1507 and 1612 complement each other in the data, while the second rule is misleading as 1612 is complementing 1303 but 1303 does not complement 1612.

Then interpreting mined patterns, possibly returning to any of steps 1 through 5 for further iteration. This step can also involve visualization of the extracted patterns and models or visualization of the data given the extracted models.

4.2.7 Utilization of knowledge

Finally is acting on the discovered knowledge: using the knowledge directly, incorporating the knowledge into another system for further action, or simply documenting it and reporting it to interested parties. This process also includes checking for and resolving potential conflicts with previously believed (or extracted) knowledge.

In this example, after the evaluation and interpretation, the first rule could be feed back to product designer. When the designer design similar fan blade, he should refer to the first rule such as “IF ‘ab’ section of ‘Height’ is nominal THEN ‘aa’ section of ‘Width’ is S-Upper” to avoid design mistake.

It must be noted that the data mining process is an iterative way to extract valid, previously unknown information from data, and revise the empirical models via feedback. Often the patterns about quality characteristics cannot be easily identified at the beginning and thus we should discuss with domain experts again to check whether any data or information was missing. It usually needs several iterations to revise the models to enhance the accuracy and effectiveness of knowledge. Most previous work on DM process has focused on step 5, the data mining implementation. However, the other steps are as important (and probably more so) for the successful application of DM in practice.

4.3 Knowledge Support Framework

Contemporary design process becomes increasingly knowledge-intensive and collaborative. Knowledge-intensive support becomes more critical in the design process and has been recognized as a key solution towards future competitive advantages in product development. To improve the design process, it is imperative to provide knowledge support and share design knowledge among distributed designers. Marsh [51] found the proportion of designers’ time absorbed by information acquisition activities to be 20-30%. Marsh also found that the majority of information is obtained from personal contacts, who in 78% of cases retrieved it from memory.

However, with the increasing flow of experts in manufacturing companies, knowledge base have to established to store more and more knowledge to meet the needs of product designers, especially for those novice designers. Here we propose one framework which could extract quality-related knowledge to support technical decisions for product designers.

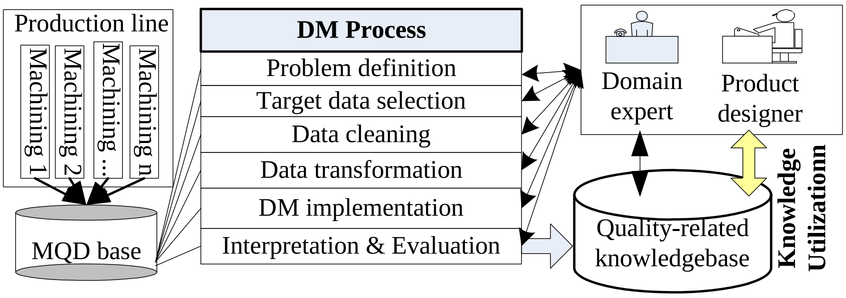

Figure 7. Framework of Knowledge Support for Technical Design Decision-making

The ultimate objective of our work is the development and implementation of MQD-based Design Decision Support System (MQD-based DDSS), which acts as an aid tool for support design decisions concerning quality aspect. Fig. 7 represents the conceptual framework of the MQI-based DDSS which will be developed in our future work. In this framework, large quantities of MQD are recorded in MQD base, through our DM approach, quality-related knowledge are discovered and stored into the knowledge base after evaluation and interpretation. Then this knowledge could be provided to product designers. All these process should involve the participant of domain expert to ensure the effectiveness and efficiency of our proposed approach.

5 CONCLUSIONS AND FUTURE WORKS

Product design is knowledge-intensive process and involves large quantities of decisions. The efficiency and effectiveness of these decisions depends on the provision of many kinds of related knowledge to designers from different sources throughout the lifecycle. Quality related knowledge is one of the most important knowledge sources.

This work proposes one knowledge discovery approach using DM, which extracts quality-related knowledge from large quantities of MQD generated during the product manufacturing process. To understand what kind of decisions are made and what kind of knowledge these decisions need, decision making during the engineering design process is analyzed and classified into two main categories, namely organizational and technical decisions. Then, this paper analyzed and classified product design knowledge into three categories, namely, product-related, process-related and product support knowledge. To efficiently using quality-related knowledge to support design decisions, a data mining based knowledge discovery approach is proposed. This approach can extract quality related knowledge from large volume of manufacturing quality data.

Some further works need to be investigated in-depth.

(1) Design decision model need to be expressed which could be in the form of mathematical expression. The expression should include the knowledge which is input or output of the decisions.

(2) Knowledge needs of different kinds of decisions during different product design stages should be analyzed in-depth. This work will assist the efficient implementation of the proposed DM based knowledge discovery approach.

(3) The DM approach should be refined. More aspects about steps 1-6 should be taken into account, e.g. the selection criteria of DM methods and DM algorithms, the evaluation criteria, etc.

(4) The successful development of MQD-based DDSS is the key issue to achieve our ultimate objective of supporting product design decisions.

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