AN INTELLIGENT INFORMATION SYSTEM FOR ENABLING PRODUCT MASS CUSTOMIZATION

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Abstract: We propose to develop an intelligent design decision-support system to enable mass customization through product configuration using intelligent computational approaches. The system supports customer-driven product development throughout the product's life cycle and enables rapid assessment and changes of product design in response to changes in customer requirements. The overall system consists of four subsystems: customer requirement analysis subsystem, product configuration subsystem, product lifecycle cost estimation subsystem and product data management subsystem. Various challenging issues for developing the system are investigated, and a number of methodologies and techniques to resolve the issues are presented. The proposed system will allow SMEs to effectively compete with larger companies who command superior resources.

1 INTRODUCTION

Due to the globalization of business, mass customization has become a crucial business strategy for product manufacturers that aims at satisfying individual customer needs with near mass production efficiency (Pine, 1993). It recognizes each customer as an individual and provides each of them with attractive 'tailor-made' features that can only be offered in the pre-industrial craft system. As mass customization allows companies to garner scale of economy through repetition, it is capable of reducing costs and lead time. Hence, mass customization achieves a higher margin and is more advantageous. With the increasing flexibility built into modern manufacturing systems and programmability in computing and communication technologies, companies with low-medium production volumes may attain an edge over competitors by implementing mass customization (Jiao and Tseng, 1999). However, mass customization has presented many difficult challenges to companies. Two major challenges are:

- Product innovation and customization must address increasingly complex customer requirements (Leckner and Lacher, 2003).
- Successful launching of new products relying on complex information spanning a product's life cycle and development of value chain (Newcomb et al., 1996).

In order to implement successful mass customization, companies must develop the necessary infrastructure to satisfy the requirements of time-to-market, variety, and economy of scale along with customer's constraints (Jiao and Tseng, 1999; Lau, 1995; Chung et al., 2005). Many companies fail to realize this customer-driven product development as they lack innovation capability and have limited use of technology tools. The situation becomes more critical for small and medium-size enterprises (SMEs) (Svensson, 2001; Svensson and Barfod, 2002).

To address the above challenging issues, we propose to develop an intelligent design decision-support

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system to enable mass customization through product configuration using intelligent computational approaches. The system supports customer-driven product development throughout the product's life cycle and enables rapid assessment and changes of product design in response to changes in customer requirements. The paper is organized as follows: We review related work in Section 2 and present the architecture and elements of the proposed system in Section 3. In Section 4, we investigate various challenging issues for developing the system, and propose a number of methodologies and techniques to resolve the issues. We conclude the paper in Section 5.

The proposed system will assist companies in accumulating capabilities of quick response to customer preference and rapid development of product design that is "right-the-first-time"; this is a crucial key to successful mass customization. It will also allow SMEs to effectively compete with larger companies who command superior resources.

2 RELATED WORK

Although mass customization presents a new paradigm for the manufacturing industry, it has also received criticism that it is a revolutionary paradigm without a coherent framework (Kotha, 1994). Whilst there is a huge amount of managerial literature on mass customization, it still remains an open issue as to how information systems should be designed and implemented for the realization of mass customization. (Tseng, 1998) addresses the issue of how to implement mass customization with the support of concurrent engineering (CE) where it focuses on developing a mass customization oriented product family architecture and applies machine learning techniques to cluster design parameters according to their ability to satisfy functional requirements. (Jiao et al., 2002) discusses the opportunities and challenges of mass customization for the manufacturing industry and service providers. It also outlined a technological road map for implementing mass customization based on building block identification, product platform development, and product life-cycle integration. (McMahon and Giess, 2005) focuses on the management of product lifecycle management (PLM) data for long term access and related system and management issues are addressed. (Roach et al., 2005) presents a new design system that integrates existing computer design tools and information management tools to produce design variants. The system facilitate companies to develop a mass customization design process. Traditional expert systems have also been adopted to automate the product design (Akagi and Fujita, 2002). However, they are rigid and difficult to apply to mass customization. Compared to past research, our work focuses on practically implementing mass customization with referred product lifecycle cost information using intelligent computational approaches.

3 SYSTEM FRAMEWORK

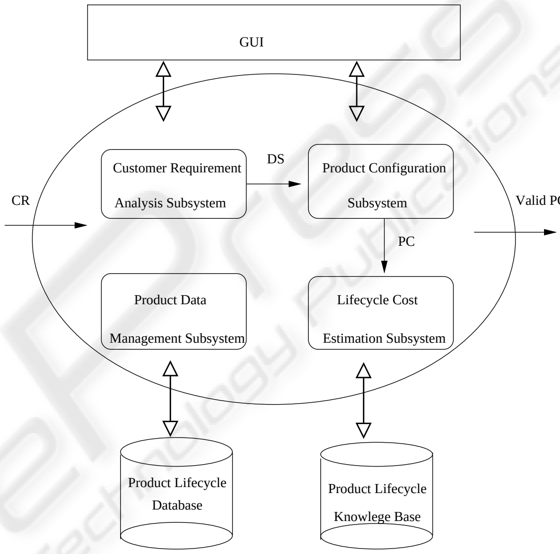

Figure 1: An intelligent system for enabling mass customization.

We propose an intelligent information system as the enabling technology for mass customization. The main feature of the system is its principal role as a supporting facility for manufactures to rapidly develop product variants of a product family in response to customer requirements. The framework of the overall system is depicted in Figure 1. It consists of two major components: An integrated product lifecycle database and an integrated product lifecycle knowledge base, and four subsystems: product data management subsystem, customer requirement analysis subsystem, product configuration subsystem and product lifecycle cost estimation subsystem. These components are further described as follows.

Integrated Product Lifecycle Database (PLD). Product lifecycle data that are conventionally scattered in different departments (and possibly in different companies within a supply chain) are collected and stored into PLD (possibly through a product lifecycle management system) consisting of essentially product family and components data as well as relationships among components, customer requirements, product cost data and other information required by the computation of the system. Figure 2 illustrates the conceptual product family data model linked with various lifecycle data where product components are defined as the basic units that are treated by the lifecycle processes. PLD is highly dynamic and should be sustained along the product lifecycle processes (design, manufacturing, procurement, service, and recycle).

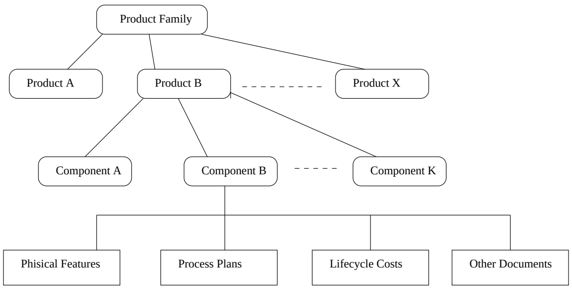

Figure 2: An integrate product lifecycle data model.

Integrated Product Lifecycle Knowledge Base (PLK). PLK is tasked to provide intelligence to the whole system and is employed to store product lifecycle knowledge; specifically for now, the domain specific relationships between customer requirements (CR), design specifications (DS), and product configurations (PC). The knowledge is extracted from PLD and built using self-learning algorithms using the subsystems. The PLK is constantly updated from ever-evolving data in PLD.

Product Data Management Subsystem (PDM). The subsystem provides users with the functionalities of creating, updating, maintaining and viewing information stored in PLD. Among them, the foremost functionality of PDM is to define product families and edit product/component properties within a family. Various formats of data and documents (such as word document, and CAD drawings) should also be viewed through an integrated viewer without calling any external applications.

Customer Requirement Analysis Subsystem (CRA). Generally customers do not have sufficient product expertise. They cannot express their preferences in terms of technical specifications. (Rogoll and Piller, 2002) have shown that there is no standard software solution for designing products that is able to fulfill optimal requirements from customer's perspectives. The CRA subsystem aims to efficiently and effectively capture and understand customer requirements and focuses on transforming the requirements into concrete design specifications from which a successful design can result.

Product Configuration Subsystem (PCS). This subsystem aims to generate qualified product configuration from a given set of design specifications that are produced by CRA. The configuration solution has to produce the list of selected components, the structure and topology of the product (Sabin and Freuder, 1996). PCS should be used throughout the product definition activities in a product's lifecycle; not only in design and development, but also in sales force automation and manufacturing, including supply chain considerations. In order to achieve success in product configuration, product/product family model mentioned in Section 3 has to be constructed to capture product structure knowledge. Product variants can be instantiated from this model.

Different approaches have been adopted to solve the product configuration problem (Blecker et al., 2004; Sabin and Weigel, 1998). Compared to existing product configurators, rather than manually acquiring configuration knowledge, novel techniques are employed by PCS to automatically generate configuration knowledge from existing product configuration data (please see details in Section 4.2).

Product Lifecycle Cost Estimation Subsystem (PLC). The subsystem aims to provide the lifecycle cost (LCC) information of a product configuration at the early design stage. LCC of a product configuration is confined as the total cost of developing, manufacturing, delivering, servicing and recycling or disposing. Table 1 shows the common cost members of PLC (Perera et al., 1999).

Table 1: Cost members of PLC.

Product Lifecycle Stages	Cost Members
Design stage	Engineering design cost Drawing cost Computer processing cost Design modification cost Production preparation cost Management cost
Manufacturing stage	Material cost Facility cost Production cost
Marketing and after-sale stage	Marketing cost Distribution cost Maintenance cost
Disposal and recycling stage	Retrieval cost Disassembly cost Reprocessing cost Landfill cost

Given a set of DS, it is possible for PCS to derive multiple configuration solutions. Hence, taking advantage of PLD, PLC analyzes and evaluates each product configuration elements in accordance with the associated cost calculated based on historical data available from PLD. The cost-effective ones are considered as valid configurations. In order to achieve a satisfactory accuracy, we propose to estimate LCC based on the approach of combining activity based costing (ABC) technique (Emblemsvag, 2003) and intelligent self-learning techniques, such as neural network (Lotfy and Mohamed, 2002), support vector machine (Scholkopf and Smola, 2002), and so on. PLC helps track and analyze the cost of activities associated with each phase of a product's lifecycle. Consequently, visibilities across these activities are increased, their performances improved and the product lifecycle costs reduced.

All the subsystems have their own graphical user interfaces. They operate independently and are transparent to one another, and are interconnected through PLD and PLK. This enables the whole system to be easily maintained and extended.

4 ISSUES AND APPROACHES

In order to build the system framework described in Section 3, we investigate major research issues and propose approaches to resolve them below.

4.1 Automating Transformation of Customer Requirements Into Design Specifications

It is an indispensable task to capture and understand customer requirements and subsequently to transfer them into design specifications for successful product design. The procedure involves a tedious elaboration process enacted between customers, marketers and designer. On the other hand, customer requirements information must be managed throughout the entire product development process, involving such tasks as creating, disseminating, maintaining and verifying requirements. A latest review (Jiao and Chen, 2006) has listed widely used techniques to manage customer requirement information, and suggested a future route of intelligent knowledge management. However, existing techniques still need a lot of human interaction and suffer from a lack of computer-aided automation support.

We propose to apply a combination of association-rule mining and Quality Function Deployment (QFD) approach (Prasad, 1998) in CRA to facilitate the automation of transforming CR into DS. First of all, there is a need to construct standard models to represent CR and DS. CR are linguistic statements, such as "The drill is powerful", etc., while a DS consists of a design metric (with unit), a weighting of importance, and an target value, such as "Maximum speed - 5 - 900rpm" means the maximum speed of the new drill should be 900rpm while the importance of this DS is "5". The instances of CR and DS of a product family are stored in PLD. The standardized definitions provides a base for dynamically deriving the relationships between CR and DS metrics from the historical case as a product design is completed. These mapping relationships are build up as association rules in PLK by a supervised learning algorithm. After DS metrics are identified, we adopt widely-used QFD method to prioritize specification metrics and derive their target values. With complete information provided (including CR, degrees of metrics in satisfying specific customer needs, customer evaluations and benchmarkings of existing products), we can derive the target values of metrics using House of Quality matrix calculation method in QFD.

4.2 Automating Generation of Constraint-based Configuration Knowledge

The core of configuration task is to select and arrange combinations of components which satisfy given design specifications. A number of significant works and results have been produced (Blecker et al., 2004; Sabin and Weigel, 1998), especially the problem solving algorithm in constraint-based configuration, has been greatly enhanced in term of efficiency and accuracy. In this approach, product configuration tasks can be treated as a constraint satisfaction problem (CSPs) (Tseng et al., 2005; Xie et al., 2005). Each component is defined by a set of properties and a set of ports for connecting to other components. Constraints among components restrict the ways various components can be combined to form a valid configuration. The initial requirement specifications and optimization criteria are treated as constraints in the process. The solution is the final configuration that all constraints are fulfilled.

Despite the success of the mentioned approaches, the configuration knowledge acquisition is usually done manually. We propose to adopt a similar association rule mining approach as in Section 4.1 to discover useful patterns between DS and product components, as well as the correlation among product components. An indicator, namely support degree, is used to indicate the probability of exist of the relationship between one specification and one component. The relationship exists when the support degree is larger than the predefined threshold. Existing set of data in PLD which has captured the mapping between the two is used as training data set. These patterns are translated into constraints knowledge and stored into PLK, and used for configuration reasoning in PCS. An example rule can be "if the maximum speed of drill is 900rpm, then the DC motor A1 is selected". Many other rules that we have not been easily aware of can be discovered as the association rules formation through finding out the large item sets by setting the minimum support and confidence thresholds. Finally, a qualified (but may not be cost-effective) PC can be derived. A partial configuration for an instance of a cordless drill family can be: "DC motor (A1) + Housing set (H3) + Gear assay (G9)" where inside brackets are the identifiers of selected component variants.

4.3 Estimation of Lifecycle Cost

It is well known (Dowlatshahi, 1992) that the design of the product influences between 70% and 80% of the total cost of a product. Therefore, design decisions at the early stage of life cycle made by considering lifecycle cost implications may substantially reduce the LCC of the product they design. Either underestimate or overestimate of LCC will lead to financial loss of the company. Three review papers (Niazi et al., 2006; Layer et al., 2002; Asiedu and Gu, 1998) have summarized the existing techniques of estimating LCC using certain criteria. We observed that all techniques are dedicated to particular applications. They are developed either for specific segments in a life cycle, or for specific machining and manufacturing processes, or for specific parts and products, or for specific manufacturing systems. According to (Niazi et al., 2006), one main trend is to apply ABC technique in order to achieve more accurate estimation result.

Recently an ABC based framework has been proposed to calculate the full product lifecycle cost (Xu et al., 2006). However, it is difficult to apply the approach due to the lack of sufficient activity information to conduct a ABC study at the early design stage. We propose to apply the state-of-the-art machine learning techniques and ABC technique together in PLC subsystem depending on information available. When sufficient activity and resource information can be clearly identified to develop a new product variant, ABC approach would be used, and the LCC of a product/component is calculated based on the equation below:

$$LCC = \sum_{i=1}^{n} UR_i \times CAQ_i \tag{1}$$

where n is the total number of lifecycle activities in the product, UR_i is the unit cost rate of the i_{th} activity while CAQ_i is the estimated consumption quantity of the i_{th} activity. Otherwise, intelligent regression algorithms would be employed to predict the LCC based on historical data. We will conduct a benchmarking study on various learning algorithms including regression, artificial neural network, and support vector regression (SVR) on estimating LCC (No existing work using SVR to estimate LCC has been reported). Particularly, we will focus on learning in an on-line setting (Ma et al., 2003) because it refrains from retraining from scratch when each time a new sample is added to the training set. This is mostly desired whenever the LCC of a new product becomes available and the estimation model needs to be updated. To the best of our knowledge, no work has been done on studying the issue. The best on-line learning algorithms would be implemented in a prototype of PLC.

5 CONCLUSION

We propose to develop an intelligent information system to assist enterprises in realize mass customization. Due to its open architecture, the system can be easily deployed with existing enterprise information systems, such as ERP, PLM, and so on. By learning from the accumulated product lifecycle data and employing design knowledge in PLK as well as taking account into the product lifecycle cost, the system is able to rapidly respond to changing customer requirements and efficiently produce right product variants. The system is now its preliminary stage of development. Various learning algorithms are being investigated and a prototype is under implementation. The overall objective of the system benefits enterprises by enable them to accumulate product design and development capability by adopting a product life cycle knowledge-centric approach.

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