CIRP Annals - Manufacturing Technology 57 (2008) 137–140

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: http://ees.elsevier.com/cirp/default.asp

Incorporating probabilistic model of customers' preferences in concurrent engineering

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ARTICLE INFO

Keywords:
Product Design
Concurrent Engineering
Customers' Preferences

ABSTRACT

Concurrent engineering has been generally accepted as an important approach to reduce time to market. For years, the focus of concurrency has been design and manufacturing. With customers' inputs becoming more crucial for product development, incorporating customers' preferences into the design process has become significant in the continuing quest for reducing time to market. Because customers' preferences involve intricate interdependency on factors such as product attributes, deterministic methods often fall short of representing and manipulating their probabilistic nature. This paper presents a probabilistic model that could continuously incorporate and adapt customers' preferences into the concurrent engineering methodology.

1. Introduction

Concurrent engineering has emerged as an important approach to bring processes in product design and manufacturing executed in parallel. It has been widely recognized as a viable strategy for companies to reduce time to market and achieve overall cost savings. The scope of concurrent engineering has been between design and manufacturing. Although the concurrent engineering has made substantial progress in reducing time to market, industry still experiences considerable delays in launching new products. It has been reported that most of the product delays are caused by the changes of specifications [1]. Mistakes in specifying the products or mis-position of the products in the market can be traced to the gaps between product development team and customers expressing their needs. As mentioned by Tseng et al. [2–4], difficulties in communication between customers and designers often lead to convoluted interpretations between customers' needs (CNs) and product specifications.

However, the interaction between customers and product development team differs from the established research results in bridging the gap of design and manufacturing:

- Customers, as a group, are much less defined and usually, they are scattered outside the enterprise. The interactions between product design team and customers have to overcome the difficulties of identifying the right customer group, to prevail over organizational barriers and to transcend the scattered locations.
- It is a common practice that product development team enlists marketing personnel acting as the agent to collect, validate and synthesize requirement information. However, the information transfer from customers to product design team can be problematic. This is often due to marketing person's lack of technical understanding and design expertise. The consequence of information transfer difficulties is very similar to the interface between design and manufacturing. It frequently results in excess cost and long product development lead time.
- Intuitively, if the product development team can directly interact with the appropriate customer base, there will be sufficient gain in information transfer to improve the product development process, particularly in reducing errors in specification definition and delays in product launch. However, in most cases customers are not naturally attuned to interact with the product development. For instance, customers may not have the full knowledge about what can be offered and product constraints such as manufacturability and safety requirements. It may also be difficult for customers to articulate what they want in the context for design team to understand. Furthermore, the procedure of getting customers' specifications directly can often be tedious and time consuming, requiring seemingly redundant or trivial dialogues between the users and designers or design toolkit [5].

In this paper, the objective is to present a foundational mathematical model so that customers' preferences can be captured and accumulated directly into the product development processes. Customers' preferences are often not in deterministic forms. In addition, customers usually express their preferences as conditional to other factors, internal or external to the product design. In fact, the process of acquiring product specification is no longer a traditional process of passively accepting customers' preferences. Instead, a bidirectional preferences information flow becomes more practically acceptable. Considering these facts, the proposed approach applies probabilistic models, Bayesian Network (BN), to document and communicate customers' preferences for different functions such as marketing, sales, design and manufacturing teams to work together. A

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0007-8506/$ – see front matter © 2008 CIRP.
doi:10.1016/j.cirp.2008.03.134

specification-capturing environment is created in which customers can present their needs efficiently by reducing redundant or trivial dialogues between the users and product development team. The conditional probability in Bayesian Network also embodies the product configuration knowledge base to identify infeasible solution as early as possible, propose customized query sequence to adapt to different customers' response and provide guidance to users who have little domain knowledge. As a result, it offers an extension of concurrent engineering to sales and marketing to improve definition of product specification.

2. Probabilistic model of customers' preferences

2.1. The nature of customers' preferences

The research on the nature of customers' preferences has drawn much attention from marketing, economics, psychology, and management science. It studies both the internal factors and the external influences on the customer's preference. Basically, customers' preferences are considered as random variables due to the following findings [6]:

- *Customers are heterogeneous*. Customers differ a lot in terms of their personalities, values and a range of other characteristics. Therefore there is no deterministic model to represent every individual customer's preference.
- *Choice decisions differ*. Even for a given customer, a model that can describe his preference towards one product may not work properly for another product.
- *The context of purchase differs*. Customers vary in their decision-making criterions due to the purchase situation (on-line purchase, in-store selection, etc.), emotional mood, purchasing budget and the user of the product.
- *Customers' preferences towards different product attributes are not independent*. The choice in one attribute often has side effects on others.

However, existing researches mainly concern about the extra-product preferences, i.e., the preferences towards different products. For product design task, it should also take into consideration the intra-product preferences on component/attribute level to identify the suitable product configuration for an individual or a niche market. Thus a unified framework incorporating both the extra-product and intra-product preferences is necessary to meet the needs for concurrent engineering extension.

2.2. Bayesian network representation of the intra-product preference

A Bayesian Network is a directed acyclic graph [7] represented by a triplet (V, A, P) in which:

- V is a variable set which is represented by nodes in the BN. In this paper V is the product attribute/component set.
- A is a set of arcs which connect the nodes. The arcs represent the conditional-dependent relationships among the variables. V and A constitute a directed acyclic graph $G = (V, A)$.
- P is a conditional probability set. $P = \{P(X|\text{parent}(X)): X \in V\}$. Here parent($X$) is the set of predecessor nodes of X. P quantifies the effect of the parents on the children.

During the product development stage, product knowledge is often sparse; the Bayesian Network can be built from data accumulated in the interaction with customers [8]. To represent customers' preferences towards the components/attributes within a product, we need firstly identify some key components that are crucial to implement the basic functions in the design domains. For example, an audio card is important for a PC with audio processing purpose. These key components are used as root nodes. Then the components which root nodes influence directly are added and links are drawn to reveal the dependent relationship and so on, until we reach the leaves which have no direct causal influence on other variables [7]. The conditional probabilities associated with the nodes in the network can be calculated by

$$P(N_i = v_{ik}|\Pi_{N_i} = w_{ij}) = \frac{N_{ijk} + 1}{N_{ij} + r_i} \tag{1}$$

where v_{ik} is a value of variable N_i, w_{ij} is an instantiation of the parent set Π_{N_i}, r_i is the number of different values of variable N_i, N_{ijk} is the number of cases with variable N_i having the value v_{ik}, and Π_{N_i} is instantiated as w_{ij} with $N_{ij} = \sum_k N_{ijk}$. The conditional probabilities can be updated once new data are acquired. They are actually the compromise between the knowledge discovered from the data and the prior belief about the probability distribution of customers' potential likelihood towards different components. We assume the prior probability uniformly distributed, i.e., if $N_{ijk} = N_{ij} = 0$:

$$P(N_i = v_{ik}|\Pi_{N_i} = w_{ij}) = \frac{N_{ijk} + 1}{N_{ij} + r_i} = \frac{1}{r_i} \tag{2}$$

When sufficient data are obtained, the knowledge discovered from data will dominate the prior belief because if N_{ijk} and N_{ij} are large enough:

$$P(N_i = v_{ik}|\Pi_{N_i} = w_{ij}) = \frac{N_{ijk} + 1}{N_{ij} + r_i} \approx \frac{N_{ijk}}{N_{ij}} \tag{3}$$

Some other parameters setting criteria can also be used to indicate the prior belief about the probability distribution.

It should also be noted that product physical constraints can fit perfectly into the BN if they are considered as degenerated intra-product preferences. For example, $P(B = b_1|A = a_1) = 0$ means that b_1 and a_1 are not compatible physically. Similarly, $P(B = b_1|A = a_1) = 1$ stands for that the selection of a_1 will surely result in the selection of b_1 due to the physical constraints. Thus by using the Boolean conditional probabilities to represent products' physical constraints, the manufacturability knowledge is also encoded into the Bayesian Network.

3. Specification defining by utilizing preference model

Based on the Axiomatic Design [9], the design methodology consists of four clearly defined domains which are characterized by customer needs (CNs), functional requirements (FRs), design parameters (DPs) and process variables (PVs). The specification definition is the process of capturing and transforming CNs into a representation that designers can follow [10]. In cases that customers are not familiar with the domain knowledge, explicit linkage among CNs, FRs and DPs may not be feasible. Customers may describe what they want in an ambiguous language such as strong engine for a sport car. On the other hand, for the same product (a set of defined DPs), the Bayesian Network may vary a lot because of different sets of CNs. For example, the components' dependent relationship of a graphical workstation differs from that of a scientific computation server. Therefore, the top down zigzag mapping process of Axiomatic Design should be followed for specification definition task.

3.1. Acquisition of preliminary preferences

In this phase, the probe queries are proposed to help customers select the best suitable product model. The main concern is that customers may not possess a clear idea about detailed product attributes to meet their needs because of the limitation of professional knowledge. Here, a process of elimination is designed to narrow configuration sets which are outside of customers' preferences. The maximum a posteriori (MAP) approach is used to select the customer's desired product segmentation [11], i.e.:

$$h_{\text{MAP}} = \arg\max_{h \in H} P(h|E) = \arg\max_{h \in H} \frac{P(E|h)P(h)}{P(E)} = \arg\max_{h \in H} P(E|h)P(h) \tag{4}$$