A RECOMMENDATION BASED FRAMEWORK FOR ONLINE PRODUCT CONFIGURATION

Nikos Karacapilidis
IMIS Lab, MEAD, University of Patras, 26500 Rio Patras, Greece

Thomas Leckner
Institut für Informatik, Technische Universität München, Boltzmannstr. 3, D-85748 Garching, Germany

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Abstract: Adopting a mass customization strategy, enterprises often enable customers to specify their individual product wishes by using web based configurator tools. With such tools, customers can interactively and virtually create their own instance of a product. However, customers are not usually supported in a comprehensive way during the configuration process, thus facing problems such as complexity, uncertainty, and lack of knowledge. To address the above issue, this paper presents a framework that aids customers in selecting and specifying individualized products by exploiting recommendations. Having first focused on the characteristics of configurator tools and the principles of model-based configuration, we then introduce the concept of masks for product models. The main contribution of this paper is the proposal of an integrated approach for supporting model-based product configurator tools by similarity-based recommendations. Our approach in providing recommendations has been based on the widely accepted theory of Fuzzy Sets and its associated concept of similarity measures, while recommendations provided are based on the processes of stereotype definitions and dynamic customer clustering.

1 INTRODUCTION

Mass customization, as a business strategy, aims at aiding companies to react to the growing individualization of demand, by giving them a more customer-centric role (Piller, 2001; Pine, 1993). At the same time, it aims at providing individualized products at a price which is close to that of standardized products. The adoption of such a strategy is admittedly associated with the need for major changes in various perspectives, such as product design and manufacturing, technology and innovation management, marketing, logistics, and information management.

On the other hand, there are also problems in supporting the customer to express his wish for an individual product. The customer should easily become aware of a product's "degrees of freedom", while he needs tools that enable him to translate his product wish to an instance of a predefined product family. Compared to custom-made products, companies cannot afford to offer professional consultants to help the customer in the above process. To address the above issues, there is a trend for developing and deploying online configurator tools that support customers to go through an interactive and virtual individualization of a product by using an internet browser. However, configurator tools demonstrate a series of shortcomings such as confusion, frustration and uncertainty that often push customers towards the dropping out of the configuration process.

To overcome such problems and efficiently support a customer during the process of configuring a product, the approach discussed in this paper builds on the integration of configuration and recommendation features. Recommendations are based on predefined stereotypes that best match the individual customer's profile. The remainder of the paper is structured as follows: Section 2 comments in detail on the functionality and the limitations of configurator tools. The representation of a product's model and the underlying configuration and recommendation issues are described in Section 3. The proposed framework and its associated processes are then comprehensively discussed in Section 4. Finally, Section 5 outlines final remarks and future work directions.

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2 CONFIGURATOR TOOLS

2.1 Basic functionality

Online configurator tools provide the essential means for supporting mass customization, by enabling a customer to virtually assemble a product according to his individual needs and preferences (Sabin and Weigel, 1998). Well-known examples of such tools can be found in the homepages of big automakers and computer vendors. Usually, a configurator tool is built around a specific form of product model. Therefore, one of the most fundamental functionalities of a configurator tool is to manage and represent the underlying product and configuration models (Tiihonen and Soininen, 1997). The product model represents the product's physical and logical structure, which usually has been predefined by the manufacturer. On the other hand, the configuration model represents the customer's current instance of the product model, which is shaped upon the customer's selections and restrictions.

Another basic functionality of a configurator tool is to provide customers with an overview of the available "degrees of freedom" and, more important, to enable customers to manually configure and manipulate them. Moreover, configurator tools often integrate mechanisms for checking the correctness of a configuration model. These mechanisms exploit methods and algorithms originally coming from the Artificial Intelligence discipline to deal with problems such as constraint checking and constraint satisfaction (Felfernig *et al.*, 2001).

2.2 Enhanced functionality

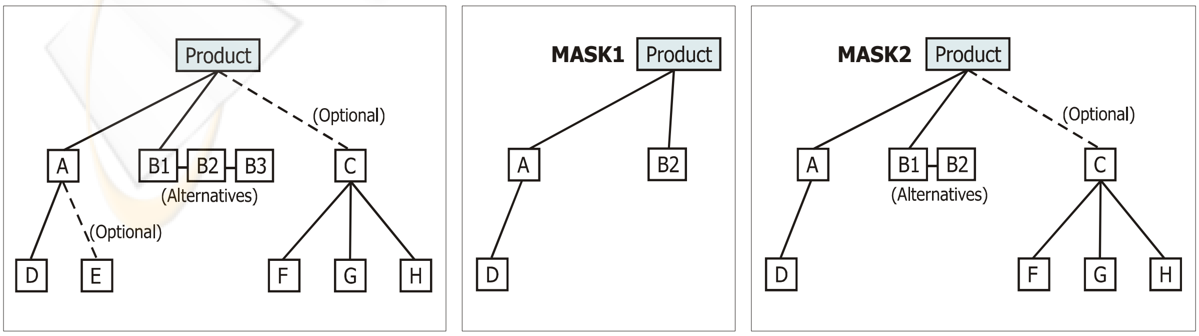
In addition to the above fundamental functionalities, there are tools that demonstrate some more advanced features. More specifically, a configurator tool may provide access to a database of previously configured products and components via different catalogue systems. For instance, such a database may include *participatory catalogues* (Schubert, 2000) that are enriched with ratings and/or comments of other customers and can be filtered by special orders (e.g., according to the name of the customer, the average rating of certain groups etc.). In such a way, the customer gets access to the collective knowledge of the community of customers and can take into account their opinions and experiences for the individual decision making (Leckner, 2003).

It might be also possible that the configurator tool assists the customer during the process of configuration on the basis of the product model. This means that the customer makes the main decisions, while the system propagates their consequences and somehow "explains" the product model to the customer (Inakoshi *et al.*, 2001). Further automation of the configuration process is also possible by such approaches, where the customer makes only some basic decisions and the system configures the rest of the product automatically (Ardissono *et al.*, 2001).

Configurator tools may also provide recommendations to the customers in an active manner. To give an example, this can be performed through personalised defaults for the product's degrees of freedom or through restricted product models (see Section 3.3). Different approaches for the creation of such recommendations have been proposed in the literature, which address the issue independently or in a hybrid mode, combining more than one of such methods (Renneberg and Borghoff, 2003). Personalized recommendations are always based on further information about the customer, which is stored in the customer's user profile.

2.3 Limitations

Configurator tools allow the specification of form, fit, function and modalities of a product (Leckner, 2003). In the ideal case, the customer can enter directly the above specification into the company's information system. However, configurator tools demonstrate some limitations and shortcomings. First of all, the manual configuration of a product usually takes a lot of time and effort from the customer, especially if the product is complex. This is the case with products characterized by multiple degrees of freedom, which is a very likely scenario in the contemporary marketplaces and mass customization



(a) (b) (c)

Figure 1: Masks for alternative and optional components

initiatives.

Another problem with configurator tools is that even if the customer is willing to spend enough time, he often lacks the know-how and experience in using the tool and properly configure the product according to his individual preferences and needs. Even worse, assuming that the customer has enough time, know-how and experience, he often does not exactly know what he wants. This is a general problem with such tools, since the customer is about to configure something complete new, which he cannot see, feel or test until he buys it. For the above reasons, the process of virtually configuring a product often leads to confusion, frustration, uncertainty and, consequently to the abandonment of the configuration process (Huffman and Kahn, 1998; Piller *et al.*, 2003).

To overcome these problems, customers should be supported in a more efficient and effective way during the process of configuring a product. An approach to overcome the customer's confusion and uncertainty builds around the concept of virtual communities, where customers support each other during the overall process (Rheingold, 1998; Leckner, 2003). This approach is further motivated by the fact that individual decisions often depend on decisions made by others (Wind *et al.*, 2001). Another approach to be exploited concerns provision for recommendations that help the customer shape his decision in an automatic way. In some respects, such recommender systems also exploit Artificial Intelligence techniques. Section 4 is particularly devoted to such recommendations, the aim being to overcome the customer's uncertainty, confusion and frustration.

3 PRODUCT MODEL

3.1 Representation of the product

The backbone of every configurator tool is the underlying product model, which represents the product's physical and logical structure. Additionally, such a model defines the associated degrees of freedom, which are actually the product's elements that can be directly modified by the customer. Representative examples are the attributes of a product as well as its alternative and optional components. Every degree of freedom can have a range of valid values and a default value. Moreover, certain restrictions and interdependencies between different degrees of freedom are possible (Männistö *et al.*, 2001). In the ideal case, the product model contains all the product-related "knowledge" about the product, while the configurator tool can provide this knowledge in an appropriate way to the customer (Tiihonen *et al.*, 1998).

The product model is initially defined by professional product designers of the manufacturer. We assume that every physical product consists of a set of components, the connected structure of which can be described by a component-tree. Each component can in turn consist of a set of components and/or a set of attributes. Attributes can be based on various data types. For example, attributes of numeric interval type are defined by an upper boundary, a lower boundary and a default value. The configuration model derives from the product model by incorporating the customer's selections regarding the associated degrees of freedom.

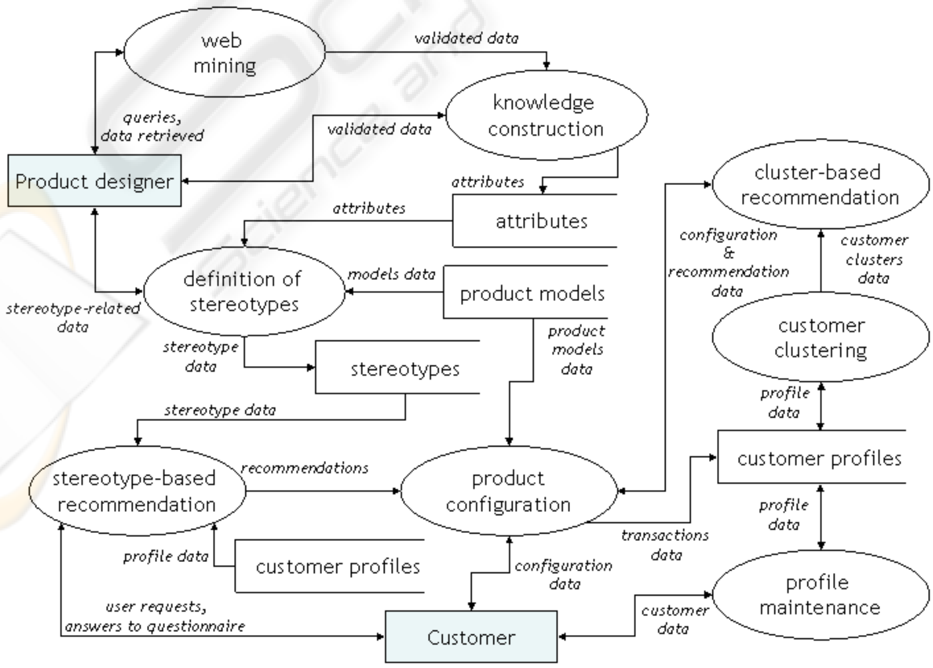


Figure 2: The data flow diagram of our approach.

3.2 Restricted product model

Although the idea of model-based product development is not new (Anderl and Trippner 2000; Felfernig *et al.*, 2001), special requirements have to be taken into account when enabling the customer to configure his individual product. On the one hand, the product model should not be too complex, so that the customer can understand and manipulate it. On the other hand, the product model must not be too simple; otherwise, the customer has not enough possibilities to express his individual product wishes and preferences. In the ideal case, every customer will get a personalized version of the product model, which is restricted in accordance to the customer's individual needs and interests.

This idea leads to the concept of *masks* for product models, which is comprehensively described in (Leckner and Lacher, 2003). Figure 1(a) depicts a specific component-based product model in its entirety, whereas Figures 1(b) and 1(c) two valid masks of it (MASK1 and MASK2, respectively). As shown, we follow a tree-like representation of a product model. The degrees of freedom of MASK1 and MASK2 are obviously smaller than that of in the original product model. We should note here that each component of the model is associated with a set of attributes, which may in turn impose additional degrees of freedom. Finally, one can easily understand that some masks correspond to a completed product configuration where no alternative or optional components exist (e.g., MASK1), while others need further manipulation by the customer (e.g., MASK2).

Another easily conceivable example for the usage of masks on product models can be given through a product's attribute of numeric interval type. Let the possible values for the power of an engine be constrained to the interval [40...300 kW] in the product model. However, restrictions imposed for a specific user may result in possible values within the interval [110...200 kW]. The restrictions for another user may result in a different interval, say [80…130 kW]. In addition, the default value of this attribute can be also personalized according to the specific customer.

Such a restricted product model can be seen as a type of recommendation. Another type of recommendation is to personalize the selected values of each degree of freedom in accordance to the customer's user profile. Restricted product models together with personalized selected values also can be predefined by the manufacturer to satisfy certain stereotypes of customers with adequate product models. Concepts for assigning customers to a certain stereotype and ideas about defining such stereotypes dynamically are discussed in the following section.

4 THE OVERALL FRAMEWORK

Our approach (see Figure 2) maintains a detailed profile for each customer. Such profiles contain information about the customer's basic and demographic attributes, general interests and life style, specific product interests and buying history. Some pieces of such information are gathered when the customer uses the proposed system for the first time, through a specially constructed questionnaire, while others through the customer's interaction with it. Moreover, based on predefined rules, the company maintains a set of *stereotypes*, which are basically based on attributes related to the profession, general interests and life style of the customers.

Stereotypes are associated with the product models stored in the company's database and are used to restrict their degrees of freedom (they are actually associated with predefined product model masks). An example illustrating the definition of two such stereotypes, namely "engineer" and "lawyer", is given below.

```
public String stereotype(UserProfile customer) {
   String job=customer.basic.business.jobtitle;

     // definition of stereotype "engineer"

   if ((job=="engineer") or (job=="mechanist")
      or (job=="electrician") or (job=="designer")
      or (job=="natural scientist")
      or (customer.interest.computers>70))
   return "engineer";

     // definition of stereotype "lawyer"

   if ((job=="lawyer") or (job=="magistrate")
      or (job=="judge") or (job=="tax inspector")
      or (customer.interest.computers<30))
   return "lawyer";
   ...
}

     // assign stereotype to product model

switch (stereotype(customer)) {
  case "engineer": ProductModel=MASK1; break;
  case "lawyer": ProductModel=MASK2; break2;
  ...
}
```

As shown, our approach uses a set of rules that are initiated upon the customer's profile information (information about one's profession and interest in computers is only used in this example). The second part of the above example corresponds to the association of masks (like those shown in Figure 1) to the two previously defined stereotypes.

4.1 Stereotype-based recommendations

To aid customers better configure a product, our approach exploits the concept of fuzzy similarity measures to decide how close a customer is to a predefined stereotype. Based on the results of this procedure, the system recommends to the customer the product mask(s) that is (are) associated to the stereotype the customer is more close.

More specifically, each stereotype defined by the company corresponds to a fuzzy set A that is structured according to the scores assigned for each individual customer's attribute considered. To more realistically decide about the attributes to be considered and the scores to be assigned, the company may go through appropriate web mining and knowledge construction processes (Cho *et al.*, 2002; Nahm and Mooney, 2002). While of much importance, such processes are out of the scope of this paper. Instead, we concentrate on the process of associating a predefined stereotype to a specific customer.

Each time a customer uses the system, our framework extracts information from his profile to construct a fuzzy set B, which also encapsulates the scores assigned to the attributes under consideration (i.e., the attributes used for the definition of stereotypes). In fact, these scores express the magnitude in which a customer is interested in or attracted by the set of attributes F_i that characterize each product O_j.

To give an example, the choices offered to the user can be in the set {minimal interest, less interest, neutral, much interest, extensive interest}, where each choice is associated to a value in the interval [0.2 … 1.0] (alternative ratings, following different granularity levels, may be also applied). The above fuzzy set is associated with the specific user and is stored in the system's database.

The next step concerns the comparison of a specific customer's set B with each of the predefined, stereotype-based fuzzy sets A. To do this, our approach uses the *similarity measure* $Q_{A,B}$ that is based on the difference of grades of membership and the volume of the two fuzzy sets. The $Q_{A,B}$ similarity measure was selected among various fuzzy sets similarity measures (Wang, 1997), after evaluating their properties. $Q_{A,B}$ was the only one which was a *proximity measure* (a normalization of the attributes' ranges and/or values allowed is required when applying this measure). In fuzzy sets theory, a similarity measure is called a proximity measure when it stands: $Q_{A,B} = Q_{A^\wedge, B^\wedge}$ where $A^\wedge$ and $B^\wedge$ are the supplements of A and B, respectively. Using this proximity measure, we can efficiently consider the influence of both high and low similarity. It is:

$$Q_{A,B} = \{\sum_{i=1}^{n}[1 - abs(A(i) - B(i))]\}/n \qquad (1)$$

where $A(i)$ is the score of attribute i stored in the database (that is, the one that corresponds to the stereotype), $B(i)$ the score of the same attribute that is given by the user, and n the total number of attributes for a stereotype. The results of this process are temporarily stored in a table containing the score (similarity) of each stored stereotype against the user's preferences. In the sequel, the best N results and their associated scores are retrieved (number N is defined by the user).

In other words, our approach provides the N most similar stereotypes to the description given by the user. Our framework may also provide another round of recommendations, by classifying the N retrieved best stereotypes according to each individual attribute. As a result, the customer is informed about which of the N stereotypes performs better according to each attribute and may get motivated for further contemplation. It should be noted here that at this stage the customer may have still to decide about the alternative or optional parts of a product mask.

4.2 Customer clustering-based recommendations

To further aid customers configuring a product, our approach also provides them with the ability to retrieve recommendations based on data extracted through the process of customers clustering (see Figure 2). Upon the users' wish, the system is able to further help them in making up their mind, by retrieving and providing information regarding products already bought by customers with similar profiles. The results provided here are restricted to products of the same category. As in stereotype-based recommendations, the similarity measure described in Equation (1) is applied here to retrieve similar customers.

5 CONCLUSION

The main contribution of this paper is the proposal of an integrated framework for supporting model-based product configurator tools by similarity-based recommendations. We have first highlighted issues involved in the process of creating personalized recommendations to support customers virtually specifying products with a configurator tool. We then discussed basic functionalities and shortcoming of existing configurator tools, and we introduced a set of product modelling aspects. Our approach in providing recommendations has been based on the widely accepted theory of Fuzzy Sets and its associated concept of similarity measures, while recommendations provided are based on the processes of stereotype definitions and dynamic customer clustering.

Future work directions concern the complete integration of the proposed recommendation methods in our already implemented product configuration system. In addition, we intend to incorporate the concept of fuzzy similarity measures into the filtering pipeline (for more details on this issue, see (Stegmann *et al.*, 2003)). Other important issues to be explored in the future concern the development and deployment of innovative methods for customer profile acquisition (based on methods of natural language processing) and the enhancement of model-based configurator tools by community functionalities (Leckner, 2003). The ultimate aim of our overall research effort is to more efficiently support the customer during the process of configuring a product, thus enabling him to make rational choices that - as much as possible - express his wishes and interests.

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