Adaptive Constraint and Rule-Based Product Bundling in Enterprise Networks

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***Abstract*— Product bundling refers to the combination of several products for sale as one product. Current bundling approaches lack the ability to adapt, focusing mostly on the creation of pre-computed static bundles, which prove to be inefficient considering the dynamically changing prospective customer needs and product availability, as is particularly the case in enterprise networks. This paper describes a novel approach for dynamic generation of personalized, constrained and rule-based product bundles in such environments. The proposed agent-based approach involves estimation of substitution and complementarity associations between products and constructing bundles according to individual customer preferences. The process adapts automatically to changing circumstances, such as customer profile, product availability and constraint and rule diversity. The proposed approach is discussed in the context of e-Furniture, an agent-based system supporting networking of furniture and wood product manufacturing enterprises.**

***Index Terms*—Adaptive product bundling, constraint-based bundling, rule-based product bundling, enterprise networks.**

I. INTRODUCTION

Bundling is a marketing strategy involving constructing and offering combinations of products or services that are expected to be of interest to customers [1]. Product bundling can offer many opportunities both to potential customers and to businesses, such as reducing logistics, packaging, and transaction costs, increasing sales and market share, and improving customer service, all of which could eventually lead to increased profitability [2]. For example, common bundling applications in daily life include bundling of vacation packages, software services, insurance packages, and telecommunication packages [3]. In the general case, a bundle is not restricted to contain products originating from only one supplier, but it is quite common to combine products from different suppliers whose availability and price varies dynamically, as is often the case in enterprise networks [4]. For example, it is common for shippers in logistics networks to collaborate and combine their shipment requests in order to negotiate better rates. As another example in the food industry businesses often combine products in bundles, such as organic cold meat and wines, in order to increase their sales.

The search for optimal product bundles is a complex and dynamic process which requires the combination of products in bundles in a way to satisfy varying consumer needs and preferences, achieve supplier objectives and maximize product compliance [5]. The complexity and dynamism is further increased when bundling extends to enterprise networks due to the large number and dynamic availability of heterogeneous product items and bundling criteria. Zanker et al. in [6] present product and service bundling as a defined configuration problem [7], where the artefact being designed is assembled from a set of pre-defined components, which in our case are represented by product categories. However, to define the most suitable combination of products additional knowledge is needed [6]. Such knowledge can be explicitly obtained through bundling rules and constraints. In this way, one can define product combinations that are either allowed or restricted. For example, a sofa should be combined with an armchair and a mobile phone with headphones.

In this paper we extend ideas from our previous work [8] on the adaptive generation of personalized product bundles by introducing constraints and rules in the bundling process. The main contribution of this paper is the joint use of constraints and rules enabling user preferences to be considered in finding the optimal product bundles through a dynamically adaptive process. The remainder of this paper is structured as follows: in Section II we provide the necessary background and link this paper to our previous work on bundling, while in section III we describe our approach which considers rules and constraints in bundling. In section IV we describe an exemplar bundling scenario and we discuss implementation issues and in section V we discuss relevant work. Finally, in section VII we conclude our work and we discuss our future research plans.

II. BACKGROUND

The e-Furniture system [8, 9] is an agent-based infrastructure developed in order to support ‘smart’ collaboration in furniture and wood product enterprise networks. e-Furniture covers both B2B transactions and B2C transactions and the main innovation of the system is its capability of bundling products and services taking into account individual requirements of both manufacturers and customers.

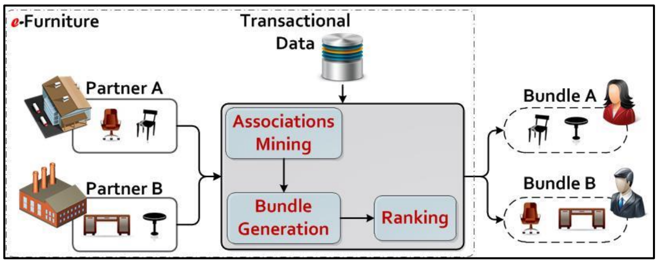

Fig. 1. Personalized product bundling in e-Furniture

Bundling products of different providers is a key technique for SME's to increase their range of offered products and hence increase customer satisfaction. In the case of smart business networks in particular, product bundles can be created dynamically according to customer requirements and the solutions offered by the partners in the business network.

Figure 1 illustrates the dynamic product bundling process in e-Furniture, which is achieved through the estimation of substitution and complementarity associations between products using associations mining techniques as proposed in [8]. Substitution associations reflect the degree to which two products are similar and can substitute each other, while complementarity associations reflect the degree to which an item enhances the purchasing possibility of another. Substitution associations can be obtained by applying similarity measures ([10, 11]) while complementarity associations can be extracted by applying rule mining techniques ([12, 13]) on transactional data. Thus, each bundle consists of a primary product, which can either be the item selected by the user or a substitute item defined by substitution associations, and additional complementary products defined by complementarity associations. The created bundles are then ranked according to the affinity index, which is a measure of the degree of a customer preferring a particular product combination.

However, the research area of networked enterprises represents a complex, large scale and multidisciplinary domain, involving distributed, heterogeneous, and autonomous entities [14, 15]. To adaptively generate product bundles in such dynamic environments, individual requirements of both manufacturers and customers need to be considered in the bundling process. Such requirements can be explicitly provided through constraints and bundling rules. Therefore, domain experts and customers are able to directly define their preferences to the system. For example, a customer may be interested only for chairs under a specific price or an expert could define that sofas should only be combined in a bundle with armchairs.

III. CONSTRAINT-BASED ADAPTIVE PRODUCT BUNDLING

Adaptation is a very important aspect of the bundling process of e-Furniture system. The bundles should not only be able to be personalized to customer preferences, but also to adapt dynamically and in real-time to changes, that may be imposed by customer historical data, product availability and diversity of bundling constraints and rules. In our approach we propose to address these issues by formalizing bundling constraints and rules and incorporating constraint and rule resolution in the bundling process.

A. Constraint Problem Solving

Constraint Satisfaction Problems (CSPs) appear in many areas, such as resource allocation in scheduling and temporal reasoning. Tsang in [16] define a CSP by a tuple $P = \{X, D, C\}$, where $X = \{x_1, x_2, \dots, x_n\}$ is a finite set of variables, each associated with a domain of discrete values $D = \{d_1, d_2, \dots, d_n\}$ and $C = \{c_1, c_2, \dots, c_n\}$ a set of constraints.

Each variable x_i can take on the values from its non-empty domain d_i. A constraint c_j further restricts the valid assignments within a set of variables. For each partial value assignment to variables it is possible to determine if a constraint has been violated or not. In addition, all constraints $c_j \in C$ are defined to be either *hard* ($c_j \in C_{hard}$) or *soft* ($c_j \in C_{soft}$), where $C = C_{hard} \cup C_{soft}$ and $C_{hard} \cap C_{soft}$. Soft constraints may be violated by variable assignments if such violations are required to obtain a solution. Each violation is typically associated with a penalty value, the sum of which is minimized for an optimal solution.

B. Constraint and Rule-based Product Bundling

Based on the above formal description of CSPs, our domain problem can be specified as follows:

1) Variables

- Let X be a set of variables divided in subsets such that $X = X_{CU} \cup X_{PR} \cup X_{CP} \cup X_{PP}$.
- Let $X_{CU} = \{cu_1, \dots, cu_n\}$ be a set of variables representing the users of the system.
- Let $X_{PR} = \{pr_1, \dots, pr_m\}$ be a set of variables representing the products of the system.
- Let $X_{CP} = \{cp_1, \dots, cp_k\}$ be a set of variables representing customer properties, which include customer historical and demographical data.
- Let $X_{PP} = \{pp_1, \dots, pp_l\}$ be the set of variables representing product properties. Product properties include product characteristics such as price, color, material etc. Each product pr_m has multiple properties from the subset X_{PP}.

2) Domains

- A set of domains $D = \{d_1, \dots, d_j\}$ represents the different product categories and companies of the enterprise network. Each product pr_m may belong to multiple domains d_j.

3) Constraints

- A set of constraints $C = C_{PR} \cup C_{CP} \cup C_{PP} \cup C_D$ consists of subsets representing application of constraints in the different variables and domains.
- $C_{PR} = \{cpr_1, \dots, cpr_i\}$ represent the constraints applied at the product level.
- $C_{CP} = \{ccp_1, \dots, ccp_h\}$ represent the constraints applied at the customer properties level.

- $C_{PP} = \{cpp_1, \ldots, cpp_q\}$ represent the constraints applied at the product properties level.
- $C_D = \{cd_1, \ldots, cd_t\}$ represent the constraints applied at the domain level.

4) Bundling Rules

Rule-based techniques exploit a set of rules specified in the system in order to drive the product bundling process. Rules are declarative and are typically defined by a system author based on information provided by an expert in the knowledge domain pertaining to the e-commerce site in question [17]. Rules can be added to the system to perform dynamic incremental modification of the product data, based upon the product information and information about the user. One of the most important advantages of the implementation of rules is that the system can be easily customized at runtime, without having to modify and recompile the Java code [18].

Rules are defined in the form of “If <condition> then <consequent> restrictions” [19], identifying functional dependencies between user requirements and product properties. For example, if a customer spends a certain amount of money in a single order, then a discount coupon should be offered to him/her.

C. Product Bundling Process

The information flow of the dynamically adaptive product bundling process is depicted in the diagram of Fig. 2. The process begins with the user input, which can be an item that the user selected to view. Using product information and customer historical transactions substitution and complementarity associations between products are calculated as in [8]. In addition, user and administrator defined criteria in the form of constraints and rules are used to lead the association mining process. For example, the administrator could have defined that for a selected item from the category ‘sofas’, substitution associations should be extracted only for items that fell in the same category. In the same way, a user could have defined that he/she is only interested in sofas that are below a certain price threshold. The generated associations are stored in an associations dataset, which is then used for bundle generation along with the respective constraints and rules. For example, the generated bundles should, not exceed a certain combined price. Therefore, a list of candidate bundles is created and is forwarded for personalization or ranking according to customer implicit preferences. In order to rank the candidate bundles the customer’s personal profile information are used. Constraints and rules also apply to this step of the process in order to produce the final bundle recommendation list. An example of such a rule is ‘if a customer has already purchased one of the items that are included in a bundle, then the bundle should be rejected’.

The proposed process is dynamically adaptive to the environmental input. Therefore, each time a new constraint or bundling rule enters the system, the recommended bundle list is automatically updated in order to reflect the current preferences.

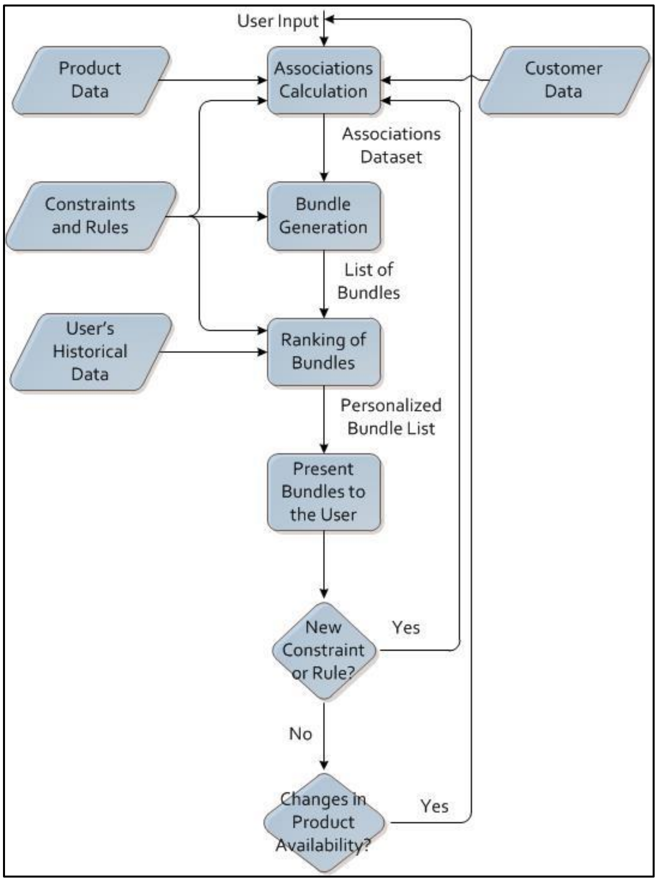

Fig. 2. Information flow within the adaptive bundling process

D. Multi-Agent Architecture

The multi agent architecture for dynamic product bundling consists of five basic agent types as illustrated in Fig. 3. Product information and customer profiles are stored in a product and a customer history database respectively. In addition, the system has a constraints and a rules repository, which contain user defined constraints and bundling rules respectively. Both constraints and bundling rules are involved in all the discrete phases of the adaptive personalized bundling process (associations mining, bundle generation, ranking) as described in the previous paragraph.

Specifically, the user agents (UA) implement the user interface both for customers and administrators. The management agent (MA) is responsible for the management of the constraints and rules through the Drools Business Logic Integration Platform [20]. Drools is a business rules management system and reasoning engine for business policy and rules development, access, and change management. In addition, Drools allows the implementation of constraints as score rules. Rules can be defined using the drools rule language or as XML data. The associations mining agent (AMA) is responsible for the generation of substitution and complementarity associations between products by executing associations mining algorithms [8] using the users’ historical data, product information, constraints and rules. The bundle generation agent (BGA)

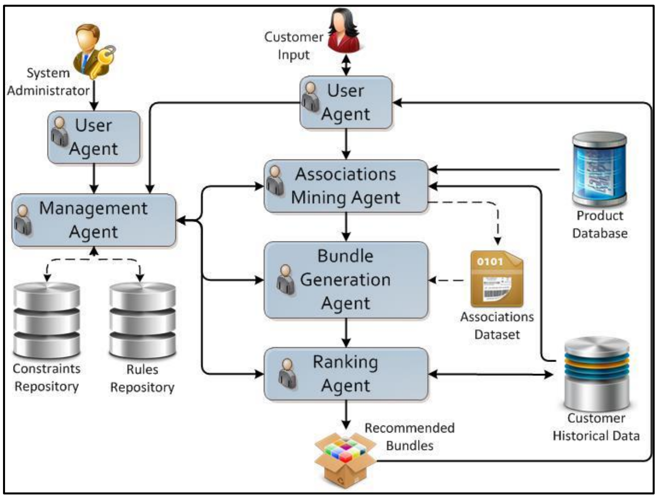

Fig. 3. Adaptive constraint and rule-based product bundling architecture

then by using the associations, the constraints and the rules generates a list of candidate bundle. Last but not least, the ranking agent personalizes the list of bundles using the customer's profile and the appropriate constraints and rules.

IV. An Exemplar Bundling Scenario

Let us consider a scenario where customer A visits the e-furniture web-based application searching for a sofa. The web interface gives him the opportunity to narrow down his search by selecting pre-defined criteria, such as preferred price range, colour, pattern, material and manufacturer. By providing these constraints, a more personalized search list can be provided to customer A. Thus, customer A decides to refine the search by defining the maximum price at 700 euro. Therefore, the system returns initially a list of all sofas under 700 euros. From the provided list he selects sofa D from manufacturer A in order to view more information. By exploiting this information, the system automatically creates a personalized list of bundles.

Specifically, using the user defined constraint 'maximum price' lists of substitute and complementary items are extracted through substitution and complementarity associations respectively. Table I shows the list of substitute and complementary items. System administrators define constraints and bundling rules that apply to the bundling process through the graphical user interface shown in Fig. 5, such as 'the items of a bundle should have the same frame material' and 'manufacturer A wants to bundle his products only with manufacturer C'. Therefore, a list of candidate bundles is generated as shown in the second column of Table II. After the ranking of the generated bundles, the list of the proposed bundles to customer A is configured as shown in the third column of Table II. Finally, after the constraints applied to that phase of the process ('show only the two highest rated bundles'), only the first two bundles of the proposed list are presented to the customer.

The proposed system is also able to automatically adapt to changes imposed by the environment. Thus, when the user defines a new constraint by selecting 'white' as the preferred colour, the bundling process dynamically adapts to the respective changes, as shown in the fourth column of Table I. The proposed bundles are modified accordingly (see fourth column of Table II) and, after ranking, the final proposals to the user are the two first bundles, as shown in the fifth column of Table II.

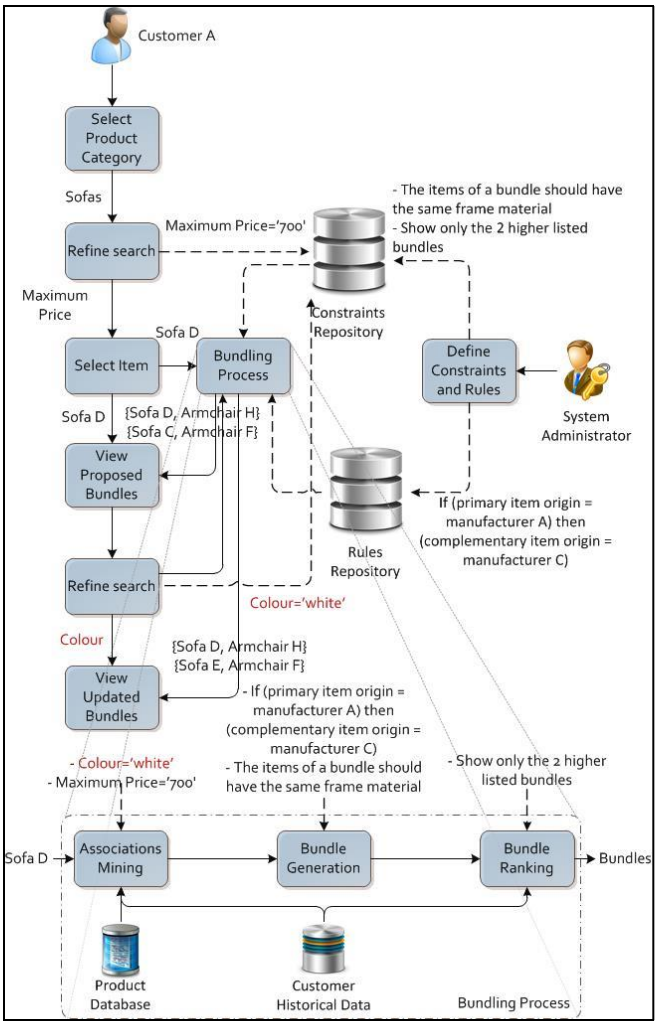

Fig. 4. Adaptive bundling scenario using user defined constraints and rules

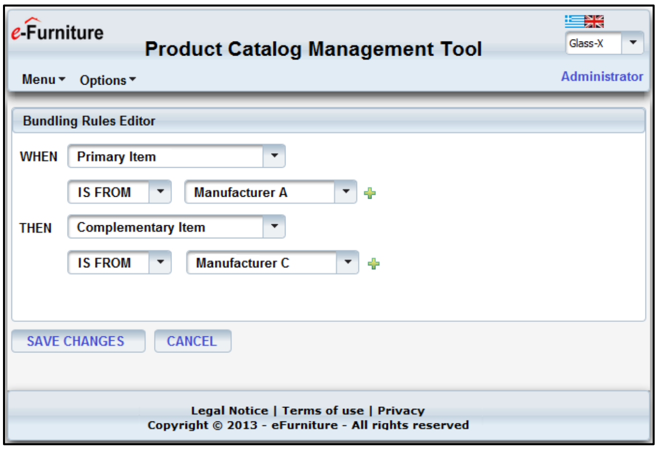

Fig. 5. User interface for generation of bundling rules

TABLE I. SUBSTITUTE AND COMPLEMENTARY PRODUCTS FOR SOFA D

	Primary Items	**Complementary Items**	**Updated Primary Items**
1	Sofa D Price: 500 euro Color: White Frame Material: Wood Manufacturer: A	Table I Frame Material: Metal Manufacturer B	Sofa D Price: 500 euro Color: White Frame Material: Wood Manufacturer: A
2	Sofa E Price: 500 euro Frame Material: Metal Color: White Manufacturer: B	Armchair H Frame Material: Wood Manufacturer: C	Sofa E Price: 500 euro Frame Material: Metal Color: White Manufacturer: B
3	Sofa C Price: 700 euro Frame Material: Metal Color: Black Manufacturer: A	Table J Frame Material: Wood Manufacturer: B	
4		Armchair F Frame Material: Metal Manufacturer: C	

TABLE II. PRODUCT BUNDLES

	Initial Bundles	**Personalized Bundles**	**Updated Initial Bundles**	**Updated Personalized Bundles**
1	Sofa D Armchair H	Sofa D Armchair H	Sofa D Armchair H	Sofa D Armchair H
2	Sofa E Table I	Sofa C Armchair F	Sofa E Table I	Sofa E Armchair F
3	Sofa E Armchair F	Sofa E Armchair F	Sofa E Armchair F	Sofa E Table I
4	Sofa C Armchair F	Sofa E Table I		

V. RELATED WORK

The most common approach in recommender systems is collaborative filtering (CF) [21, 22], content-based filtering (CBF) [23] and demographic filtering [24]. CF approaches suffer from cold-start, scalability and sparsity [25], since they require a large amount of existing data on a user to make accurate recommendations. Similarly to CF, demographic methods provide recommendations based on a demographic user profile [26]. On the other hand, CBF treats recommendation as a user-specific classification problem where items are classified as likely to be interesting or not based on product features [27]. Since CBF recommender systems process item features, they do not suffer from new item problem but new user problem remains [25].

Another approach is knowledge-based recommender systems that use conversational interactions with the users in order to collect explicit user preference and requirements information. There are two well-known approaches to knowledge-based recommendation, case-based [28, 29] and constraint-based [19, 25, 30]. Case-based systems treat recommendation primarily as a similarity-assessment problem, while constraint-based approaches takes into account explicitly defined constraints [16]. Thus, constraint-based recommendation becomes important when there are specific requirements that a solution must meet [19].

To overcome the shortcomings of the aforementioned approaches, hybrid recommender systems combine multiple techniques together to achieve some synergy between them [31]. Several researchers are exploring hybrid methods of combining CF and CBF methods, which helps to avoid certain limitations of CBF and CF systems [32, 33]. CF and CBF hybrid recommender system can be combined for example through a weighted model, which implements both methods separately and combines their predictions by giving adjustable weight to each recommendation [34], or a mixed model, in which recommendations from the two techniques are combined together in the final recommendation list [34, 35]. Zanker et al. in [6] introduce a constraint-based approach for product and service bundling based on a mixed hybrid recommendation strategy. However, they do not take into account the user’s history in order to enhance adaptation and personalization.

VI. CONCLUSIONS

In this paper we extended our previous work [8] for the dynamic generation of personalized product bundles in enterprise networks by introducing constraints and bundling rules to the proposed approach. The created bundles include a primary item, obtained either by explicit user input or from a generated substitution list, and a number of complementary items selected from a generated complementarity list. The proposed approach is able to dynamically adapt to changes imposed by the users through search criteria which are then translated as constraints, and through bundling rules which lead the recommendation process, as well as product availability.

Our future plans include an extensive evaluation of our approach in terms of scalability by comparing the results with other approaches, including bio-inspired approaches, and test its acceptance through users’ feedback. An issue that needs to be addressed is the complexity incurred when the number of constraints and bundling rules increase as well as diagnosing possible conflicts between constraints. Finally, in our current work bundling is based only on product information stored in a central repository. Additional research issues arise when considering obtaining product information directly from partner distributed repositories, including semantic compatibility of product representations and performance of distributed product searches.

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