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An Agent-based Customized Recommender System for Product and Service Family Design

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Abstract

This paper introduces an agent-based recommender system to support customized recommendations for product and service family design in electronic market environments. In this research, a preference learning mechanism is used to recommend appropriate products or services to customers and determine a preference value for each market segment in the product or service family. We demonstrate the implementation of the proposed recommender system using a multi-agent framework. Through experiments, we illustrate that the proposed recommender system can be used for customized recommendation and market segment design in various electronic market environments.

Keywords
Mass Customization, Product and Service Family Design, Multi-Agent System

1. Introduction
These days, many companies are increasing their efforts to provide customized products or services based on flexible systems with economical and rational volume and cost. By sharing and reusing assets such as components, modules, processes, information, and knowledge across a family of products and/or services, companies can efficiently develop a set of differentiated products by improving flexibility and responsiveness of product and service development [1]. Product family design is a way to achieve cost-effective mass customization by allowing highly differentiated products around a platform while targeting products to distinct market segments [2].

Electronic markets and web-based content have improved traditional product and service development processes by increasing the participation of customers and applying various recommender systems to satisfy individual customer needs. The growing number of electronic markets for product and service development has significantly increased information related to design and the complexity of transactions, making it difficult to control the electronic markets with human resources [3]. In recent years, agents and multi-agent systems have become a powerful and prevalent methodology for investigating and developing complex systems. An agent-based technique based on agents' roles and tasks can provide appropriate methods to solve product design problems [4, 5]. Agents have been used extensively in product design and can be used in product family design if developed properly [6].

The objective in this paper is to introduce an agent-based recommender system to support customized recommendations and family design for products and services in dynamic market environments. In the proposed system, product and service preferences are identified from customers' preferences and are used to provide customers with customized product and service recommendations. The proposed recommender system uses agent-based decision-making for recommending products and services in a distributed and dynamic environment.

2. Literature Review
A successful product family requires balancing the trade-offs between the economic benefits and performance losses incurred from having a shared platform. The basic development strategy within any product and service family is to leverage the product platform across products that target multiple market segments. Simpson, et al. [7] categorized platform design approaches as either top-down (proactive platform) or bottom-up (reactive redesign). The top-down approach manages and develops a family of new products based on a product platform, while the bottom-up approach seeks to redesign an existing set of products around a platform. Recent trends seek to apply and extend

concepts from product family design into new service development. Families of services and service platforms have been developed and applied in various service industries based on design theories and methodologies for products and manufacturing systems [8, 9]. Meyer and DeTore [9] proposed a platform-based approach to develop new services using methods and processes for applying product family and product platform design and used their approach to define a new service platform in an international insurance company. Jiao et al. [10] discussed how design theories and methodologies for products and manufacturing systems can be applied to the design of service delivery systems for mass customization. They treat the service delivery system as the product instead of an operational system.

As companies strive to minimize cost and time when developing new products by sharing and reusing distributed design knowledge and information, multi-agent systems provide an ideal mechanism to efficiently develop various products by integrating distributed design knowledge and information [5]. The obtained design knowledge and information can be used to construct a recommendation system for product design and development. Madhusudan [11] developed a flexible agent-based coordination framework for new product development in a distributed design process system. Tan, et al. [12] developed a multi-agent framework to provide information that helps designers, engineers, and managers work together to improve initial designs by satisfying a wider variety of concerns. Tran and Cohen [13] proposed a reinforcement learning and reputation algorithm-based algorithm for buyers and sellers in agent-based electronic marketplaces that maximized expected value of goods for buyers and expected profit for sellers. Our work extends a multi-agent framework to create a recommender system to support product and service customization as discussed next.

3. A Recommender System for Product and Service Family Design

Figure 1 shows how the proposed recommender system supports the process of developing a family of products and services in a dynamic market environment. In the initial phase, customers are classified into groups based on their characteristics and preferences. Products or service are also clustered as groups for recommending to customers. Using transaction data and evaluation related to customers' purchases, we can identify product or service preferences for each customer group, and then products or services are recommended to customer groups based on these preferences. Product or service preference information can help market segmentation for product and service family design by identifying trends among the recommended products and services.

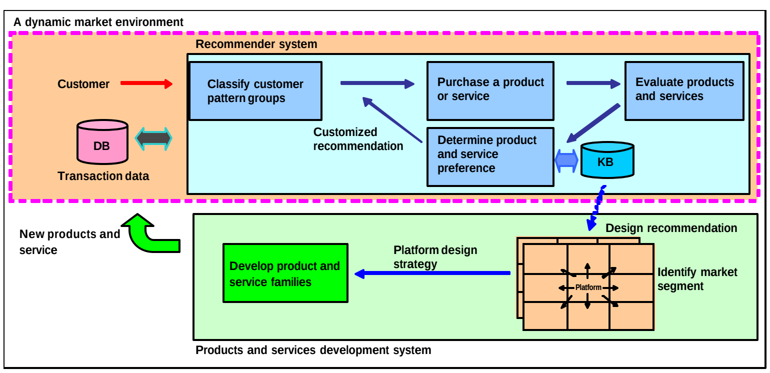

Figure 1: The Process of Developing a Family of Products and Services

Based on the above mentioned recommender system, we propose a multi-agent system (MAS) architecture in Figure 2 for determining product and service preferences in a dynamic market environment. The proposed architecture has two components: (1) an electronic market (e-market) and (2) an agent-based recommender system. The e-market represents a dynamic market environment, and the recommender system gives recommendations from agent-based learning for determining a product or service preference value using market mechanisms. These two environments are elaborated in the following two sections.

3.1 Electronic Market and Preference Value

A dynamic environment follows rudimentary e-market features such as business behaviors between buyers and sellers, dynamic pricing, and alternative selections [3, 13]. This e-market provides an agent environment where agents are economically motivated. The nature of an e-market allows economic agents (buyers and sellers) to freely enter or leave the e-market and negotiate with each other to obtain economic benefit. As shown in Figure 2, there are two types of agents for recommendation in an e-market: buyers and sellers. Depending on their strategy and market conditions, buyers and sellers purchase and provide products or services, respectively. In this paper, product and service preference values are defined as the degree of customers' preferences in relation to the product or the service in an e-market. Customers' preferences are represented by the variation of their selections in the market and can be affected by their satisfaction, design technology and trends, price, and the quality of the products and services. A product or service having a high preference value in a family of products and services will be more strongly recommended to a customer. This customer can be related to a particular group having similar purchasing behavior. To determine a preference value effectively, we propose a multi-agent system that incorporates a market mechanism. The next section introduces the proposed multi-agent system in detail.

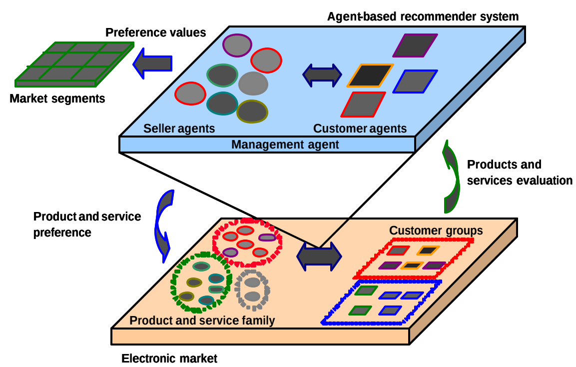

Figure 2: Agent-based Recommender System Architecture in an Electronic Market Environment

3.2 Agent-based Recommender System

To facilitate the process of developing a recommender system, a multi-agent system (MAS) is developed based on an electronic market environment. As shown in Figure 2, there are three types of agents in the proposed MAS: (1) a manager agent (MA), (2) customer agents (CAs), and (3) seller agents (SAs). The main task in the proposed MAS is to determine product or service preference values using a market-based learning algorithm for customized recommendation in a family of products and services. The MA provides to interface between the e-market and the MAS and manages information related to customers and products or services in the e-market. The MA also classifies customers and products or services as groups by their characteristics and assigns them to CAs and SAs by their roles and tasks, respectively. The MA manages CAs, SAs, the CA's requirements, and the SA's products or services. The MA provides the product or service preference for recommending customers to select a specific product or service in the e-market. Based on the learning algorithm, the CAs fulfill the requested tasks with SAs using an auction mechanism and return the result to the MA. The number of CAs is determined by the number of customer groups. After CAs perform their tasks, the information of the product and service preference is translated into new knowledge for identifying market segments. SAs can provide various products or services in terms of price and quality according to SAs' strategy or market situation. Therefore, a preference value can be used to recommend a specific product or service to a customer. In the proposed MAS, agents use knowledge to decide actions for performing their roles. Knowledge related to product and service preference is stored in a knowledge base and used to define agents' activities and tasks. The roles and knowledge of each agent are summarized in Table 1.

Table 1: Agents' Roles and Knowledge for the Proposed Multi-Agent System

Agent	Roles	Knowledge
Manager Agent (MA)	• Interface with e-market and agent system • Classification for customers, products, and services • Management for CAs and SAs	• Customer, MAs, and SAs information • Products and services information • Inference algorithm
Customer Agents (CAs)	• Decision-making: select a product and a service • Product and service preference update • Evaluation for the quality of products and services	• Products and services information • Strategy for negotiation • Learning algorithm • SAs reputation and MA information
Seller Agents (SAs)	• Products and services sale	• Products and services information • Strategy for negotiation • MA information

3.3 Learning Algorithm for Decision-Making

A preference value for a product or a service can be affected by customer's preference and satisfaction, design technologies and trends, price, and quality. In this research, we consider the quality and price of a product and a service as the preference factors related to customers' preference and satisfaction. The approach of Tran and Cohen [13] is applied to develop a learning algorithm for determining the preference value in the proposed MAS.

In the proposed MAS, a CA requests a set of products to select an appropriate one for the customer. Let M be the set of product families, P be the set of prices, and I be the set of all CAs, and D be the set of all SAs in the marketplace. M, P, I, and D are finite sets. A CA determines the preference of all SAs in the market using the function r^{CA}: $D \mapsto (-1,1)$, which is called the *CA's preference function*. The preference can be described as the value of the function according to customers' satisfaction. A preference value is set to 0 initially and updated based on transactions. To recommend a product or service and update the preference of a SA, a CA uses a utility function (u_i) that is computed from the difference between the expected product value (f_i) and the true product value (v_i):

$$u_i = v_i - f_i \qquad (1)$$

where f_i is estimated by an expected product value function $f_i : M \times P \times D \mapsto \Re$. The real number $f_i(m,p,d)$ represents the CA's expected product value of recommending product m from SA_d paying price p. Meanwhile, v_i is determined by examining the quality of the product provided from the SA_d and estimated by a true product value function $v_i : M \times P \times Q \mapsto \Re$, where Q is a finite set of real values representing product function (quality). Since SAs may offer the product m with different functions (qualities) and a SA may alter the quality of its products based on its market strategy, the CA trusts SAs with a high preference value and chooses the SA with the maximum expected product value among the SAs. The utility value is used for learning the expected product value function through a reinforcement learning mechanism:

$$f_i(m,p,d) \leftarrow f_i(m,p,d) + a u_i \qquad (2)$$

where a is the learning coefficient ($0 \le a \le 1$). If $u_i \ge 0$, then the expected product value is updated with the same or a greater value than before. In this case, a chance to choose SA_d is increased if the SA_d provides a continuously proper product m at price p in the next auction. Otherwise, if $u_i < 0$, then the expected product value is updated with a smaller value than before. The preference rating of a SA is defined as the amount of the increasing or decreasing preference value and needs to be updated when the expected product value is updated. Based on reputation updating approaches [13], a preference updating calculation is developed for determining a preference rating value.

4. Implementation

To demonstrate the proposed MAS and recommender system, we implemented a multi-agent framework using JADE[1] (Java Agent Development framework) and JARE[2] (Java Automated Reasoning Engine). JADE is a software framework to develop agent applications that use FIPA specifications to manage agent communication. JARE is an environment for doing logical inference in Java. JARE can be used to model an agent's knowledge base. The implementation focuses on recommendation between a CA and SAs to select a product. To evaluate the proposed MAS and recommender system, consider a scenario where two customer groups purchase products within a product family. One customer group uses a product preference value to select a product and the other group does not use one. Products can have four different functions that affect its quality. A product is selected by the customer's preferences. Based on this scenario, we consider an e-market populated with one manager agent (MA), two customer agents (CAs), and four seller agents (SAs). Since JADE is a type of middleware and a framework to develop multi-agent systems, we can use JADE's capabilities to perform the functions of a MA instead of developing a MA separately. Two CAs are developed and have two different strategies to choose an appropriate product. In this scenario, a product's price, cost, and quality are considered as preference factors for determining a product preference value in the e-market. The cost and price of each product depends on its quality. In order to compare alternative products from different SAs, four SAs are developed based on different market strategies. Each agent's knowledge is based on its role (see Table 1), which is used for capturing information and inference.

4.1 Preliminary Experiment and Analysis

Based on the aforementioned scenario, six agents were developed as CAs and SAs for the experiment of selecting products in an e-market. In the experiment, two CAs purchased the same product 100 times from four SAs and

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[1] www.jade.tilab.com
[2] www.jare.sourceforge.net

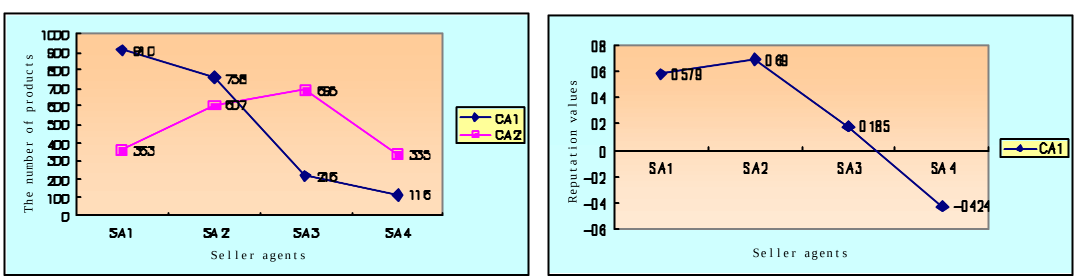
learned from the transaction history. Each experiment was performed 20 times to compare and analyze the behavior of the two CAs. We used finite and discrete values for the price, which varied randomly from 100 to 2000. The quality is proportional to the cost of the product. We assume that the product quality has a normal distribution with mean 1000 based on the cost range. The CAs' strategies and the SAs' alternative design strategies are:

- CA1 uses reinforcement learning along with product preference.
- CA2 uses reinforcement learning without product preference.
- SA1: adjusts product's quality based on request and initial quality is 1000.
- SA2: provides a product with a fixed average quality value (q=1000).
- SA3: provides a product with quality chosen randomly from the interval [100, 2000].
- SA4: first tries to attract a CA with high quality (q=1500) and then cheats them with very low quality (q=300).

In this experiment, product preferences are categorized based on the value of preference function: (i) high preference ($r^{CA} \geq \Theta, 0 < \Theta < 1$), (ii) low preference ($r^{CA} \leq q, -1 < q < 0$), and (iii) non-preference ($q < r^{CA} < \Theta$), where Θ is a high preference threshold and q is a low preference threshold. Non-preference means that a CA does not determine the preference of a SA because of insufficient information. The preference value is set to 0 initially and updated based on each transaction. If there are no SAs that have high preference, then CA randomly chooses a SA with a small probability p among SAs with the non-preference. Parameters related to the learning and preference algorithm are defined as follows:

- The product value function is: 2xquality–price, i.e., product quality is twice as important as product price.
- The threshold value for a high preference SA is 0.3 and a low one is -0.3.
- The learning rate a and exploration rate p are both 0.9999, and they decrease until they reach 0.1.
- The penalty factor is 1.5, which makes increasing the preference 50% harder than decreasing it.

Figure 3(a) shows the number of purchases between SAs with different strategies. Based on the SAs' preference values, CA1 preferred to purchase products from SA1 and SA2. The random strategy of SA3 worsened its preference. SA4 should have the worst average preference; so, the number of purchases from SA4 is the lowest. CA2 used reinforcement learning without preference recommendation. CA2 selected more products from SA2 and SA3 than SA1 and SA4, since the average product qualities of SA2 and SA3 are higher than the others. The results show that CA1 has more ability to recommend appropriate SAs than CA2 does. Figure 3(b) shows the average final reputation values for the different SAs for CA1. As we have expected, SA4 had a low preference value < –0.3, and SA3 was a non-preference agent. SA1 had a higher preference value than SA1, but for CA1, both of them were good enough to be considered equally preferable.



(a) (b)

Figure 3: (a) Number of Products Selected by CAs and (b) Average Final Preference Values of SAs by CA1

We performed one-way Analysis of Variance (ANOVA) to determine whether any significant differences existed between selecting products with different strategies based on these results. In this test, the level of significance (p-value) is 0.05. Table 2 shows the result of ANOVA for CA1 and CA2. In Table 2, the p-values of CA1 and CA2 are less than 0.05; therefore, we conclude that there are *significant differences* in selecting products with different strategies for CAs. Through the experiment, we demonstrated that two CAs selected proper products according to recommendations based on preference values in an e-market that was represented by SAs' different products. We expect that the proposed MAS can provide an appropriate method to determine a preference value for recommendation that can be adapted to various e-markets.

Table 2: The Result of ANOVA for CA1 and CA2

Agent	Source	DF	SS	MS	F-value	P-value
CA1	Factor	3	23139	7713	8.47	0.00
	Error	76	69183	910		
	Total	79	92322			
CA2	Factor	3	4773	1591	1.58	0.201
	Error	76	76447	1006		
	Total	79	81220			

5. Closing Remarks and Future Work

In this paper, we modeled an e-market with a multi-agent-based recommender system consisting of economically-motivated agents to explain agents' behaviors and roles. A preference mechanism was used to recommend an appropriate product and determine a preference value for market segment design in a product family. We have implemented the proposed MAS using JADE and JARE, and demonstrated how to use product preference for recommending a product based on customers' preference. Based on agents' roles and tasks, the preference mechanism can be applied to determine service preference values. Therefore, the proposed MAS can help design market segment for a product and service family that can be adapted to various e-market environments. Future research efforts will focus on improving the efficiency and effectiveness of the recommender system, enhancing agents' knowledge to better reflect various market environments, and expanding its application to web-based product and service family design.

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