International Journal of Smart Business and Technology
Vol.7, No.2 (2019), pp.45-54
http://dx.doi.org/10.21742/ijsbt.2019.7.2.05

Research on Distributed Intelligent Recommendation Algorithms for Personalized Customization from Consumer to Enterprise

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Abstract

With the continuous improvement of production technology and the improvement of people's living standards, mass-produced products can hardly meet people's growing material and cultural needs, and users' individual needs are becoming more assertive. The development of personalized customization from Consumer to Business (C2B) is one of the important ways for manufacturing enterprises to transform and upgrade. However, companies cannot personalize customization at this stage, and users have not introduced smart recommendations to assist in customization when they participate in the customization process. The existing research on personalized intelligent recommendations for manufacturing enterprises is only for optimizing and adjusting the algorithm itself. It does not effectively combine the characteristics of personalized customization step by step. Attributes and attribute customization content are independent and interrelated. To better guide users' product customization and decision-making, users can accurately describe their needs and improve customization efficiency. Intelligent recommendation is introduced in the personalized customization of products, and improvements are made based on the original item-based collaborative filtering recommendation algorithm. A step-by-step intelligent recommendation algorithm is proposed for C2B personalized customization, and a car customization case is introduced. This paper introduces the internal mechanism and recommendation steps of the recommendation algorithm in detail and introduces an example to simulate the recommendation process of the algorithm. Experimental results and recommendation results show that this paper's recommendation algorithm for C2B personalized customization is feasible and effective.

Keywords: *C2B personalized customization, Intelligent recommendation, Collaborative filtering, Decision support*

1. Introduction

With the continuous improvement of industrial production technology and the improvement of people's living standards, mass-produced products are difficult to meet people's growing material and cultural needs, and the personalized needs of users have become stronger [1], and the C2B personalized, customized business model has emerged [2]. This model allows product personalization and economies of scale to be coordinated, and it is beneficial to ensure the user's personalized requirements while maximizing user needs to meet the large-scale production needs of major manufacturers. Although major companies have

Article history:
Received (September 15, 2019), Review Result (October 16, 2019), Accepted (November 10, 2019)

Print: 2288-8969, eISSN: 2207-516X, IJSBT

gradually begun to establish the concept of C2B personalized customization, the actual application effect is not ideal. On the one hand, there are not many manufacturing companies that practice the establishment of a C2B personalized customization platform. On the other hand, in the established platforms, the aggregation and collection of user needs are ineffective, and there are almost no intelligent recommendation systems or algorithms that assist users in personalized customization.

C2B personalized customization means that manufacturing companies do not provide complete products but provide a platform where users can express their needs at will. The user configures the type and attributes of the required product on the platform, customizes a personalized product that meets their requirements, and completes the transaction after the manufacturer produces the product. Literature [3] uses a recommendation algorithm based on association rules to provide recommendations for user customization. It conducts an in-depth analysis from the perspective that different attribute values of the unified attributes of customized products are often mutually exclusive. Aiming at application service providers, literature [4] puts forward the idea of "function selection and process customization" and believes that this idea can meet the individual needs of ASP users and application services. Literature [5] puts forward the idea of the enterprise's designers and users' coordinated configuration through the Internet. Still, because of the limited number of enterprise designers, this method is costly and inefficient and cannot be widely promoted. Literature [6] introduces the idea of collaborative filtering recommendation in product design and customization, extracts user preference information from the user’s historical customization records of products and project evaluation, and uses this to recommend customized modules that users may be interested in. Generally speaking, related research scholars have explored the customization issues of manufacturing enterprises from different angles, but in general, most of them have been explored at the theoretical level [7]. At the same time, there are very few recommendations for each step-in customization [8][9], including systematic research on recommended system frameworks, modules, and algorithms. The above-mentioned classic recommendation algorithms have certain inapplicability when applied to C2B personalized customization. 1) The recommended object is not a whole but a discrete attribute value. 2) The user's characteristics are challenging to obtain, and it is impossible to model the user accurately. 3) The mutual exclusion between the attribute and attribute values is not considered. 4) The recommendation process and results cannot be dynamically adjusted according to changes in user behavior during the customization process.

2. Step-by-step improvement strategy of intelligent recommendation algorithm

The intelligent recommendation algorithm in traditional e-commerce has the characteristic of recommending complete and independent products, which cannot be directly used to assist user customization in C2B personalized customization [10]. This section is based on the C2B personalized customization environment, based on the existing collaborative filtering algorithm; from the use of implicit feedback data, independent recommendation steps, and product attribute correlation as part of the intelligent recommendation data input 3, aspects have been improved, and proposed a step by step. The intelligent recommendation algorithm is designed to better assist users in completing the personalized customization process.

Use implicit feedback data.

Due to the particularity of the C2B personalized customization platform, the explicit feedback data required by the collaborative filtering recommendation algorithm is difficult to obtain [11]. Therefore, implicit feedback data is mainly used when analyzing users' interest preferences. The implicit feedback data only uses 0 and 1 to reflect the user's preference for items. If the user selects a certain attribute value of the product, it means that the user likes the product's attribute value and his preference is 1. Otherwise, its preference is 0. The use of implicit feedback data effectively avoids the problem of explicit feedback data being challenging to obtain and, at the same time, simplifies the computational complexity of the model, making the entire processing process clearer.

Separate independent recommended steps

For personalized, customized products, each step of customization is relatively independent, but the result of each step of customization has an impact on the next step of recommendation results. The stepwise intelligent recommendation system separates the recommendation steps and performs separate recommendation algorithm calculations for different product attributes and customization steps. According to the customized result of the previous step, the input data part of the recommendation algorithm of this step can be adjusted in time so that the recommendation result of this step can be instantaneous and dynamic. In addition, due to the wide variety of products generated by personalized customization, if the overall configuration scheme is recommended as an object according to the existing thinking, the data sparsity problem [12] will be very serious, and the recommendation result is not ideal. For the recommendation of independent customization steps, the object of recommendation at each step is a certain number of attribute values of a certain attribute of the product, so it can effectively solve the problem of data sparsity, reduce the amount of calculation, and improve the accuracy of recommendation.

Consider the relevance of attributes.

A customized product can have customized attributes, and the attribute value division of each attribute is very important. In stepwise intelligent recommendation, the correlation and mutual exclusion between product attributes and attributes and between customization steps and steps will affect the recommendation results. For example, in car customization, there are displacements of 1.0 L and 2.0 L for the displacement attribute customization options, and the user selects the attribute value of 1.0 L. So, in the next step in customizing car model attributes, it is impossible to recommend SUV models to users based on their preference for large cars because a 1.0 L displacement car cannot drive a large car such as an SUV.

3. Step-by-step intelligent recommendation algorithm design

The step-by-step intelligent recommendation algorithm exists to assist users in personalized customization. The principle is to improve the classic collaborative filtering algorithm and add the idea of step-by-step recommendations. At the same time, it considers the relevance of product attributes and uses implicit feedback data to explore users' interests and preferences. The step-by-step recommendation algorithm in personalized customization is divided into the following steps.

Collect user history customization records.

Each successful customization will generate a customized record D_n for the user Ui, who has customized on the platform. Each configuration scheme is expressed as the subscript i representing the $i-th$ product attribute that needs to be customized and the subscript j_i representing the j_i-th attribute value option that can be selected in the $i-th$ attribute. The function of the stepwise intelligent recommendation algorithm is to recommend the corresponding a_{ij} for different i at each step to assist users in making customized decisions.

This paper adopts a stepwise intelligent recommendation algorithm, and the attribute value is studied as an item in the traditional recommendation algorithm.

Calculate the similarity of item attribute values.

Collaborative filtering algorithms are divided into user-based and item-based collaborative filtering algorithms. This article preferentially selects an item-based collaborative filtering algorithm as the basic algorithm before improvement. In item-based collaborative filtering, the following formula can be used to define the similarity between two items.

$$W_{pq} = \frac{|N(p)nN(q)|}{\sqrt{|N(p)||N(q)|}}$$

where $|N(p)|$ indicates the number of users who liked the item, and $|N(p)nN(q)|$ Represents the number of users who like both p items and q items. This calculation method can reduce the weight of q items and avoid recommending the most popular products.

To reduce data sparseness and facilitate production, this paper appropriately considers the configuration content attributes of the product in the recommendation. It decomposes the user's product configuration plan into a collection of attribute values. Let A_i represent a certain attribute that needs to be customized; then, in determining the customization of the product, the number of component attributes of the product is determined, and the value range of i is fixed. For the convenience of presentation, a_{ij} represents the $j-th$ attribute value of the $i-th$ custom attribute, and the value range for different i and j is different.

Measure the interest preferences of target users.

Based on collecting the similarity among the attribute values, measure the attributes that users may be interested in. In the item-based collaborative filtering algorithm, the user's interest in item j is generally calculated using the following formula:

$$P_{uj} = \sum_{i \in N(u) \cap S(i,K)} w_{ji} r_{ui}$$

This formula is also applicable to the stepwise intelligent recommendation algorithm. Where $S(i,K)$ is a collection of K types of attribute values with the highest similarity to attribute value $j, N(u)$ is a collection of attribute values that the user u has customized or is interested in w_{ji} is the similarity between the attribute value j and the attribute value i, which can be obtained from the attribute value similarity matrix. And r_{ui} is the degree of the user's interest in the attribute value i. This article uses an implicit feedback data set. When user u have acted on item i, r_{ui}=1. In addition, while considering the user's previous historical customization behavior interest preferences, it is also necessary to consider the influence of the attribute value determined in the previous steps on the recommendation of the attribute currently being customized during the user customization process.

Generate recommendation results to assist in customization.

After the user's interest in the attribute value of the current attribute is calculated, the first N types of interest attribute values can be recommended according to the user's interest in different attribute values P. After the step-by-step calculation of the similarity of the item attribute values and the step-by-step measurement of the target user's interest in the attribute values, a complete recommendation selection result- the customized solution set D_n is formed. The program set is a combination of the personalized results of each attribute, and the user completes the customization of the attribute after receiving the recommended results of each step.

The whole step-by-step intelligent recommendation process is shown in Figure 1. Based on the user's historical customization records or browsing records, it enters the personalized customization stage and adopts stepwise intelligent recommendations to assist the user's recommendation process. According to the historical customization records, the similarity matrix is calculated further to measure the interest preference of the target user. The recommendation result for attribute one is obtained, and the user makes a customized choice based on the result. Then, according to the user's historical customization records, the recommendation and customization results of attribute one are calculated through the similarity matrix to measure the interest preference of the target user, and the recommendation result for attribute two is obtained. The user makes a customized selection based on the result of the recommendation. By analogy, a complete user recommendation and customized program are finally formed.

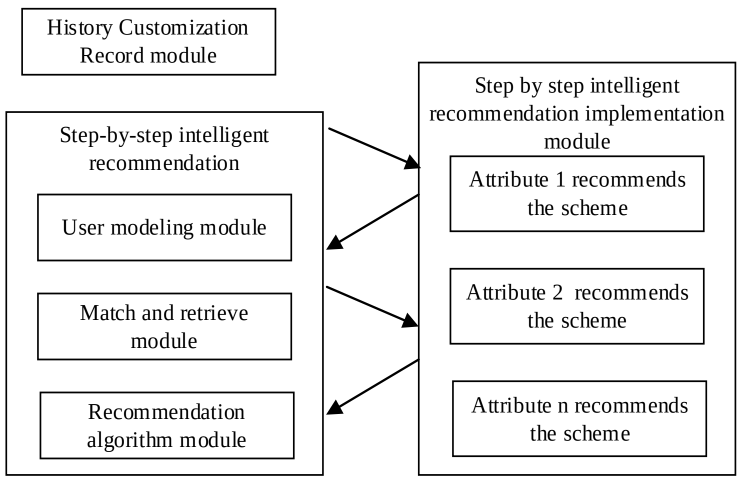

Figure 1. The step-by-step intelligent recommendation process

4. Application examples

Using Microsoft Excel 2016 software to simulate a C2B personalized customization platform for an automobile manufacturing company, users can customize cars that meet their individual needs through the platform. This paper focuses on exploring the feasibility and practicability of the step-by-step intelligent recommendation algorithm, so only four attributes of car color, engine specification, car model, and lamp style are selected for recommendation research. Assuming 20 attribute values of car colors, orange, red, cyan, etc., can be selected. There are nine attribute values for vehicle displacement: 1.5L DVVT inline four-cylinder engine, 1.0T dual-injection turbocharged engine, etc. There are 15 kinds of car style attributes to choose from. There are four types of lamp style attributes: round, diamond, ellipse, and triangle. For the convenience of presentation, use the $j_i - th$ attribute value representing the $i - th$ attribute respectively ($i = 1, 2, 3, 4$; $j_1 = 1, 2, 3, \ldots, 20$; $j_2 = 1, 2, 3, \ldots, 9$; $j_3 = 1, 2, 3, \ldots, 15$; $j_4 = 1, 2, 3, 4$)。 It is assumed that the current platform shares the historical customization or preference records of 30 users U_i, U_i ($i = 1, 2, 3, \ldots, 30$) indicates the $i - th$ user. Each customized scheme can be expressed as $D_i = a_{1j_1}, a_{2j_2}, a_{3j_3}, a_{4j_4})$. Use the RAND function of Excel to randomly generate k ($k = 100$) customized records, as shown in Table 1.

Table 1. User customization records

No.	Ui	A1	A2	A3	A4	Di
001	U30	A1 13	A2 5	A3 13	A4 1	D1
002	U1	A1 3	A2 4	A3 1	A4 1	D2
003	U27	A1 12	A2 2	A3 7	A4 1	D3
004	U16	A1 13	A2 8	A3 10	A4 2	D4
……	……	……	……	……	……	……
097	U24	A1 18	A2 6	A3 5	A4 1	D47
098	Ui4	A1 10	A2 5	A3 15	A4 3	D48
099	U1	A1 1	A2 8	A3 15	A4 3	D49
100	U12	A1 8	A2 4	A3 4	A4 2	D50

This article selects the 30th user, U_{30}, as the target user. In the subsequent process of algorithm operation, a stepwise intelligent recommendation is made for all the customization processes of this user.

Color attribute

For the recommendation of the color attribute A1, it is first necessary to customize the data according to the user's history, calculate the similarity between the attribute values $\{a_{11}, a_{12}, a_{13}, \dots, a_{120}\}$ in the color attribute, and generate a similarity matrix. This article selects user U_{30} as the target user and calculates the degree of interest of user U_{30} in the value of the relevant attribute. Set $K = 3$, that is, select the three attribute values that are most similar to the attribute values selected by U_{30} and generate the user interest degree calculation process as shown in Figure 2.

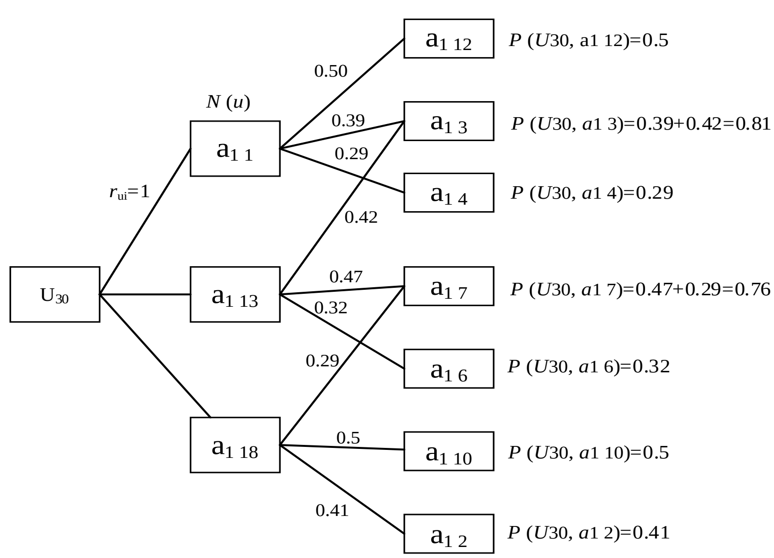

Figure 2. User interest calculation process

According to the size of the user's interest level P_{uj} for each attribute value of the color, the recommended results are shown in [Table 2].

Table 2. Color attribute recommendation result records

	Recommended results	a1j	Puj
U30	1	a1 3	0.81
	2	a1 7	0.76
	3	a1 12	0.5
	4	a1 10	0.5
	5	a1 2	0.41

The recommendation list is not used as the basis for the user's final selection but is only used to assist the user in making better decisions. The intelligent recommendation in personalized customization is only used to help users find the attribute value options they are interested in faster. Assume that user U_{30} selects the attribute of $\{a_{12}\}$ red for customization and enters the next step in the customization process of the car engine.

Engine attribute recommendation

The steps in the engine attribute customization are the same as the color attribute A1. The first step is to generate an attribute value similarity matrix and calculate the target userU_{30}'s interest in each attribute value of the engine attribute, as shown in Figure 3.

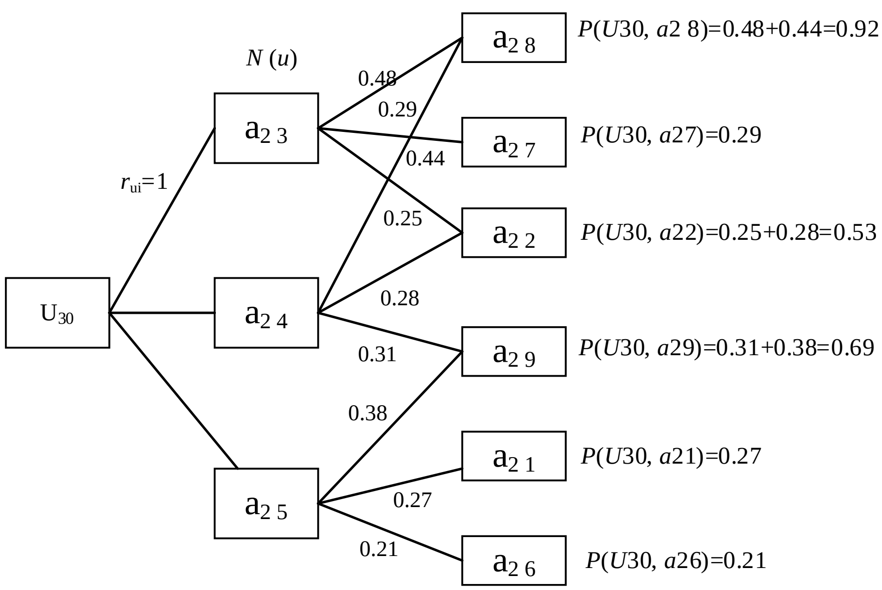

Figure 3. Attribute 2 user interest calculation process (1)

For the recommendation of the attribute two engines, the custom attribute value of the color attribute should be considered. That is, the user's interest in each attribute value of the engine attribute should be calculated for the user who has customized the red attribute, and the result is shown in Figure 4. Comprehensively generate a recommended list of engine attribute values, as shown in Table 3.

The user can assist in completing the customization process of Attribute 2 and A2 according to the prompts of the recommendation list. However, the role of the recommendation system is to assist the user in making selection decisions, so it does not directly affect the user's final customization result. The final result customized by the user may not be in the recommended list. Suppose that the user did not choose according to the recommended content in the customization of A2 but chose the attribute value of $\{a_{21}\}$, the 1.5LDVVT inline four-cylinder engine as the customized content.

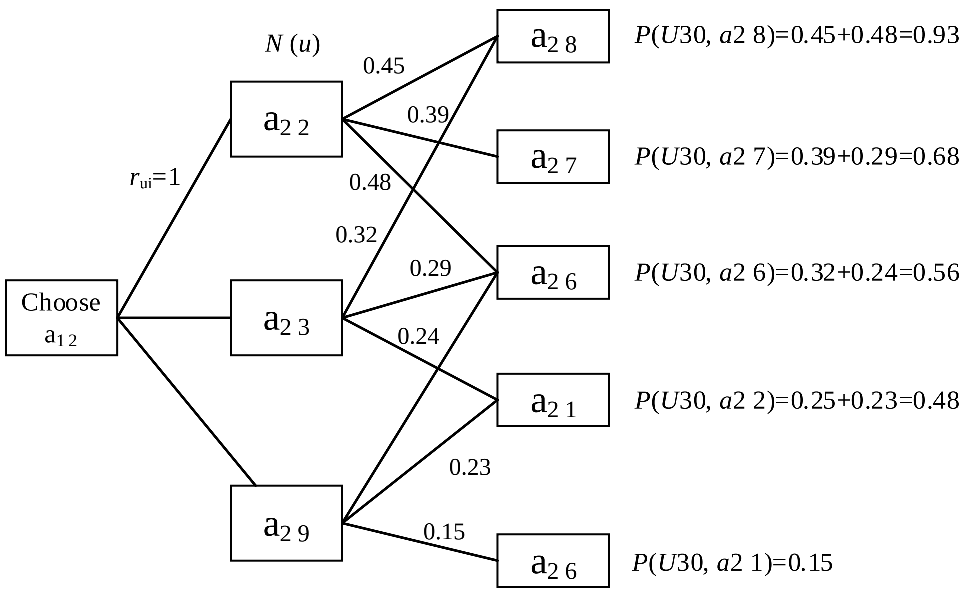

Figure 4. Attribute 2 user interest calculation process (2)

Table 3. Engine property recommendation result records

	Recommended results	a_{2j}	P_{uj}
U_{30}	1	$a_{2\,8}$	1.85
	2	$a_{2\,2}$	1.01
	3	$a_{2\,7}$	0.97
	4	$a_{2\,6}$	0.77
	5	$a_{2\,9}$	0.69

Recommendations for vehicle attributes

In the customization of attributes three and A3, the steps are the same as above. While considering the interest preferences of user U_{30}, it is also necessary to consider the influence of the user's interest preferences caused by the attribute values corresponding to attributes 1 and 2 that have been customized. Generate the similarity matrix between the attribute values in attribute three and calculate the interest preference value of the corresponding attribute value to obtain the recommendation result, as shown in Table 4.

Table 4. Model property recommendation result records

	Recommended results	a3j	Puj
U30	1	a3 15	2.25
	2	a3 1	1.99
	3	a3 10	1.49
	4	a3 12	1.48
	5	a3 3	0.97

Users can customize the attributes based on the above-recommended list of vehicle attributes based on their own needs. Suppose the user selects $\{a_{315}\}$, the 15th car model, to customize it.

Recommendations for lamp attributes

In the recommendation of car light attributes, we hope to stimulate an environment where attribute values are mutually exclusive. Assume that for the No. 15 models, it is impossible to install triangular lights. Then, if the value of the custom attribute the user selects in step 3 is $\{a_{315}\}$, when recommending attributes four and A4, the $\{a_{44}\}$ attribute should not be recommended. In the customization process, if there is mutual exclusion between the two attributes in the initial system, the manufacturer should enter the relevant mutually exclusive content in advance to ensure the implementation of the recommended results. The customization process is completed after the user selects the attribute value $\{a_{41}\}$ as the custom attribute.

In summary, in the process of customization, the user involved a total of 4 product attributes, so a total of 4 recommendation results were generated, and the user customized according to the recommendation to obtain a complete customization result $D101 = \{ a_{12}, a_{21}, a_{315}, a_{41}\}$. On the one hand, the customized results generated are used in the production of the manufacturing enterprise. On the other hand, they are recorded as new data in the historical customized record database.

The entire customization process is carried out in an orderly manner. After completing the customization of the subsequent steps, the previously selected attribute values can also be modified again, and the recommended content will be adjusted according to the current customization situation. This effectively ensures that the recommendation results can be dynamically changed with user needs, with strong autonomy and flexibility.

5. Conclusion

To better assist the user's customization process in C2B personalized customization, this paper proposes an intelligent recommendation algorithm that can be used for C2B personalized customization based on the classic collaborative filtering algorithm. The internal mechanism and recommendation steps of the recommendation algorithm are introduced in detail, and examples are introduced to simulate the recommendation process of the algorithm. Experimental results and recommendation results show that this paper's recommendation algorithm for C2B personalized customization is feasible and effective.

References

[1] Y. Qiao, X. Yang, and E. Wu, 'The research of BP neural network based on one-hot encoding and principal component analysis in determining the therapeutic effect of diabetes mellitus," IOP Conference Series: Earth and Environmental Science, vol.267, no.4, **(2019)**

[2] H. Gou, T. Tang, and Y. Ye, "Deep FM: A factorization machine-based neural network for CTR prediction," Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, pp.1725-1731, **(2017)**

[3] I. Duntsch and G. Gediga, "Confusion matrices and roughest data analysis," Journal of Physics: Conference Series, vol.1229, no.1, **(2019)**

[4] H. Li, H. N. Li, and S. Zang, "Intelligent learning system based on personalized recommendation technology," Neural Computing and Applications, vol.31, no.9, pp.4455-4462, **(2019)**

[5] S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges," IEEE Communications Magazine, vol.53, no.4, pp.117-125, **(2015)**

[6] S. Ulukus, A. Yener, and E. Erkip, "Energy harvesting wireless communications: a review of recent advances," IEEE Journal on Selected Areas in Communications, vol.33, no.3, pp.360-381, **(2015)**

[7] N. Zhao, S. Zhang, R. Yu, "Exploiting interference for energy harvesting: a survey, research issues, and challenges," IEEE Access, no.5, pp.10403-10421, **(2017)**

[8] H. Wu, Q. J. Lin, and J. Zhuang-de, "A temperature and strain sensor based on a cascade of double fiber Bragg grating," Measurement Science and Technology, vol.30, no.6, pp.111-119, **(2019)**

[9] J. Wind and A. Rangaswamy, "Customization: The next revolution in mass customization," Journal of Interactive Marketing, vol.15, no.1, pp.13-32, **(2001)**

[10] R. Brunelli and T. Poggio, "Face recognition: Features versus templates," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.15, no.10, pp.1042-1052, **(1993)**

[11] D. Glodberg, D. Nichols, and B. M. Oki, "Using collaborative filtering to weave an information tapestry," Communications of the ACM, vol.35, no.12, pp.61-70, **(1992)**

[12] P. Lops, M. De Gemmis, and G. Semeraro, "Content-based recommender systems: State of the art and trends," Recommender Systems Handbook. Springer US, pp.73-105, **(2011)**