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Discovery Strategy and Method for Remanufacturing Service Demand Using Situational Semantic Network

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ABSTRACT Due to customer individual difference, limitation of cognitive process and insufficient real-time response of cloud-based remanufacturing service platform, the problems such as disordered demand expression, difficulty in extracting implicit customer demand, and insufficient real-time performance of demand acquisition may be encountered. To this end, this paper presents an edge computing-based dynamic demand discovery and acquisition strategy. On the basis of existing methods and experimental results of implicit demand acquisition, a potential demand discovery method based on situational semantic network is proposed in this study. Firstly, the semantic similarity of ontology concept is used to calculate the correlation strength of registered keywords, and then registration keyword semantic network is constructed accordingly within the edge computing server. Afterwards, the keywords matrix of all web pages within single search behavior is obtained by data aggregation, the core attribute keywords of single search behavior are procured by the Kmeans algorithm and the retrieval keyword semantic network is constructed. After aggregating the two types of keywords semantic networks, the core semantics of aggregated semantic network are extracted by the pangrank method and customer situation semantic network reflecting current potential requirements is formed. Finally, an application example was demonstrated to verify the correctness and practicability of the remanufacturing service demand discovery strategy. This method has the potential to be applied in the intelligent management demand acquisition system of enterprises and urban communities, which provides reference for realization of intelligence technology in digital cities.

INDEX TERMS Remanufacturing service (RMS), customer demand discovery, edge computing, situational semantic network.

I. INTRODUCTION

Intelligent, service-oriented and sustainable development are the main development directions of smart cities. Cloud-based remanufacturing service (RMS) is not only a new way to improve the capability of personalized service of remanufacturing [1] based on the cloud manufacturing (CMfg) model [2], [3] but also an important way to promote the sustainable development of smart cities.

To carry out the research on cloud-based remanufacturing service and its process realization, the concept of RMS was proposed by combining the idea of reverse supply chain service [4] and service-oriented manufacturing. Moreover, a modularization method [5] of remanufacturing service resources has been proposed to dispose large quantity of service resources involved in the complex remanufacturing service system. However, it is necessary to obtain remanufacturing service module, clarify the customer demand and realize the remanufacturing service module matching at the same time, to determine the service solution [6], [7]. Hence, the discovery and acquisition of service demand is a key to simultaneous realization of remanufacturing service matching, solution determination and process completion.

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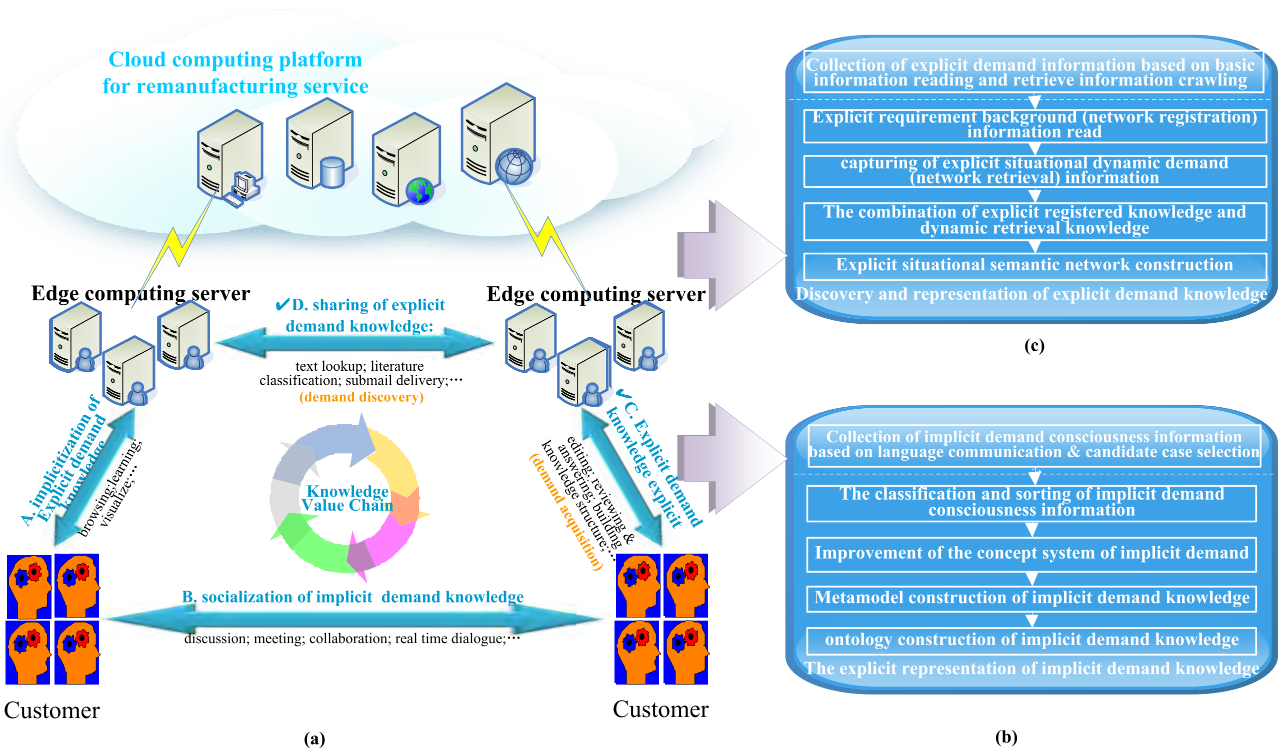

FIGURE 1. **Edge computing-based acquisition and transformation of customer demand knowledge. (a) "Visual-hidden" loop of customer demand knowledge. (b) Explicit visualization of customer implicit demand knowledge.**

To find an appropriate method of knowledge acquisition, this paper analyzes the dynamic circular transformation process of customer explicit and implicit demand knowledge from the perspective of epistemology and knowledge chain [8], as shown in Fig.1(a). The process mainly consists of four cyclic steps: A. & B. the formation of implicit demand knowledge, C. explicitization of implicit knowledge (Fig. 1 (b)) and D. discovering and sharing explicit knowledge (Fig. 1 (c)).

In the dynamic cycle transformation process, we know that the customer demand is a vague concept, the disorganization and incorrect expression of customer demand can be caused by customer individual difference and difference in cognitive process, so that customer demand cannot be expressed in a certain value or word. Therefore, it is difficult to obtain customer demand directly through their behavior. How to discover the customer demand through aggregating analysis of customer behavior data in cloud-based remanufacturing service platform (CRMSP) and build a bridge between customers and CRMSP? The answer is synchronized, which means the acquisition of customer demand based on CRMSP includes two parts - the first one is acquisition and explicitization of implicit demand knowledge (the unexpressed demand within customer's mind), and another one is discovery of explicit demand knowledge (the non-standardly expressed demand within Web).

In view of the huge amount of customer demand and the higher requirements for the real-time response ability of CRMSP, an edge computing-based network layout mode of CRMSP is necessary for remanufacturing service demand acquisition. The former, supported by the edge computing server (ECS), refers to realizing collection of "implicit demand awareness information" through interaction between device edge (PC or smartphone) and customers, and thus completing acquisition of implicit customer demand; the latter refers to discovering the potential customer demand hidden in ECS. In this regard, the main contributions of this paper are presented as follows:

(1) Based on the idea of building candidate ontology and generating the final ontology [9], this paper proposes an ontology-based strategy for dynamic discovery and acquisition of remanufacturing service demand. Firstly, a candidate ontology library for remanufacturing service requirements in ECS is established. Then, the accurate acquisition of remanufacturing service demand is realized through "leading-acquisition" of implicit subjective demands.

(2) In addition, this paper focuses on the knowledge discovery method of potential customer demand based on explicit knowledge hidden in ECS, and a discovery method of potential demand is studied based on situational semantic network. The semantic similarity of ontology concept is adopted to calculate the correlation strength of customer registered keywords, and the registration keyword semantic network is constructed accordingly. Further, the keywords matrix of all web pages within single search behavior is obtained by data aggregation. Then, the core attribute keywords of

single search behavior are procured by Kmeans algorithm and the retrieval keyword semantic network is constructed. After aggregating the two types of keywords semantic networks, we extract the core semantics of aggregated semantic network by Pangrank method and the customer situation semantic network is formed.

The potential demand discovery method based on customer retrieval behavior can not only help customers to clarify their requirement, but also provide a referential idea for remanufacturing service decision-making from different perspectives. Moreover, the proposed method enables the demand acquisition of intelligent management of enterprises and urban communities to be possible, which providing a basis and reference for the realization of artificial intelligence technology in digital cities.

II. RELATED WORK

On the premise of short time and low cost, discovering and obtaining customer demand quickly and accurately is the first step to develop a remanufacturing service plan. At present, the main factors affecting the accuracy in customer demand acquisition include customer's inability in expressing their demand and difficulties in quantitative description on demand information [10]. According to the difference of demand acquisition approaches, the demand acquisition methods can be divided into three categories [11].

(1) The traditional customer demand acquisition methods include customer consultation survey, customer recommendation, etc. The former refers to obtaining the original data of customer service expectation through question guidance and communication [12]. The later refers to recommending existing service schemes for customers who are difficult or uncertain to describe their demands to obtain accurate service demand information through selection and modification of the service solution.

(2) Enterprise database analysis is to discover and obtain customer service demand hidden in enterprise data by information extraction technologies [13], data aggregation and mining techniques [14].

(3) The web-based information discovery and acquisition method is to discover and obtain customer demand information through traditional computing-based or cloud computing-based aggregation processing and mining of service data in network information [13] and analysis of customer search behaviors in the Web. For example, Ying Liu *et al.* proposed the concept of kansei engineering, and captured (potential) customer demand on product design by quantifying customer emotions and needs [15]. Furthermore, the demand ontology model was constructed to address the problem within diversification of product family design (PFD), and a user demand mining method based on concept similarity was proposed [16]. Wang C *et al.* proposed a multi-dimensional customer demand acquisition method based on requirement ontology and cognitive process to solve the problem of insufficient acquisition of customer demand and low reusability [12]. Xu H *et al.* proposed a customer real-time demand discovery method based on literature search system in order to provide personalized document retrieval results [17]. Sunny S *et al.* proposed an aggregation scheme that uses communication to collect sample data for iterative tracking [18].

However, the above traditional methods are limited by their own disadvantages. In addition, the enterprise database-based and web-based methods mainly attempt to discover and acquire customer demand on products (physical products, services, literature, etc.) via data aggregating and mining technologies as well as demand cognitive analysis techniques. The main technical ideas adopted include knowledge information classification [19], knowledge information selection [20], and knowledge information extraction. The technical methods adopted includes data aggregation, semantic analysis [21], [22], etc. Although these ideas and methods have considered the deficiency in customer cognition, they do not take into account the correlation between customer history demand and current demand. Moreover, existing demand information acquisition methods lack the consideration on the characteristics of industry demand and the diversity, vagueness and concealment of demand information, so they are difficult to guarantee the efficiency and accuracy of demand acquisition. Additionally, the data network architecture and data processing mode based solely on traditional computing or cloud computing can no longer meet higher implementation requirements for real-time demand acquisition and processing. Therefore, new demand information acquisition strategies and methods combining edge computing method [23] should be studied urgently.

III. DYNAMIC DISCOVERY AND ACQUISITION STRATEGY

Based on the idea of "explictization of implicit knowledge" and discovery of explicit knowledge in Fig. 1 (b) and (c), an edge computing-based dynamic discovery and acquisition strategy of remanufacturing service demand information is proposed, as shown in Fig. 2. The demand acquisition process includes two core steps:

(1) Acquisition of implicit demand knowledge based on ontology learning within device edge. The candidate ontology of remanufacturing service demand is constructed, and then the man-machine interactive web pages (M2M Web-RSCSD) for remanufacturing services demand are presented in the form of Web table. On man-machine interaction Web pages, customers are guided to select layer by layer to realize acquisition of implicit demand knowledge. Using ontology learning- based automatic acquisition technology of demand knowledge, effective demand concept selected by customer and effective concept values recorded in the man-machine interaction Web table are obtained. By establishing the concept system and knowledge metamodel of customer implicit demand, knowledge ontology, customer demand ontology, and DOM document of customer demand as well as explicitization of implicit demand knowledge can be realized.

(2) Discovery of explicit demand knowledge based on situational semantic network within ECS. The "customer

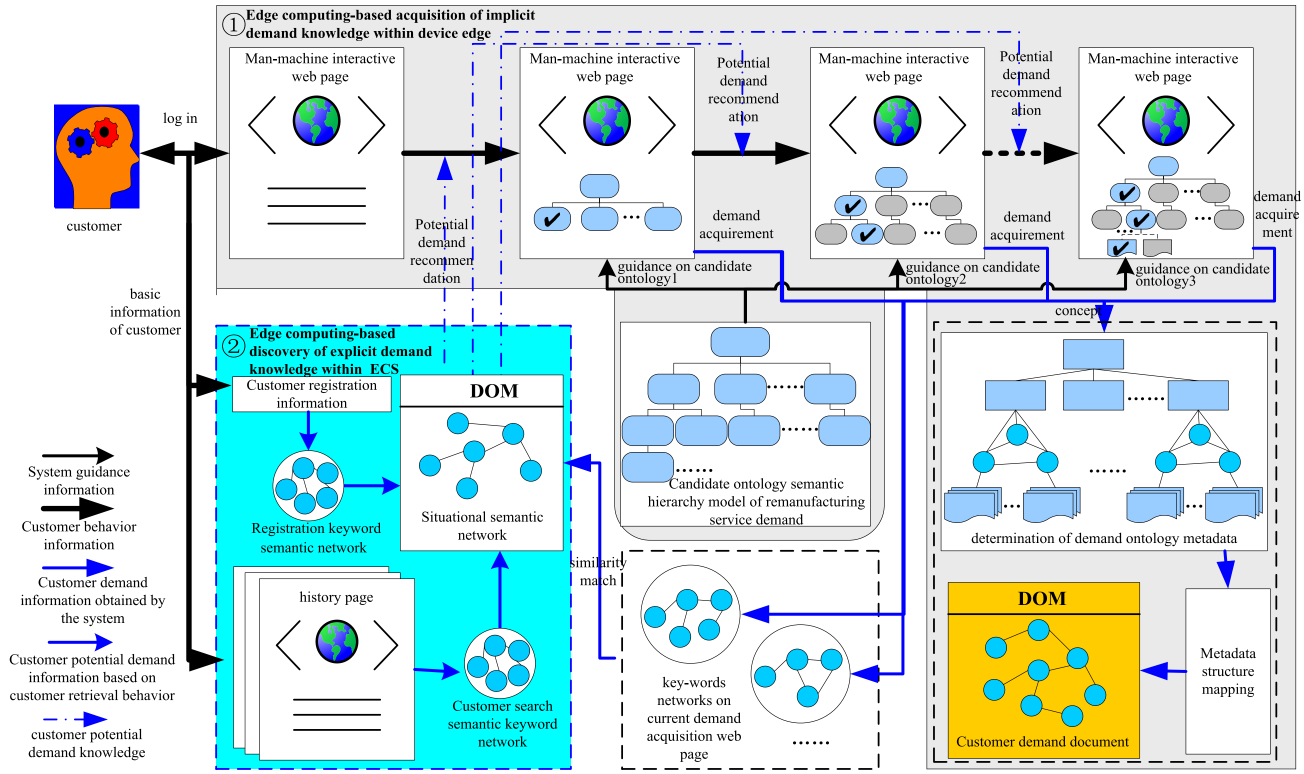

FIGURE 2. Edge computing-based dynamic discovery and acquisition strategy of remanufacturing service demand.

registration keyword semantic network'' is constructed according to the key words system registration. According to the record of customer retrieval behavior, the ''semantic network of customer retrieval keywords'' is constructed. Then the ''customer scenario semantic network'' is extracted and dynamically compared with keyword network on the multiple pages to determine the keyword with the highest similarity. The keyword with the highest similarity, i.e. the ''potential demand'', is pushed to the customer to improve the customer demand ontology.

The whole demand acquisition process is presented in the form of graphics and selection, which reduces the input of fuzzy text. Additionally, by making full use of candidate ontology and potential demand, customers can gradually clarify and quantify their implicit demand awareness, so that the accuracy and completeness in acquisition for implicit demand knowledge are guaranteed, which provides basis for selection of scheme decisions and remanufacturing service module matching.

IV. SERVICE DEMAND DISCOVERY METHOD BASED ON SITUATIONAL SEMANTIC NETWORK

The remanufacturing service demand discovery and acquisition process corresponding to Fig. 2 is shown in Fig. 3. In the grey part, the construction of remanufacturing service demand ontology (candidate ontology) as well as the guidance and automatic acquisition of implicit demand knowledge based on ontology learning are presented [8]. This paper focuses on the blue part in Fig. 3 (b), that is, to build situational semantic network in ECS based on customer registration behavior and historical search behavior, and then discover the potential demand to improve the acquisition of customer demand.

The service demand discovery process based on situational semantic network mainly includes following procedures. (1) The unstructured customer registration keyword information is represented as a structured data type, so as to allow the knowledge platform to understand the keyword semantics of customer registration [8]; (2) by analyzing the historical customer search behavior, the core semantics of historical Web pages visited by customers are extracted. On the basis of extracted semantics of historical Web pages and semantics of registration keywords the situational semantic network can be constituted. In this original method, customer backgrounds represented by their registration keywords are associated to the customer dynamic demand information represented by their search behavior, which helps to capture accurate potential customer demand within a specific context. On the one hand, it can be pushed as feedback to the customer, which not only helps customers to define and standardize the requirements description, but also improves accuracy and efficiency in demand acquisition. On the other hand, different data aggregation results of customer potential demand can be pushed to stakeholders, which is conductive to the decision making of remanufacturing services.

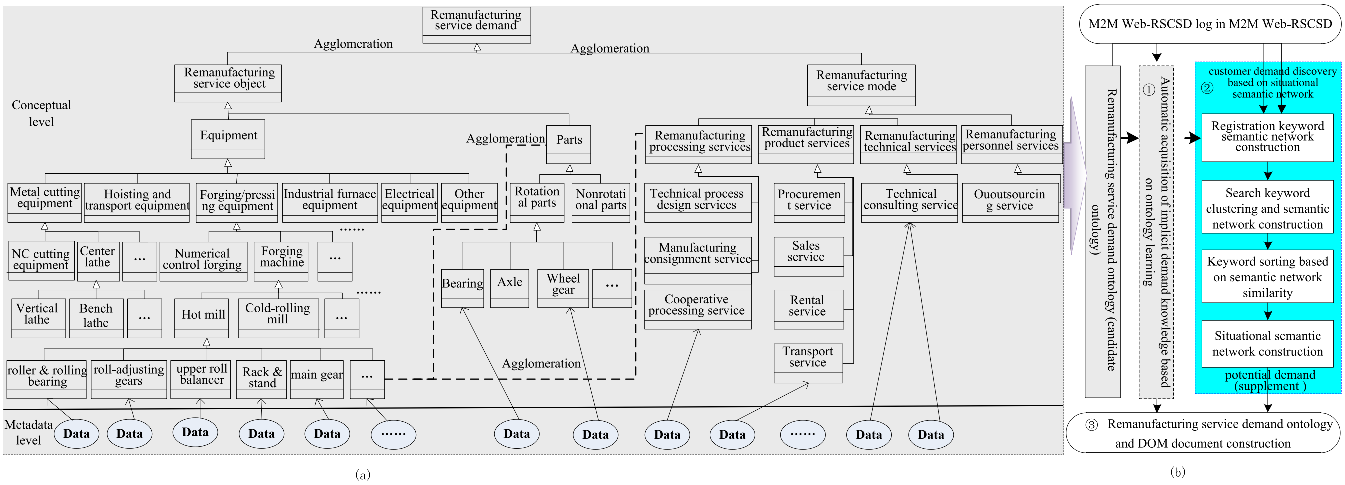

FIGURE 3. A dynamic process of remanufacturing service demand discovery and acquisition. (a) Remanufacturing service demand ontology (candidate ontology) semantic metadata model. (b) The dynamic discovery and acquisition process of remanufacturing service demand.

A. CUSTOMER REGISTRATION KEYWORD SEMANTIC NETWORK CONSTRUCTION

1) REPRESENTATION OF CUSTOMER REGISTRATION KEYWORD SEMANTIC NETWORK

When registering in the ECS of CRMSP, the customer needs to select or input n focused areas or object keywords, so that the platform can easily set up a keyword-registration network for the customer, as shown in Fig. 4. The network is an undirected network represented by a quad:

$$\mathrm{KZWN} = \{\mathrm{KZV}, \mathrm{W_{KZV}}, \mathrm{KZE}, \mathrm{W_{KZE}}\} \tag{1}$$

where $\mathrm{KZV} = \{\mathrm{kzv_i} | \mathrm{i} = 1, \ldots, \mathrm{n}\}$ is the registration keywords nodes set.; The node $\mathrm{kzv_i}$ represents a customer registration keyword. The corresponding node weight is $\mathrm{w_{kzv_i}}$, which refers to the subjective concern given when registering. Node weights set is denoted as $\mathrm{W_{KZV}} = \{\mathrm{w_{kzv_i}} | \mathrm{i} = 1, \ldots, \mathrm{n}\}$. $\mathrm{KZE} = \{\mathrm{kze_{j(a,b)}} | \mathrm{j} = 1, \ldots, \mathrm{m}\}$ is a set of undirected edges. The undirected edge $\mathrm{kze}_{j(a,b)}$ represents the association between key node $\mathrm{kzv_a}$ and $\mathrm{kzv_b}$. If there is a genus relation or instance relation between the two node keywords in the candidate ontology of remanufacturing service demand in Fig. 3 (a), then there are edges between them. The weight of edge $\mathrm{kze}_{j(a,b)}$ is denoted as $\mathrm{w_{kze_{j(a,b)}}}$, then the set of edge weights is denoted as $\mathrm{W_{KZE}} = \mathrm{w_{kze_{j(a,b)}}} | \mathrm{j} = 1, \ldots, \mathrm{m}\}$.

2) CALCULATION OF EDGE WEIGHT BASED ON ONTOLOGY CONCEPT SEMANTIC SIMILARITY

In the customer registration keyword semantic network shown in Fig. 4, the edge $\mathrm{kze}_{j(a,b)}$ represents the semantic relativity between the keyword node $\mathrm{kzv_a}$ and $\mathrm{kzv_b}$. This means in the candidate ontology semantic structure of remanufacturing service demand in Fig. 3 (a), there is a path $\mathrm{path}(\mathrm{kzv_a}, \mathrm{kzv_b})$ associating keyword node $\mathrm{kzv_a}$ and $\mathrm{kzv_b}$.

From the conceptual similarity between ontology $\mathrm{O_1}$ and $\mathrm{O_2}$, it can be known that for a random keyword node (concept) $\mathrm{kze_a} \in \mathrm{O_1}$ in the ontology semantic network $\mathrm{O_1}$,

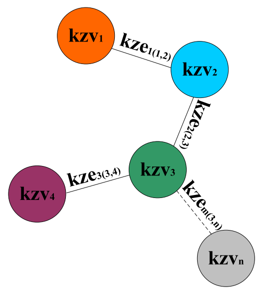

FIGURE 4. Customer registration keyword semantic network.

one or multiple corresponding keyword node/nodes (concept) with the same or similar semantics can be always found in the ontology $\mathrm{O_2}$. Based on the concept similarity of ontology and the semantic hierarchy model adopted in the candidate ontology of remanufacturing service demand, and by regarding keyword node (concept) as calculation particle, the similarity between keyword node (concept) $\mathrm{kzv_a}$ and $\mathrm{kzv_b}$ can be regarded as the conceptual distance between them [24], and the similarity between the two keyword nodes (concept) is written as weight $\mathrm{w_{kze_{j(a,b)}}}$ of edge $\mathrm{kze}_{j(a,b)}$. As a result, calculation of edge weight $\mathrm{w_{kze_{j(a,b)}}}$ can be converted into calculation of semantic similarity between the keyword node (concept) $\mathrm{kzv_a}$ and $\mathrm{kzv_b}$, and the semantic similarity calculation can be further converted into the measurement of distance between two keyword nodes (concept). With the increase of conceptual distance, the conceptual similarity gradually decreases, and the weight of the edge between the concepts decreases, vice versa. The similarity between keyword nodes (concept) is also affected by their positional depths in the semantic hierarchy diagram of candidate ontology for remanufacturing service demand in Fig. 3 (a). When the conceptual distances are the same, the greater the level difference between the two keyword nodes (concepts) is, the lower their similarity is, and the smaller the edge weight is, vice versa. Therefore, the weight $w_{kze_{j(a,b)}}$ of edge $kze_{j(a,b)}$ between keyword node (concept) kzv_a and kzv_b is (2), as shown at the bottom of this page,where $Sim(kzv_a, kzv_b)$ represents the semantic similarity between keyword node (concept) kzv_a and kzv_b. l_a and l_b represent the level of kzv_a and kzv_b in the semantic hierarchy diagram of candidate ontology for remanufacturing service demand in Fig. 3 (a), $Dis(kzv_a, kzv_b)$ is the shortest distance between the two in the semantic hierarchy, and $\alpha (0 < \alpha < 1)$ is regulation parameter. If the keyword node (concept) kzv_a and kzv_b have the same conceptual semantics, then the semantic similarity is 1. If the keyword node (concept) kzv_a and kzv_b do not meet the semantic correlation, the similarity is 0.

B. CONTRUCTION OF SEMANTIC NETWORK OF CUTOMER RETRVAL KEYWORDS

Through analysis of customer retrieval, browsing, clicking and downloading behaviors, the primary keyword of customer current retrieval can be obtained. Then, the retrieval primary keyword is used as the clustering center to cluster the keywords contained in the resource names. The first n' keywords that are closest to the cluster center and primary keywords together constitute the semantic network of customer retrieval keywords, i.e. the core semantics of this retrieval. The core semantics usually correspond to the customer actual demand for this retrieval.

1) REPRESENTATION OF SEMANTIC NETWORK OF CUSTOMER RETRIEVAL KEYWORDS

With regard to the construction and representation of **semantic network of customer retrieval keywords, on the** one hand, the semantic network of customer retrieval keywords should be consistent with the structure of customer registration keyword semantic network (Fig. 4) in order to better synthesize the customer situational semantic network; on the other hand, the keyword used by customers in the retrieval of keyword semantic network should be the primary keyword and has a core position in the semantic network of customer retrieval keywords, while the keywords extracted from browsing, clicking and downloading the retrieved results can be regarded as relevant keywords or attribute keywords of current primary keyword. Based on this, the semantic network of customer retrieval keywords can be built, as shown in Fig. 5.

The semantic network of customer retrieval keywords is an undirected network, which is expressed as:

$$KSWN_x = \{ksmv_x, KSV_x, W_{KSV_x}, KSE_x, W_{KSE_x}\} \quad (3)$$

where $ksmv_x$ is the primary keyword of the x-th retrieval;

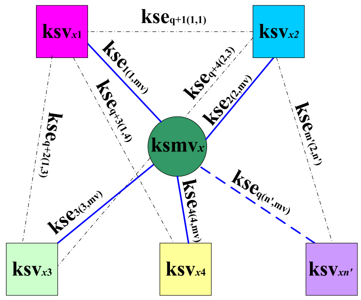

FIGURE 5. Semantic network of customer retrieval keywords.

$KSV_x = \{ksv_{xp} | p = 1, \ldots, n'\}$ is the set of attribute keyword nodes of the primary keyword node $ksmv_x$ in the x-th retrieval behavior. Node ksv_{xp} is an attribute keyword node, of which the weight is $w_{ksv_{xp}}$. Then, there is a weight set $W_{KSV_x} = \{w_{ksv_{xp}} | p = 1, \ldots, n'\}$;

$KSE_x = \{kse_{xq} | q = 1, \ldots, m\}$ represents the set of all edges between primary keyword node $ksmv_x$ and attribute keyword node ksv_{xp} as well as the set of all edges among different attribute keyword nodes ksv_{xp}. Edge kse_{xq} represents the association between two node keywords, of which the weight is denoted as $w_{kse_{xq}}$, then there is a weight set $W_{KSE_x} = \{w_{kse_{xq}} | q = 1, \ldots, m'\}$.

2) DETERMINATION OF CUSTOMER RETRIEVAL ATTRIBUTE KEYWORDS

a: DATA REPRESENTATION OF KEYWORDS IN RETRIEVE WEB PAGE

Suppose when the customer is conducting the x-th retrieval behavior with $ksmv_x$ as the primary keyword, a total of X records are retrieved, and then the customer clicks on and views Y records, where the Web page corresponding to the y-th record contains R_y keywords. Then the set of keywords corresponding to the y-th record can be denoted as $KLV_{xy} = \{klv_{xyr} | y = 1, \ldots, Y, r = 1, \ldots, R_y\}$. Finally the matrix KLV_x of keywords in all web pages visited by the customer in the x-th retrieval behavior are obtained:

$$KLV_x = \begin{bmatrix} klv_{x11} & klv_{x12} & \cdots & klv_{x1R_1} \\ klv_{x21} & klv_{x22} & \cdots & klv_{x2R_2} \\ \vdots & \vdots & \ddots & \vdots \\ klv_{xY1} & klv_{xY2} & \cdots & klv_{xYR_Y} \end{bmatrix} \quad (4)$$

In order to accurately excavate the core keywords of customer's x-th retrieval behavior, the set $KSV_x = \{ksv_{xp} | p = 1, \ldots, n'\}$ of attribute keywords browsed by the customer is constituted, and a more scientific semantic network of customer retrieval keywords is constructed in this

$$w_{kze_{j(a,b)}} = Sim(kzv_a, kzv_b) = \begin{cases} \dfrac{\alpha \times (l_a + l_b)}{[Dis\,(kzv_a, kzv_b) + \alpha] \times \max(|l_a - l_b|\,, 1)} & a \neq b \\ 1 & a = b \end{cases} \quad (2)$$

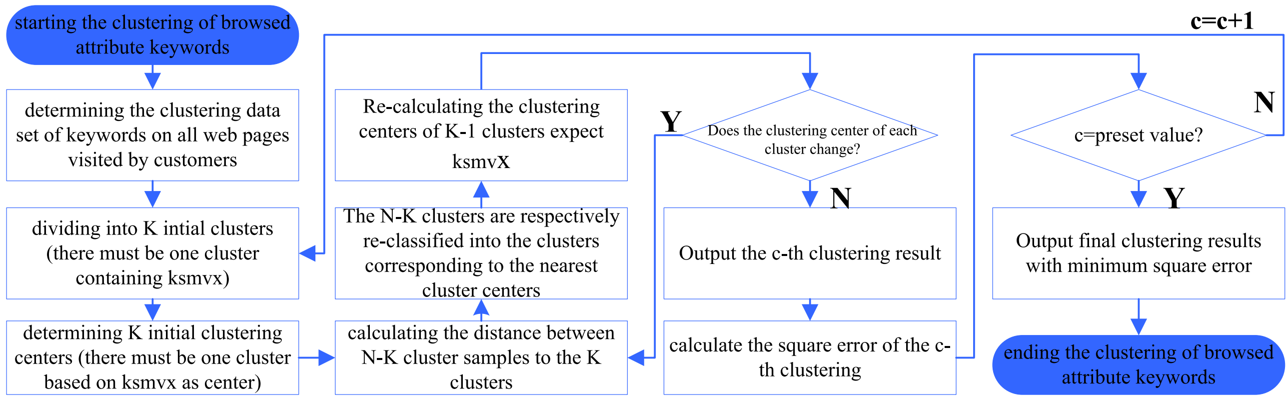

FIGURE 6. **The flow chart of Kmeans-based clustering of browsed attribute keywords.**

section. The matrix KLV_x of keywords in all web pages visited by the customer in the x-th retrieval behavior is analyzed using clustering analysis method.

b: EXTRACTION OF CUSTOMER RETRIEVAL ATTRIBUTE KEYWORDS BASED ON DATA AGGREGATION

Data aggregation is an important method of data content selection and grouping in data mining, which has been widely used in text analysis. Clustering algorithm, as a means of data aggregation processing, mainly includes partition-based method, hierarchy-based method, grid-based method, density-based method and model-based method. Typical partition-based methods include CLARA algorithm, PAM algorithm, Kmeans algorithm, and CLARANS algorithm. As a common partition-based clustering algorithm, the core idea of Kmeans clustering algorithm is "the principle of minimizing clustering performance index", that is, dividing the data into a K clusters on the basis of minimizing the error function. Kmeans clustering algorithm is an unsupervised real-time clustering algorithm [25], which has fast convergence speed and good clustering effect.

In this section, Kmeans-based clustering method of browsed attribute keywords is used to extract the set KSV_x of attribute keywords from the matrix KLV_x of keywords in all web pages visited by customers. The flow chart of this method is shown in Fig. 6.

Step 1: Determine the set of clustering samples according to the matrix KLV_x of keywords in all pages visited by customer, including a total of $N = \sum_{y=1}^{Y} R_y$ samples.

Step 2: Divide the set of clustering samples into K clusters ($K \leq N$), each cluster is $Ck(k = 1, 2, \ldots, K)$, and the number of cluster samples contained in each cluster cannot be empty; at the same time, each cluster sample must belong to only one cluster.

Step 3: In K clusters, cluster Ck is selected, for which the primary keyword ksmvx in the x-th retrieval is regarded as clustering center. In the remaining K-1 clusters, a random sample is selected as initial cluster center.

Step 4: According to the mean of each cluster sample (central object), the distance between each cluster sample and the central object is calculated. The cluster samples are reclassified according to the minimum distance, so that each cluster sample is reassigned to the closest class. The similarity between sample data in the same cluster increases constantly and the similarity between sample data in the different cluster decreases gradually.

Step 5: Calculate the mean value of each cluster after the change (center object).

Step 6: Repeat [step 4] and [step 5] until each cluster is stable.

Step 7: Output current clustering results, and the square error function is used to calculate the data intensity of current clustering results, i.e., determining the quality of the solution. The formula of square error function is:

$$E_{KLV_{xc}} = \sum_{k=1}^{K} \sum_{klv_{xyr} \in \hat{E}C_k} \left| klv_{xyr} - A_{C_k} \right|^2 \tag{5}$$

where $E_{KLV_{xc}}$ represents the sum of squared error of all cluster sample data in the c-th clustering, klv_{xyr} is a cluster sample data, A_{C_k} is the mean value of cluster C_k.

Step 8: Return to Step 2. to conduct the next clustering analysis until c-order clustering analyses are completed. From the results of c-order clustering, the minimum square error is selected, and the densest partition result of sample data is regarded as the final clustering result.

Step 9: After obtaining the final clustering results, the first five keywords of cluster centered on $ksmv_x$ as well as the first two keywords of remaining K-1 clusters are selected to constitute the set $KSV_x = \{ksv_{xp}|p = 1, \ldots, n\}$ of attribute keywords browsed by customer.

C. EXTRACTION OF CUSTOMER SITUATIONAL SEMATIC NETWORK

Through construction of customer registration keyword semantic network and customer retrieval keyword semantic network, the stable demand of customer registration industry and the current situation dynamic demand of customer can be obtained, respectively. According to the theory of episodic memory in human cognitive psychology, customer registration keywords semantic network can be integrated with

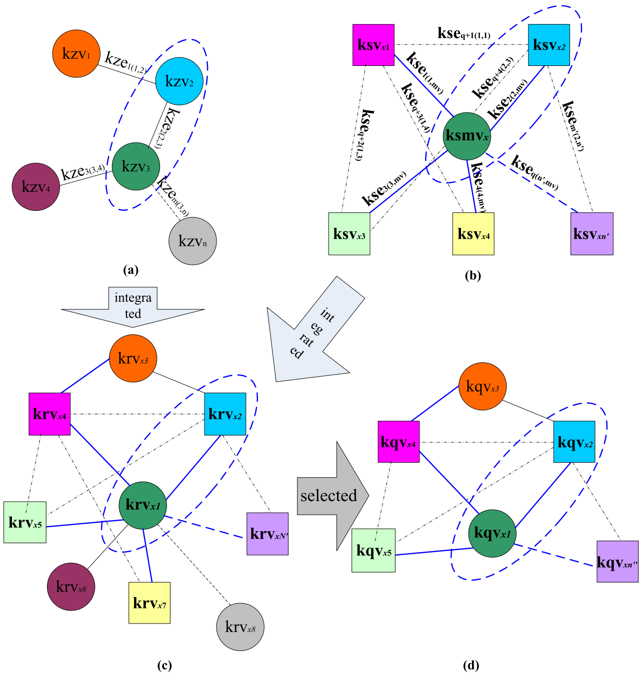

FIGURE 7. **Extraction process of customer situational semantic network. (a) Customer's registration keyword semantic network. (b) Semantic network of customer retrieval keywords. (c) integrated customer keyword semantic network. (d) customer situational semantic network.**

customer retrieval keywords semantic network. After integration, the retrieval attribute keyword is treated equally as the primary keyword. According to the value of the keywords in the semantic network after integration, the first n keywords with the highest value are selected as the core semantics to build customer situational semantic network, as shown in Fig. 7. The customer situational semantic network will be stored on the ECS, and used to represent the customer real demand in this retrieval scenario so that to push the demand in the latest customer demand acquisition.

As shown in Fig. 7 (c), the integrated keywords semantic network consists of customer registration keywords $KZV = \{kzv_i | i = 1, \ldots, n\}$, customer retrieval primary keyword $ksmv_x$, and customer retrieval attribute keyword $KSV_x = \{ksv_{xp} | p = 1, \ldots, n\}$, the total number is N'= n + 1 + n', which is unifiedly expressed as

$$KRV_x = \left\{\{kzv_i \mid i = 1, \ldots, n\}, ksmv_x, \{ksv_{xp} | p = 1, \ldots, n'\}\right\} = krv_{xh} | h = 1, \ldots, N.$$

Suppose the fused weights of three types of keywords are set to w_{kzv}, w_{ksmv}, w_{ksv}, respectively, the weights of all keywords after integration can be unified as:

$$W_{KRV_x} = \{ \left\{ w_{kzv} w_{kzv_i} \mid i = 1, \ldots, n \right\}, w_{ksmv}, \{ w_{ksv} w_{ksv_{xp}} | p1, \ldots, n' \} \} = \left\{ w_{krv_{xh}} \mid h = 1, \ldots, N' \right\}.$$

According to the idea of pangrank method in Google, the value of keyword is affected by the weight of key word, the edge and the weight of edge. Then, the value $Value_{krv_{xh}}$ of each keyword can be expressed as follow:

$$Value_{krv_{xh}} = w_{krv_{xh}} + \sum_{s=1, s\neq h}^{N'} \frac{w_{kre_{xhs}}}{w_{kre_{xh}}} \times w_{krv_{xs}} \tag{6}$$

where krv_{xh} and krv_{xs} represent the h-th keyword node and the s-th keyword node after integration, respectively; kre_{xhs} represents the edge of keyword node krv_{xh} and krv_{xs}; $w_{krv_{xh}}$ and $w_{krv_{xs}}$ represent the weight of keyword node krvxh and krvxs, respectively. $w_{kre_{xhs}}$ represents the weight of edge kre_{xhs}. $w_{kre_{xh}}$ represents the sum of weights of all edges connected to keyword node krv_{xh}.

According to the calculation formula (6) of keyword value, if the weight of the keyword connected to keyword krv_{xh} and the weight of the edge connected to krv_{xh} are both large, then the keyword is regarded as valuable keyword. In contrast, if the weight of itself is large, while the keywords connected to it are small in number and weight, then the keyword is not valuable keyword, which does not belong to the range of core values in current keyword network. According to this formula, the keyword value ranking is calculated, so that the first n keywords with the highest value can be extracted as core semantics to construct customer situational semantic network. The set of keywords in customer situational semantic network is represented as $KQV_x = \{kqv_{xl} | l = 1, \ldots, n''\}$. The customer situational semantic network can well represents the core semantics of the x-th retrieval behavior, i.e. the actual demand of customer

V. CASE STUDY

In this section, a real demand acquisition trial about "bearing remanufacturing" from the "Guolian Resources Network" was conducted to investigate the effectiveness of the proposed strategy and method. We tracked customer A's registration and retrieval behavior, as shown in Fig. 8 (a) (b), and then analyzed its demand through construction of situational semantic network.

(1) According to the n = 6 keywords and preference sequence input by the customer, the set of registration keyword node kzv_{Ai} and the corresponding weight of customer A are shown in Table 1.

According to the correlation of registration keyword node kzv_{Ai} in the candidate ontology for remanufacturing service demand in Fig. 3 (a), the set of undirected edges between nodes $KZE_A = \{kze_{1(1,2)}, kze_{2(2,3)}, kze_{3(3,4)}, kze_{4(4,5)}, kze_{5(5,6)}\}$ can be obtained. The set of edge weight can be calculated by formula (2) as $W_{KZE_A} = \{0.19, 1, 0.03, 0.05, 0.04\}$, so that the registration keyword network of customer A can be obtained as $KZWN_A = \{KZV_A, W_{KZV_A}, KZE_A, W_{KZE_A}\}$, as shown in Fig. 8 (c).

(2) By tracking the retrieval behaviors of customer A in the "Guolian resources network" platform, we can obtain the primary keywords of the most recent 3 retrieval behaviors as {ksmvAx |x = 1, 2, 3} = {remanufacturing industry, tapered roller bearing, remanufacturing}. Then, using web crawler

TABLE 1. Customer A's registered keyword node data.

i	1	2	3	4	5	6
kzv_{Ai}	Casting and forging equipment	hot rolling mill	rolling bearing	remanufacturing	commissioned processing	recycling and transportation
$w_{kzv_{Ai}}$	0.05	0.08	0.09	0.31	0.26	0.21

TABLE 2. The efficiency parameters of average demand extraction from 20 customers.

	Average time taken to obtain demand (min)	Average degree of standardization of demand expression	Average accuracy of demand description and customer wishes
(A) cloud computing-based customer demand acquisition method	46.342	0.733	0.804
(B) edge computing-based customer demand acquisition	31.256	0.945	0.752
(C) edge computing-based customer demand discovery using situational semantic network	5.183	0.956	0.892
(D) edge computing-based dynamic demand discovery and acquisition	21.324	0.991	0.957

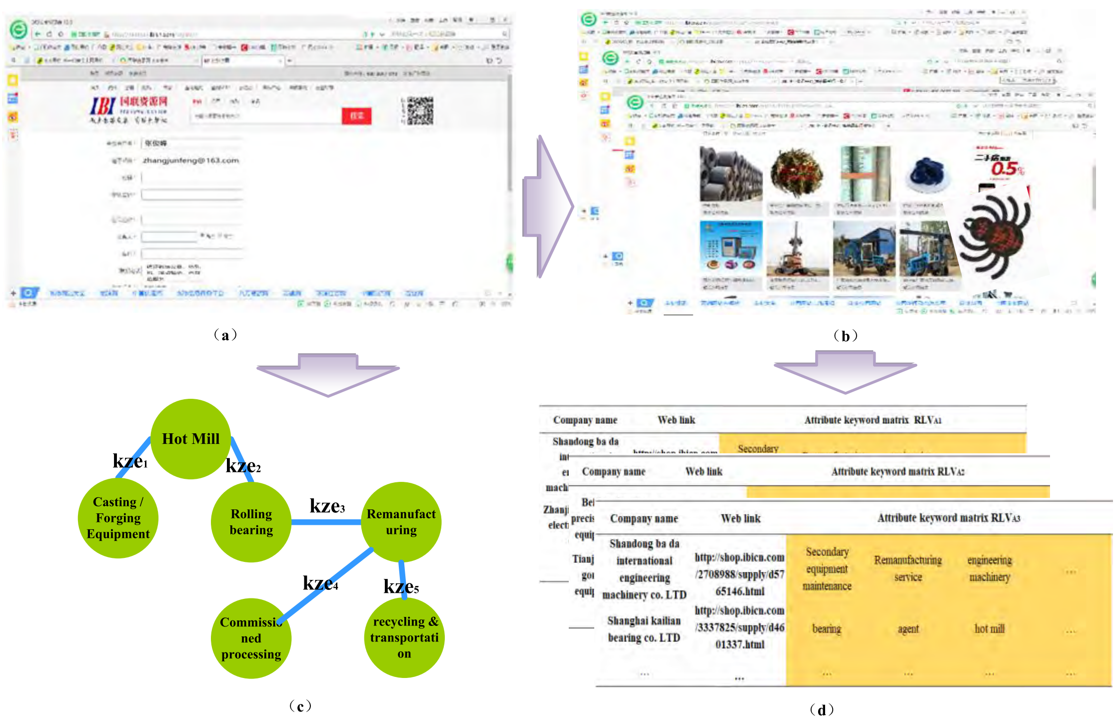

FIGURE 8. Information analysis of customer A's registration and retrieval behavior. (a) Customer A's Registration information. (b) Customer A's latesd retrieved pages. (c) Customer A's register keyword semantic network. (d) Customer A's keyword matrix for latest browsing web pages.

technology, all keywords in the retrieval page corresponding to each primary keyword were captured to construct the keyword matrix as {{KLVA1 |y = 1, ..., 9, r = 1, ..., Ry; Ry = (11, 9, ..., 2)}, {KLVA2 |y = 1, ..., 12, r = 1, ..., Ry; Ry = (18, 18, ..., 7)}, {KLVA3|y = 1, ..., 10, r = 1, ..., Ry; Ry = (32, 19,18, ..., 6)}, as shown in Fig. 8 (d).

(3) According to the keyword matrix, the sample number of each retrieved keyword dataset can be obtained as Nx = {111, 202, 132}. For each data sample set cluster Kx = (3, 5, 3), the first 5 keywords of the cluster with main keyword ksmvAx as cluster center and the first 2 keywords in the remaining 2 clusters were selected using Kmeans clustering

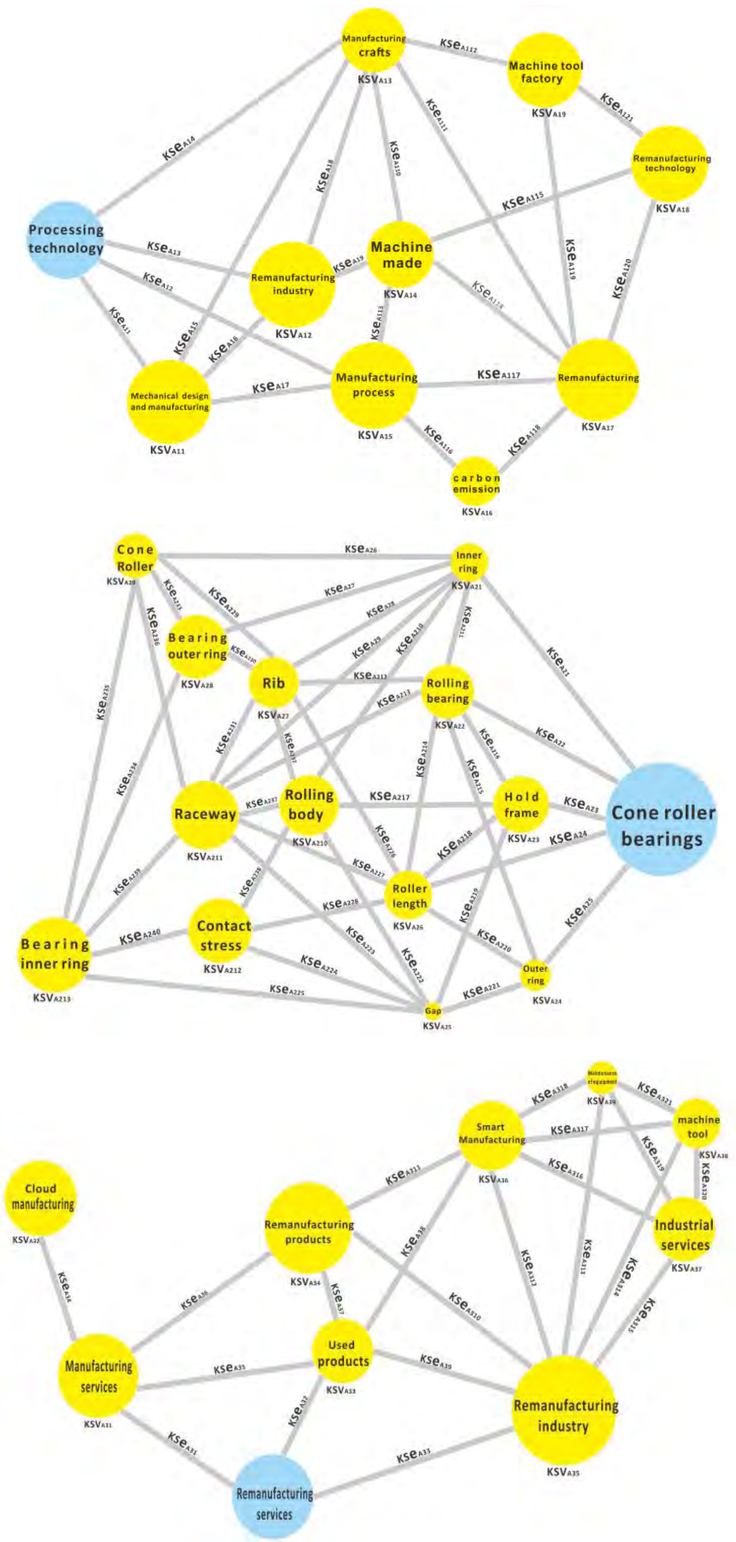

FIGURE 9. Customer A's latest semantic network of retrieval keywords.

algorithm, to form the retrieval keyword set of customer A $KSV_{Ax} = \{ksv_{xp} | p = 1, \ldots, (5 + 2(Kx - 1))\}$, as shown in Fig. 9. The weights of each group of keywords and edges are shown in Fig. 10.

(4) Customer A's registration keyword network $KZWN_A$ was integrated with the retrieval keyword set KSV_{Ax}. Then, the values of the first integrated situational network keywords, $Value_{krv_{A1}} = \{0.052, 0.065, 0.072, 0.386, 0.467,$

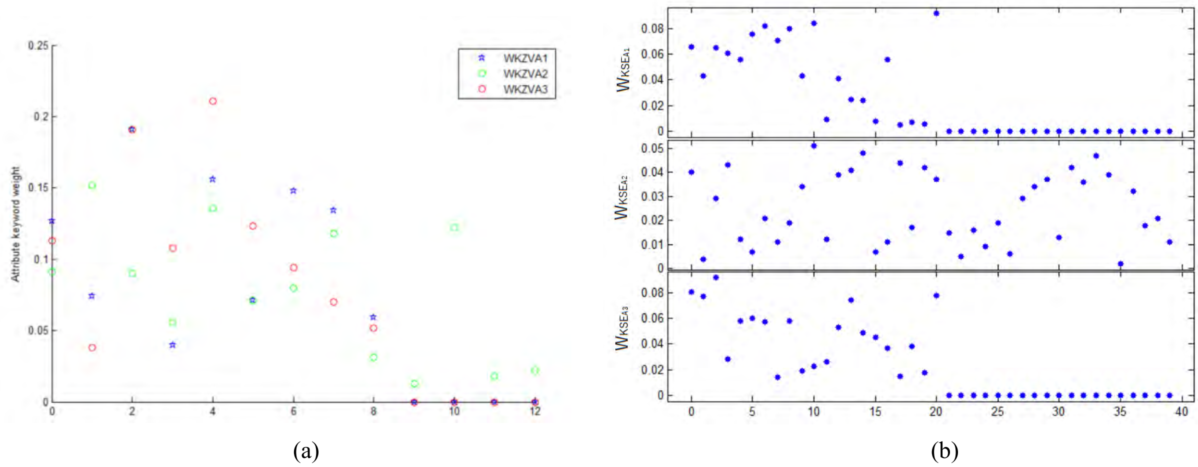

FIGURE 10. The weights of each keywords and edges of the semantic network. (a) weight of each retrieval keyword. (b) weight of each edge.

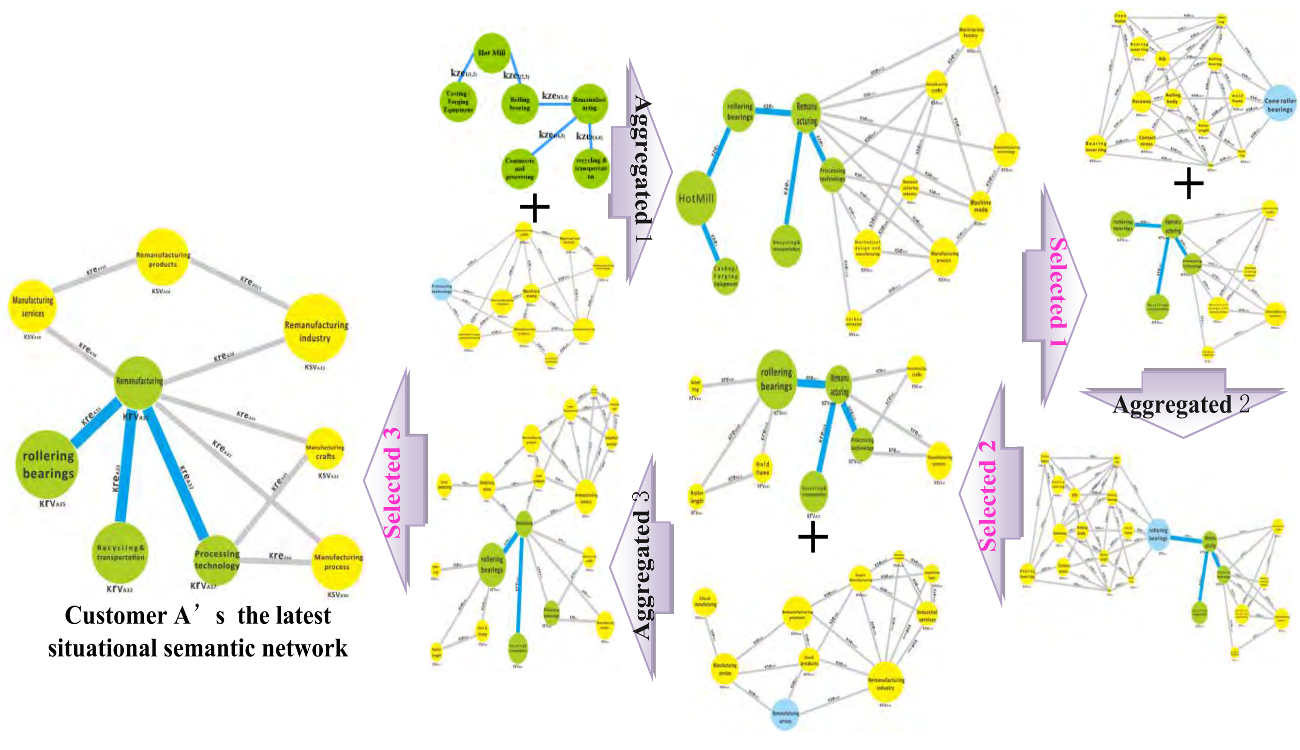

FIGURE 11. Customer A's current situational semantic network.

0.252, 0.165, 0.139, 0.191, 0.065, 0.180, 0.205, 0.064, 0.068}, were calculated using formula (6). To ensure the reliability of situational network, on the basis of 7 cognitive value vocabulary, the keywords in the first 9 of value sequencing was used to form the first client situational semantic network KRV_{A1}. Then these steps were repeatedly performed in turn to get the latest situational semantic network KRV_{A3} of customer A, as shown in Fig. 11.

(5) Contrastive analysis. Based on a CRMSP, four different methods were respectively adopted to extract the demand from 20 customers, including (A) cloud computing-based demand acquisition method, (B) edge computing-based demand recommendation, (C) edge computing-based customer demand discovery using situational semantic network, and (D) edge computing-based dynamic demand discovery and acquisition. The average time and other information are shown in Table 2. The statistical results show that the web-based methods including (B), (C) and (D) are more efficient than method (A). Due to the limitation of candidate ontology capacity, the accuracy of method (B) is only 75.2%,

which is lower than that of traditional method (A). Method (C) is fully based on objective data analysis of customer behavior, so it only takes 19.78% of method (B) in terms of operation time, and its accuracy is 18.62% higher than that of method (B). Method (D) integrates method (B) and (C), which helps customers correct requirements for interactive acquisition through taking advantage of feedback tips on identified potential customer needs, thus significantly improving the efficiency, standardization and accuracy of requirements acquisition.

VI. CONCLUSION AND FUTURE WORK

By analyzing existence form, generation mode and dynamic transformation process of implicit and explicit demand knowledge within the remanufacturing service process, an edge computing-based dynamic discovery and acquisition strategy of remanufacturing service demand is proposed in this paper.

On the basis of existing automatic acquisition method of implicit demand, we focus on a situational semantic network-based discovery method of explicit knowledge hidden in the customer behavior data within edge computing server. Firstly, the unstructured customer registration keyword information is represented as a structured data type, and the semantic similarity of ontology concept is used to calculate the correlation strength of customer registered keywords. Then, the registration keyword semantic network is constructed accordingly. The keywords matrix of all web pages within single search behavior is obtained by data aggregation. Afterwards, the core attribute keywords of single search behavior are procured by Kmeans algorithm and the retrieval keyword semantic network is constructed. After aggregating the two types of keywords semantic network, the core semantics of the aggregated semantic network are extracted by Pangrank method and the customer situation semantic network is formed.

In case study, customer A's registration and retrieval behavior on "Guolian Resources Network" is tracked and the construction process of building situational semantic network are simulated to determine its dynamic potential demand. Then, four different methods are respectively adopted to extract the demand from 20 customers based on CRMSP. The statistical results show that method (C) studied in this paper only takes 19.78% of method (B) in terms of operation time, and its accuracy is 18.62% higher than that of web-based demand recommendation method. Method (D) which combines the favorable features of method (B) and method (C), has a significantly higher acquisition efficiency, standardization degree and accuracy. It provides a reference for potential demand discovery of remanufacturing service, and lays a foundation for further research on remanufacturing service matching.

In the future, the intelligent selection and matching method of remanufacturing service resource module oriented to service demand will be studied, which will help to realize the adaptive matching of remanufacturing service resource module. The proposed method has been demonstrated in demand acquisition of intelligent management of enterprises and smart cities, providing a reference for realization of intelligence technology in digital cities.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this article, and it is the original research that has not been published previously, and not under consideration for publication elsewhere.

REFERENCES

[1] G. Paul, R. Emma, and H. Jenifer, "A review of the state of the art in tools and techniques used to evaluate remanufacturing feasibility," *J. Cleaner Prod.*, vol. 81, pp. 1–15, Jun. 2014. doi: 10.1016/j.jclepro.2014.06.014.

[2] Z. Li, A. V. Barenji, and G. Q. Huang, "Toward a blockchain cloud manufacturing system as a peer to peer distributed network platform," *Robot. Comput. Integr. Manuf.*, vol. 54, pp. 133–144, Dec. 2018. doi: 10.1016/j.rcim.2018.05.011.

[3] D. Z. Wu, J. L. Thames, D. W. Rosen, and D. Schaefer, "Enhancing the product realization process with cloud-based design and manufacturing systems," *J. Comput. Inf. Sci. Eng.*, vol. 13, no. 4, pp. 041004-1–041004-14, Dec. 2013. doi: 10.1115/1.4025257.

[4] L. Wang, X. H. Xia, Y. Q. Xiong, and M. Zhou, "Architecture of reverse supply chain service system," *Comput. Integr. Manuf. Syst.*, vol. 21, no. 10, pp. 2720–2731, Oct. 2015. doi: 10.13196/j.cims.2015.10.021.

[5] L. Wang, X. H. Xia, Y. Q. Xiong, and M. Zhou, "Modular approach and application of remanufacturing service resources," *Comput. Integr. Manuf. Syst.*, vol. 22, no. 9, pp. 2204–2216, Sep. 2016. doi: 10.13196/j.cims.2016.09.017.

[6] H. Akbaripour and M. Houshmand, "Service composition and optimal selection in cloud manufacturing: Landscape analysis and optimization by a hybrid imperialist competitive and local search algorithm," *Neural Comput. Appl.*, vol. 30, no. 9, pp. 1–22, Sep. 2018. doi: 10.1007/s00521-018-3721-9.

[7] F. Tao, Y. J. LaiLi, L. D. Xu, and L. Zhang, "FC-PACO-RM: A parallel method for service composition optimal-selection in cloud manufacturing system," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2023–2033, Nov. 2013. doi: 10.1109/TII.2012.2232936.

[8] L. Wang, X. H. Xia, J. H. Cao, and X. Liu, "Dynamic acquisition method of remanufacturing service demand and its application," *Comput. Integr. Manuf. Syst.*, vol. 24, no. 3, pp. 781–792, Mar. 2018. doi: 10.13196/j.cims.2018.03.025.

[9] D. Çelik, and A. Elçi, "A broker-based semantic agent for discovering Semantic Web services through process similarity matching and equivalence considering quality of service," *Sci. Chin. Inf. Sci.*, vol. 56, no. 1, pp. 1–24, Jan. 2013. doi: 10.1007/s11432-012-4697-1.

[10] X. Du, Y. Wei, and L. Wu, "Interactive details on demand visual analysis on large attributed networks," *Chin. J. Electron.*, vol. 27, no. 5, pp. 900–909, Sep. 2018. doi: 10.1049/cje.2017.08.014.

[11] P. Salini and S. Kanmani, "Security requirements engineering process for Web applications," *Procedia Eng.*, vol. 38, pp. 2799–2807, Jun. 2012. doi: 10.1016/j.proeng.2012.06.328.

[12] C. Wang, W. Zhao, H.-J. Wang, and L. Chen, "Multidimensional customer requirements acquisition based on ontology," *Comput. Integr. Manuf. Syst.*, vol. 22, no. 4, pp. 908–916, Apr. 2016. doi: 10.13196/j.cims.2016.04.004.

[13] S. G. Small and L. Medsker, "Review of information extraction technologies and applications," *Neural Comput. Appl.*, vol. 25, pp. 533–548, Dec. 2014. doi: 10.1007/s00521-013-1516-6.

[14] A. K. Bhardwaj and M. Singh, "Data mining-based integrated network traffic visualization framework for threat detection," *Neural Comput. Appl.*, vol. 26, no. 1, pp. 117–130, Aug. 2014. doi: 10.1007/s00521-014-1701-2.

[15] Y. Liu, J. Jin, P. Ji, J. A. Harding, and R. Y. Fung, "Identifying helpful online reviews: A product designer's perspective," *Comput.-Aided Des.*, vol. 45, no. 2, pp. 180–194, 2013. doi: 10.1016/j.cad.2012.07.008.

[16] Y. Liu, S. C. J. Lim, and W. B. Lee, "Product family design through ontology-based faceted component analysis, selection, and optimization," *J. Mech. Des.*, vol. 135, no. 8, pp. 1885–1901, Aug. 2013. doi: 10.1115/1.4023632.

[17] H. Xu, X. Chen, and X. F. Hu, "Finding method of users' real-time demands for literature search systems," *J. Comput. Appl.*, vol. 35, no. 7, pp. 1975–1978, 1983. doi: 10.11772/j.issn.1001-9081.2015.07.1975.

[18] S. Sunny and Z. Puning, "Improving quality of data: IoT data aggregation using device to device communications," *IEEE Access*, vol. 6, pp. 67830–67840, Nov. 2018. doi: 10.1109/ACCESS.2018.2878640.

[19] W. Rattasiri, S. K. Halgamuge, and N. Wickramarachchi, "Structure adaptation of hierarchical knowledge-based classifiers," *Neural Comput. Appl.*, vol. 18, no. 6, pp. 523–537, Sep. 2009. doi: 10.1007/s00521-008-0190-6.

[20] W. R. Gu, S. B. Dong, and M. Q. Chen, "Personalized news recommendation based on articles chain building," *Neural Comput. Appl.*, vol. 27, no. 5, pp. 1263–1272, Jul. 2016. doi: 10.1007/s00521-015-1932-x.

[21] W. Wang and B. Yu, "Text categorization based on combination of modified back propagation neural network and latent semantic analysis," *Neural Comput. Appl.*, vol. 18, no. 8, pp. 875–881, Nov. 2009. doi: 10.1007/s00521-008-0193-3.

[22] D. Puiu, P. Barnaghi, R. Tönjes, D. Kümper, M. I. Ali, A. Mileo, J. X. Parreira, M. Fischer, S. Kolozali, N. Farajidavar, F. Gao, T.-L. Pham, C.-S. Nechifor, D. Puschmann, and J. Fernandes, "CityPulse: Large scale data analytics framework for smart cities," *IEEE Access*, vol. 4, pp. 1086–1108, Jan. 2016. doi: 10.1109/ACCESS.2016.2541999.

[23] J. Yang, J. Zhang, C. Ma, H. Wang, J. Zhang, and G. Zheng, "Deep learning-based edge caching for multi-cluster heterogeneous networks," *Neural Comput. Appl.*, vol. 31, no. 2, pp. 1–12, Feb. 2019. doi: 10.1007/s00521-019-04040-z.

[24] A. Budanitsky and G. Hirst, "Semantic distance in WordNet: An experimental, application-oriented evaluation of five measures," in *Proc. NAACL*, Pittsburgh, PA, USA, 2001, pp. 29–34.

[25] M. Capó, A. Pérez, and J. A. Lozano, "An efficient approximation to the K-means clustering for massive data," *Knowl. Based Syst.*, vol. 117, pp. 56–69, Feb. 2017. doi: 10.1016/j.knosys.2016.06.031.

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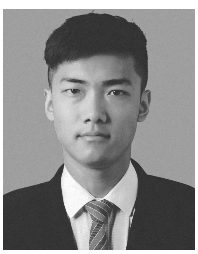

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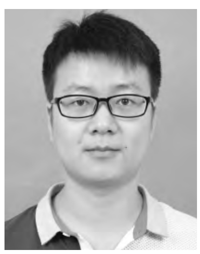

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