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Functional importance evaluation approach for cloud manufacturing services based on complex network and evidential reasoning rule

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ABSTRACT

In the uncertain cloud environment, manufacturing services monitoring is effective to ensure the normal function of cloud manufacturing service system (CMSS). However, continuously monitoring all of the manufacturing services is impractical since it is resource consuming. One feasible method is to prioritize the allocation of monitoring resources to the important services. Therefore, we propose an approach for evaluating the functional importance of manufacturing services based on complex network and evidential reasoning (ER) rule. Firstly, a domain-oriented cloud manufacturing service complex network (DoCMSCN) model is constructed and elaborated. Secondly, based on the idea of multi-granularity and multi-indicator, an evaluation model for the importance of manufacturing services is presented. Different centrality indicators of the DoCMSCN in different functional granularities are obtained and transformed into evaluation evidence. Then the ER algorithm is applied to fused the evaluation results. In the fusion process, the reliability and weight of each piece of evidence are fully considered to improve the fusion accuracy. The experimental results of vertical elevator design services show the proposed approach can effectively find the important manufacturing services and superior than the existing ones. It can facilitate the decision-making of monitoring strategy in conditions of limited resources from the functional perspective. Finally, we develop a prototype monitoring system for vertical elevator design services.

1. Introduction

As a new service-oriented manufacturing paradigm, cloud manufacturing has received extensive attentions from the academia and industry. It aims to satisfy diversified and personalized requirements of users, and truly allocate manufacturing resources on demand (Li et al., 2010; Tao, Zhang, Venkatesh, & Cheng, 2011; Xu, 2012; Wu, Thames, Rosen, & Schaefer, 2012; Zhang et al., 2014; Adamson, Wang, Holm, & Moore, 2017; Huang, Gu, Zhou, & Chen, 2018). In cloud manufacturing, cross-organizational manufacturing resources integration and operation can be realized through manufacturing services (Schulte, Hoenisch, Hochreiner, Dustdar, Klusch, & Schuller, 2014; Li, Chan, Liang, & Luo, 2016; Li et al., 2020). Each manufacturing service has functional attributes and non-functional attributes. The functional attributes are manifested in that different types of manufacturing services have different functions. The non-functional attributes are manifested in that the performance of the same type of manufacturing services with the same function is different. From the functional perspective, enterprises can customize personalized cloud manufacturing service systems (CMSSs) with different functions (e.g., product design, product processing) through service composition (Dustdar & Papazoglou, 2008; Hayyolalam, Pourghebleh, Kazem, & Ghaffari, 2019; Liu, Guo, Wang, Du, & Pang, 2019; Li, Xiong, & Wang, 2022).

In the uncertain cloud environment, the status of manufacturing service is dynamic and unpredictable. Functional abnormalities or failures of manufacturing services often occur. As a result, the diversified and personalized customization requirements of users are difficult to meet. Therefore, it is necessary to monitor the manufacturing services. However, continuously monitoring all of the manufacturing services in the cloud platform is impractical since it is time consuming and resource

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consuming (Wang, Chen, Lin, & Chen, 2014). Moreover, the importance of manufacturing services is different (Thong & Zhu, 2020). Therefore, the monitoring priorities of different manufacturing services are different. One feasible method is to prioritize the allocation of monitoring resources to the important manufacturing services (Wu, Peng, Huang, & Zhang, 2019). Thus, how to find the important manufacturing services is of great significance for the rational allocation of monitoring resources and the effective reduction of maintenance costs.

Actually, there are collaborative interaction relationships among manufacturing services with different functions. Based on the relationships, a cloud manufacturing services complex network can be constructed in which nodes representing manufacturing services and edges representing collaborative interaction relationships (Cheng, Tao, Zhao, & Zhang, 2017; Ren, Ren, & Jain, 2018). From the perspective of network, the function of the network is related to the its structure (Zhou, Zhang, Zhou, Zou, & Yang, 2012). Then, evaluating the functional importance of manufacturing services is transformed into the evaluation of the importance of nodes in the manufacturing services complex network. To improve the accuracy of functional importance of manufacturing services, a novel approach based on complex network and evidential reasoning rule is proposed. The main contributions of this paper are as follows:

(1) The customization of cloud manufacturing service system is elaborated, and the domain-oriented cloud manufacturing services complex network (DoCMSCN) model is constructed.
(2) The multi-indicator evaluation strategy based on evidential reasoning rule is proposed. Different importance evaluation indicators are converted into evaluation evidence, and then the reliability and weight of the evidence are applied in the fusion process to improve the accuracy of the fusion results.
(3) The multi-granularity evaluation strategy is designed in which the functional importance of nodes in both global network and local networks are comprehensively considered. It make the evaluation results more realistic.

The remainder of this paper is structured as follows. Section 2 discusses the related works. Section 3 introduces the DoCMSCN. Section 4 presents the node importance evaluation of DoCMSCN based on evidential reasoning (ER) rule. Section 5 gives a case study. Section 6 concludes the paper.

2. Related works

This paper aims to evaluate the importance of cloud manufacturing services through complex network theory. Therefore, in this section, the complex network in the modeling of manufacturing service relationships and importance evaluation of manufacturing services are elaborated.

2.1. Complex network in the modeling of manufacturing service relationships

As product development processes became increasingly intricate, the challenges in design and operation of manufacturing systems had increased (Mourtzis, 2020). On the one hand, manufacturing systems in pursuit of cost and time reduction without decreasing quality and flexibility were becoming more and more complex (Efthymiou, Mourtzis, Pagoropoulos, Papakostas, & Chryssolouris, 2016). On the other hand, the desire for personalization of manufacturing systems was increasing. Cloud manufacturing played a special role as a promising lever for the customization and operation of manufacturing systems (Lanza, Peukert, & Steier, 2022). In cloud manufacturing, personalized CMSSs could be customized based on the logical relationships of manufacturing services.

The complex network theory had been widely used in the modeling of service relationships. Usually, the service networks or service graphs were constructed to express the relationships (Chen, Paik, & Hung, 2015; Adeleye, Yu, Yongchareon, Han, & Sheng, 2020). Existing studies had shown that the real web services network had small world and scale-free properties (Kil, Oh, Elmacioglu, Nam, & Lee, 2009; Hwang, Altmann, & Kim, 2009; Tao, Guo, Zhang, & Cheng, 2012). For a CMSS, its structure could also be represented as a network or graph based on the relationships of manufacturing services. For example, Cheng, Tao, Zhao, & Zhang, (2017) constructed a supplydemand matching (SDM) hyper-network model. The upper layer was the manufacturing task network and the lower layer was the manufacturing service network. Based on the SDM hyper-network, manufacturing services selection or manufacturing resources matching could be researched from a new perspective (Tao, Cheng, Cheng, Gu, Zheng, & Yang, 2017; Cheng, Tao, Xu, & Zhao, 2018; Cheng, Bi, Tao, & Ji, 2020). Similarly, a Cloud 3D printing service (C3DPS) hyper-network was modeled to address complex manufacturing service management in the cloud environment (Zhang, Zhao, & Wang, 2019). Then combined with complex network theory, the supply–demand matching of C3DPS was transformed into the nodes matching in the hyper-network (Zhang et al., 2021).

Recently, the collaboration feature of manufacturing services was researched (Li, Cheng, Song, & Tao, 2020). According to the data of service interaction and cooperation in the cloud platform, Ren, Ren, and Jain (2018) extracted five kinds of relationships, namely interactive transaction, co-community, physical distance, resource-related and social similarity relationship. Based on the calculation of these relationships strength, the service synergy network (SSN) used in manufacturing service composition was derived through the weighted aggregation. Thong, and Zhu (2020) put forward a two-layer service social network from the perspective of synergy. The upper layer of this model was occupied by the manufacturing services with scare resources. The lower layer was occupied by ordinary manufacturing services. Li, Cheng, and Tao (2020) established the manufacturing services collaboration network by introducing the collaborative relations aware community of complex network. And then they investigated the failures detection, failures cascading propagation analysis and specific control strategies for the platform-based manufacturing services collaboration. Based on the graph theory, Cheng, Gao, Wang, Tao, and Wang (2022) proposed an operational robustness analysis method of the IIoT platform for manufacturing services collaboration to evaluate the tolerance and persistence capabilities of manufacturing services collaboration in the presence of supply and demand uncertainties. In their research, the IIoT platform operation network for manufacturing services collaboration was modeled as an interdependent network-of-network structure.

In conclusion, the complex network theory had been proven to be effective in the modeling of manufacturing service relationships. It provided a new perspective for the research of the CMSS. Especially, for a complex CMSS which contained a huge number of manufacturing services, the complex network could be a promising tool.

2.2. Importance evaluation of manufacturing services

Identifying important services had been attracted much attentions. It played an important role in the research of cloud service systems. For example, Zheng, Zhang, and Lyu (2010) presented a QoS (quality of service)-driven ranking approach named CloudRank to predict the quality ranking of cloud components. For the multi-tenant service-based system (SBS), Wang, He, Ye, and Yang (2018) proposed a cost-effective fault tolerance approach by providing redundancy for the critical services. The criticality of each service was evaluated based on its multi-dimensional quality and multiple tenants sharing the component service with differentiated quality preferences. Similarly, Chen, Li, & Wang (2018) evaluated the criticality of a service in the SBS based on two dimensions, namely QoS and tenants' priorities.

From the perspective of complex network, the importance of a service was usually depended on its structure information. To build fault-tolerant cloud applications, Zheng, Zhou, Lyu, and King (2012) proposed the FTCloud which was a cloud component ranking framework.

The application structure, component invocation relationships and component characteristics were used to build the component graph which was applied to measure the importance of the components. Wu, Zuo, Zhang, Zhou, and Zhao (2019) proposed a failure-sensitive structure-based component ranking approach (FSCRank), which integrates component failure impact and application structure information into component importance evaluation. Jiang, Zhang, and Cao (2019) transformed the interaction between components of service-oriented systems into service dependency graph. An improved weighted Leader-Rank algorithm is used to measure the importance of components and obtain the sequence of critical components. For manufacturing services, Wu, Peng, Huang, & Zhang (2019) put forward a Leader-Rank based manufacturing nodes ranking algorithm to rank the services according to their significance in fault tolerance. Wang, Zhang, Qian, and Zhang (2021) evaluated the credit scores of manufacturing services considering the complex network indicators. It could be used to determine the maintenance priority of failed manufacturing services.

Although the complex network theory seemed to be promising in evaluating the importance of services, existing researches had the following limitations. Firstly, the complex network theory provided many evaluation indicators (e.g., degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, leader-rank value, etc.), which reflected the importance of a node in the network from different aspects. However, for different kinds of cloud service systems in cloud manufacturing, the results given by different indicators were uncertain. Therefore, how to comprehensively use these indicators to improve the accuracy of the evaluation results was a difficult problem that needed to be solved. Secondly, most of the studies focused on the non-functional attribute of services while the functional attribute of services was ignored. Actually, the functional attribute of services was also important (Liao, & Wei, 2021). Moreover, the domain characteristic of cloud manufacturing services was less of consideration. For example, the communities/modules in the network usually represented local functions with smaller granularity. In short, the above approaches could not meet the requirements for the functional evaluation of cloud manufacturing services.

3. Domain-oriented cloud manufacturing services complex network

Generally, domain-oriented customization of cloud manufacturing service systems is relatively easy to realize. The reason is that users' requirements in a domain usually have commonalities which can be reused. The concept of the domain refers to a functional area covered by a set of application systems with identical or similar requirements (ESPRIT Consortium AMICE, 1993). It can be applied to build a complete requirement model which expresses common requirements and personalized requirements (Zhang, Zhang, Lu, Xu, Gao, & Xiao, 2018). The domain-oriented customization of CMSS is as shown in Fig. 1.

To facilitate the elaboration, some definitions are given.

(1) Domain-oriented cloud manufacturing services complex network (DoCMSCN). It refers to a network in which nodes representing abstract manufacturing services and edges representing the relationships of abstract manufacturing services.
(2) Abstract manufacturing service (AMS). It refers to the abstraction of the functional attributes in the CMSS. For example, if the function of the DoCMSCN is used for product design service systems customization, a node (AMS) in the DoCMSCN represents the function of a design activity.
(3) Manufacturing service instance (MSI). It refers to the entity registered in the cloud platform. Each MSI can be used to complete a certain function.
(4) Manufacturing service cluster (MSC). It refers to a cluster contains several manufacturing service instances with the same function. For example, MSC_2 is a cluster that contains three manufacturing service instances (i.e., MSI 4, MSI 5 and MSI 6). Since the MSI 4, MSI 5 and MSI 6 have the same function, any of

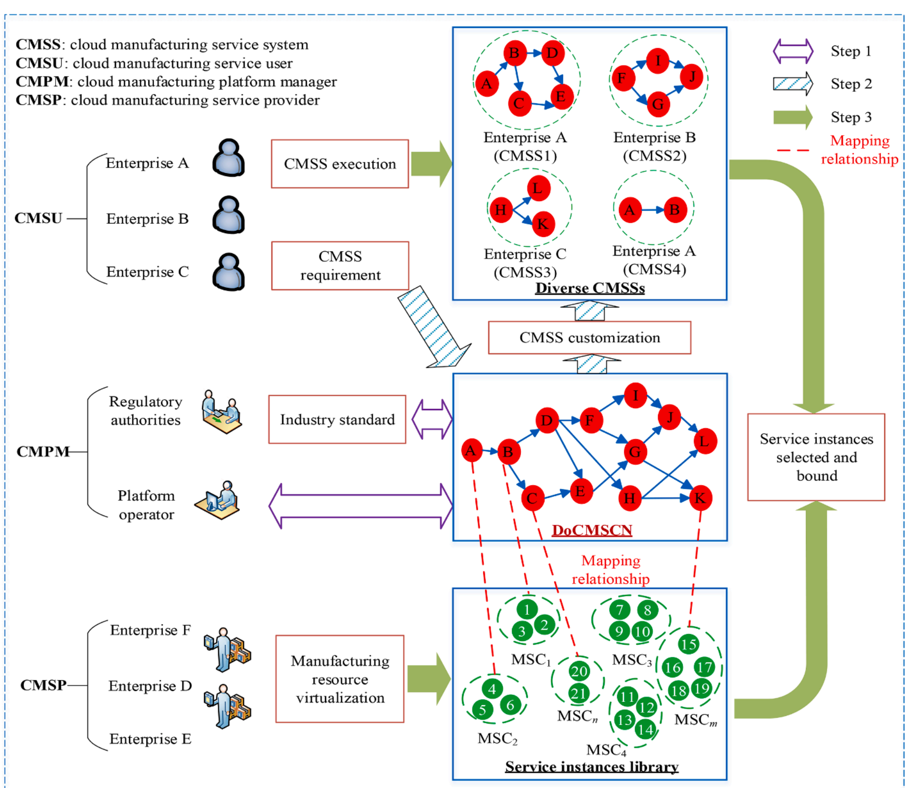


Fig. 1. Domain-oriented customization of CMSS.

the three instances can realize the functional requirement of the node A. Therefore, the mapping relationship of AMS and MSC is one-to-one. The mapping relationship of AMS and MSI is one-to-many.

As shown in Fig. 1, there are three kinds of roles in the cloud manufacturing platform, namely cloud manufacturing service user (CMSU), cloud manufacturing platform manager (CMPM) and cloud manufacturing service provider (CMSP). Then the process of CMSS customization can be described as follows. In the first step, the DoCMSCN is built by the CMPM. It can be seen a service composition template for CMSS customization. In the second step, diverse CMSSs with different functions can be customized based on service composition automatically according the requirements submitted by the CMSU. For example, enterprise A has customized two kinds of CMSSs, namely CMSS1 and CMSS4. The CMSS1 is consisted of five abstract services (A, B, C, D, E) and the CMSS4 is consisted of two abstract services (A, B). Obviously, the functions of the two CMSSs are different. The former is more complex than the later. In the third step, when a customized CMSS is running, suitable manufacturing service instances are selected and bound from the corresponding manufacturing service clusters in the service instances library. For example, when the CMSS4 is running, two service instances (the one is from MSC_1 and the other is from MSC_2) are selected and bound according to the mapping relationship. Specifically, we can select MSI 1 form MSC_1 and MSI 5 from MSC_2.

Based on the above description, users' customization requirements for CMSSs are diverse, which is mainly reflected in the difference of functional levels. From the perspective of network, the DoCMSCN can be seen as a global network with complete functions in a domain. Each customized CMSS is a sub-network with partial functions.

The main purpose of the paper is to evaluate the functional importance of the manufacturing service instances. It should be noted that the non-functional attributes of the MSIs have no effect on the evaluation results. Actually, the service instances in the same MSC are equally important from the functional perspective since they have the same function. For example, the functional importance of the MSI 1, MSI 2 and MSI 3 is the same. The functional importance of the MSI 1 and MSI 5 is different. Therefore, the research problem can be transformed into the evaluation of importance of nodes (AMSs) in the DoCMSCN according to the mapping relationship.

4. Node importance evaluation for DoCMSCN based on ER rule

In this section, the basic concepts of importance evaluation indicators of nodes in complex network and evidential reasoning rule are briefly introduced, and then a node importance evaluation model for DoCMSCN is presented. To facilitate elaboration, a list of symbols is given Table 1:

4.1. Importance evaluation indicators of nodes in complex network

Based on the complex network theory, the centrality of a node reflects its relative importance in the network. Therefore, the centrality indicators can be used for evaluating the node importance of the DoCMSCN. There are four kinds of indicators which are used frequently, namely degree centrality, betweenness centrality, closeness centrality and eigenvector centrality.

(1) Degree centrality. The degree centrality is the normalization of degree. The degree centrality of node i, denoted as $C_D(i)$, can be calculated as

$$C_D(\mathrm{i}) = \frac{k_i}{N-1} \tag{1}$$

where k_i represents the degree of node i and N represents the total number of node.

(2) Betweenness centrality. The betweenness centrality is the

Table 1
List of symbols.

Symbol	Descriptions
$C_D(i)$	The degree centrality of node i
N	The total number of node
k_i	The degree of node i
$C_B(i)$	The betweenness centrality of node i
B_i	The betweenness of node i
n_{jl}	The number of shortest paths between node j and node l
$n_{jl}(i)$	The number of shortest paths between node j and node l which passing through node i
$C_C(i)$	The closeness centrality of node i
d_{ij}	The distance of node i and node j
$C_E(i)$	The eigenvector centrality of node i
Θ	The frame of discernment
$P(\Theta)$	The power set of Θ
θ	The element except the empty set in the power set $P(\Theta)$
$p_{\theta,j}$	The degree of support for proposition θ
r_j	The reliability of evidence e_j
w_j	The weight of evidence e_j
$\widetilde{m}_{\theta,j}$	The degree of support of the evidence e_j for the proposition θ
$m_{\theta,j}$	The basic probability mass
$c_{rw,j}$	Normalization factor
$DC_{\max}$	The maximum value of the degree centrality
$DC_{\min}$	The minimum value of the degree centrality
$BC_{\max}$	The maximum value of the betweenness centrality
$BC_{\min}$	The minimum value of the betweenness centrality
$CC_{\max}$	The maximum value of the closeness centrality
$CC_{\min}$	The minimum value of the closeness centrality
$EC_{\max}$	The maximum value of the eigenvector centrality
$EC_{\min}$	The minimum value of the eigenvector centrality
$m_{DCi}(H)$	The degree of support for the importance in the frame of discernment by the degree centrality
$m_{DCi}(L)$	The degree of support for the unimportance in the frame of discernment by the degree centrality
$m_{DCi}(\Theta)$	The degree of support for the unknowness in the frame of discernment by the degree centrality
$m_{BCi}(H)$	The degree of support for the importance in the frame of discernment by the betweenness centrality
$m_{BCi}(L)$	The degree of support for the unimportance in the frame of discernment by the betweenness centrality
$m_{BCi}(\Theta)$	The degree of support for the unknowness in the frame of discernment by the betweenness centrality
$m_{CCi}(H)$	The degree of support for the importance in the frame of discernment by the closeness centrality
$m_{CCi}(L)$	The degree of support for the unimportance in the frame of discernment by the closeness centrality
$m_{CCi}(\Theta)$	The degree of support for the unknowness in the frame of discernment by the closeness centrality
$m_{ECi}(H)$	The degree of support for the importance in the frame of discernment by the eigenvector centrality
$m_{ECi}(L)$	The degree of support for the unimportance in the frame of discernment by the eigenvector centrality
$m_{ECi}(\Theta)$	The degree of support for the unknowness in the frame of discernment by the eigenvector centrality
$T_{\max}$	The theoretical maximum value of the attribute derived from the evidence e_j
$A_{\max}$	The actual maximum value of the attribute derived from the evidence e_j
M^{global}	The belief degree distribution functions of node importance in the global network
M^{local}	The belief degree distribution functions of node importance in the local network
I_{global}	The node importance value in the global network
I_{local}	The node importance value in the local network
$I(i)$	The final importance of node i
α	The weight of global network
β	The weight of sub-networks

normalization of betweenness. The betweenness centrality of node i, denoted as $C_B(i)$, can be calculated as

$$C_B(\mathrm{i}) = \frac{2B_i}{(N-1)(N-2)}$$
$$B_i = \sum_{\substack{1\leqslant j<l\leqslant N \\ j\neq i\neq l}} \frac{n_{jl}(i)}{n_{jl}} \tag{2}$$

where B_i represents the betweenness of node i, n_{jl} represents the number of shortest paths between node j and node l, $n_{jl}(i)$ represents the number of shortest paths between node j and node l which passing through node i.

(3) Closeness centrality. The closeness centrality is one of the main concepts in topological space. It reflects the degree of nodes centered in the network.The closeness centrality of node i, denoted as $C_C(i)$, can be calculated as

$$C_c(\mathrm{i}) = \sum_{\substack{j=1 \\ j\neq i}}^{N} 2^{-d_{ij}} \tag{3}$$

where d_{ij} represents the distance of node i and node j.

(4) Eigenvector centrality. The eigenvector vector centrality is the relative score assigned to each node in the network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. It can be defined by an adjacency matrix as $Ax = \lambda x$. In general, there will be many different eigenvalues λ for which a non-zero eigenvector solution exists. Only the greatest eigenvalue results in the desired centrality measure. The ith component of the normalized eigenvector then gives the relative centrality score of the node i in the network, denoted as

$$C_E(\mathrm{i}) = x_i \tag{4}$$

4.2. Evidential reasoning (ER) rule

Evidential reasoning (ER) rule is developed on the Dempster-Shafer (DS) evidence theory and ER algorithm. It uses belief degree distribution to express the degree of support for different propositions and thus to obtain evidence fused via ER rule latter. It is effective to deal with muti-source and uncertain information (Yang & Xu, 2013). In the ER rule, Θ={S_1,S_2,…,SN} represents a set of mutually exclusive and collectively exhaustive propositions, in which Θ is referred to as a frame of discernment. For any $i, j\in\{1,\ldots, N\}$, $S_i \cap S_j = \varnothing$, where $\varnothing$represents an empty set. $P(\Theta)$ or 2^{Θ} is used to represent the power set of Θ. The belief degree distribution of a piece of evidence can be expressed as

$$e_j = \left\{ (\theta, p_{\theta,j}) \middle| \forall\theta \subseteq \Theta, \sum_{\theta\subseteq\Theta} p_{\theta,j} = 1 \right\} \tag{5}$$

where $(\theta, p_{\theta,j})$ is the element of evidence e_j, which represents that the degree of support for proposition θ is $p_{\theta,j}$. θ can be any element except the empty set in the power set $P(\Theta)$. The total support of each proposition is 1.

In the ER rule, the reliability r_j and weight w_j of the evidence are defined. The reliability r_j is an inherent attribute of the evidence. It reflects the evaluation ability of the information source generating the evidence e_j for a given problem. The weight w_j is the relative importance of the evidence e_j compared with other evidence. It depends on the types of evidence involved in the fusion process, the user and the use occasions of the evidence. Therefore, it is usually a subjective parameter. The belief degree distribution function with reliability and weight is as follows

$$mj = \left\{ \left(\theta, \widetilde{m}_{\theta,j}\right), \forall\theta \subseteq \Theta; \left(P(\Theta), \widetilde{m}_{P(\Theta),j}\right) \right\} \tag{6}$$

where $\widetilde{m}_{\theta,j}$ represents the degree of support of the evidence e_j for the proposition θ when considering the reliability r_j and weight w_j. It can be calculated by

$$\widetilde{m}_{\theta,j} = \begin{cases} 0 & \theta = 0 \\ c_{rw,j} m_{\theta,j} & \theta \subseteq \Theta, \theta \neq \varnothing \\ c_{rw,j}(1-r_j) & \theta = P(\Theta) \end{cases} \tag{7}$$

where$m_{\theta,j} = w_j p_{\theta,j}$, it represents the basic probability mass;$c_{rw,j} = 1/(1 + \mathrm{w}_j - r_j)$, it represents normalization factor.

For two independent pieces of evidence $e1$ and $e2$, the degree of joint support for proposition θ can be calculated by

$$p_{\theta,e(2)} = \begin{cases} 0 \ \theta = \varnothing \\ \dfrac{\widehat{m}_{\theta,e(2)}}{\sum_{D\subseteq\Theta} \widehat{m}_{D,e(2)}} \ \theta \subseteq \Theta, \theta \neq \varnothing \end{cases}$$
$$\widehat{m}_{\theta,e(2)} = [(1-r_2)m_{\theta,1} + (1-r_1)m_{\theta,2}] + \sum_{B\cap C=\theta} m_{B,1} m_{C,2} \ \forall\theta \subseteq \Theta \tag{8}$$
$$\widehat{m}_{P(\Theta),e(2)} = (1-r_2)(1-r_1)$$

According to the formula(8), multiple pieces of evidence can be recursively merged in any order. For K pieces of mutually independent evidence, the degree of joint support for proposition θ can be calculated as follows:

$$p_{\theta,e(K)} = \begin{cases} 0 \ \theta = \varnothing \\ \dfrac{\widehat{m}_{\theta,e(2)}}{\sum_{D\subseteq\Theta} \widehat{m}_{D,e(2)}} \ \theta \subseteq \Theta, \theta \neq \varnothing \end{cases}$$
$$\widehat{m}_{\theta,e(K)} = [(1-r_i)m_{\theta,(i-1)} + m_{P(\Theta),e(i-1)} m_{\theta,i}] + \sum_{B\cap C=\theta} m_{B,e(i-1)} m_{C,i} \ \forall\theta \subseteq \Theta \tag{9}$$
$$\widehat{m}_{P(\Theta),e(i)} = (1-r_i) m_{P(\Theta),e(i-1)}$$

4.3. Node importance evaluation approach

Based on the complex network and ER rule theory, a novel approach for evaluating the importance of nodes in the DoCMSCN is proposed, as shown in Fig. 2.

Firstly, considering the diversity of CMSS customization requirements, the DoCMSCN (i.e., global network) is decomposed into several sub-networks (i.e., local networks). Secondly, for the networks with different granularities (i.e., global network and local networks), the centrality evaluation indicators are used to generate the node importance evaluation evidence (i.e., belief degree distribution function) respectively. Then, the ER algorithm is used to fuse the obtained evidence to get the comprehensive evaluation evidence including global evidence and local evidence. Finally, according to the belief degree distribution of the comprehensive evaluation evidence, the final importance values of different nodes are determined.

4.3.1. Generation of multi-granularity networks

In practical engineering, the users' customization requirements for CMSSs are often diverse, which is mainly reflected in the difference of functional levels, namely multi-granularity characteristics (Liu, Li, & Shen, 2014). Therefore, it is necessary to comprehensively consider the importance of nodes in the networks with different granularities. Then how to generate local networks via the constructed global network is a problem that needs to be solved. Generally, it can be artificial or automatic. In an artificial method, expert experience is used to decompose the global network. It is suitable for small-scale networks. In an automatic method, the global network is divided into different sub-networks

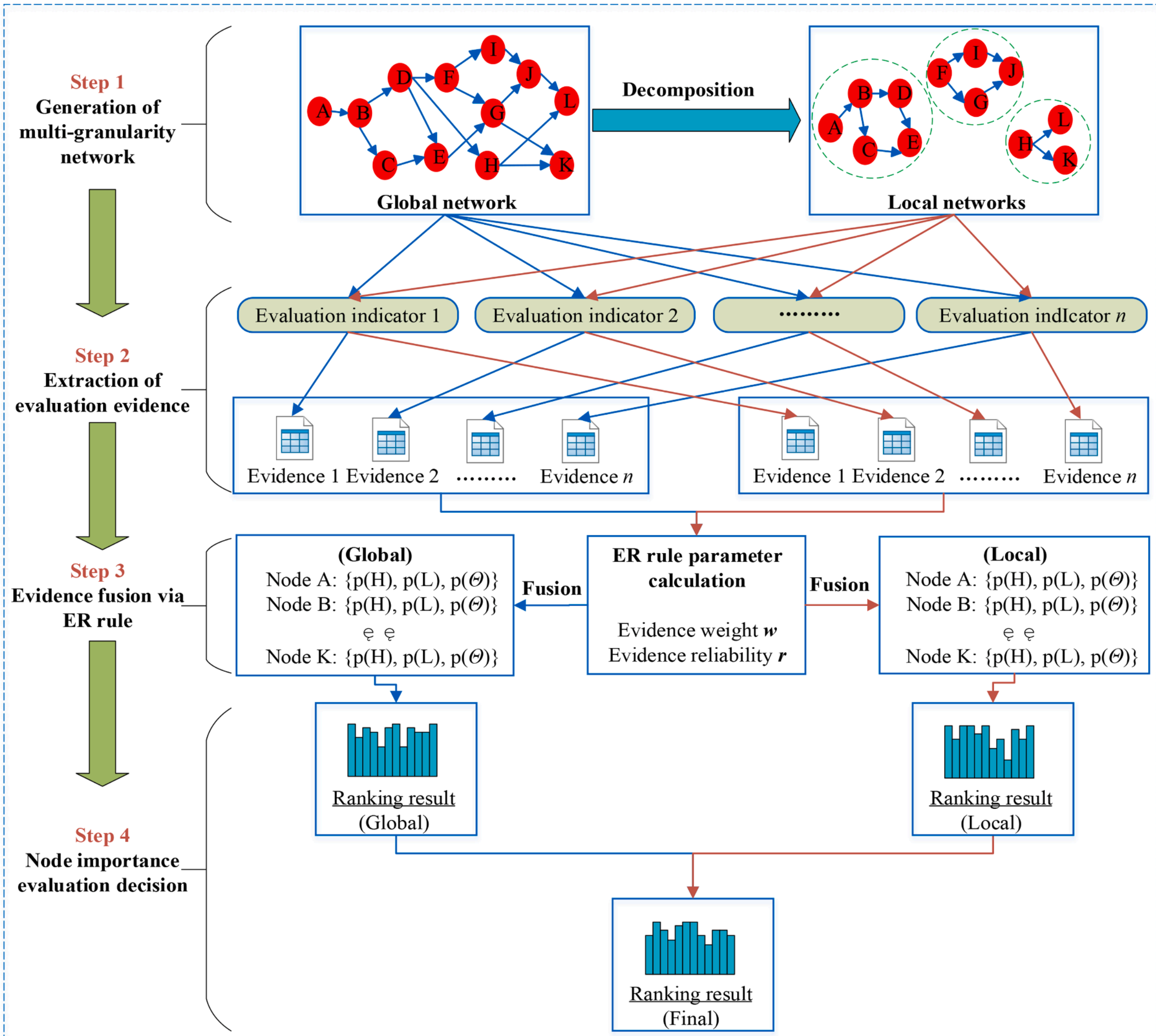


Fig. 2. Node importance evaluation approach based on ER rule.

by decomposition algorithms such as community detection algorithm. The obtained sub-networks usually represent different functional modules. Such methods are more suitable for large-scale networks. For example, our previous research has given an effective decomposition algorithm for global network (Zhang, Zhang, Lu, Gao, & Xiao, 2020), which can be directly used for the generation of multi-granularity networks. So it will not be repeated here.

4.3.2. Extraction of evaluation evidence

According to ER rule theory, the frame of discernment Θ for node importance needs to be constructed. It can be expressed as $\Theta=\{H,L\}$, where H represents the importance degree, and L represents the unimportance degree. Then the importance evaluation indicators of the nodes are regarded as the attributes which are used to extract evaluation evidence. In this paper, the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality are used. After that, the attributes are transformed into belief degree function as follows:

$$\begin{array}{l}
DC_{\max}=\max\{C_D(v_1),C_D(v_2),...,C_D(v_n)\}\ ;DC_{\min}=\min\{C_D(v_1),C_D(v_2),...,C_D(v_n)\}\\
BC_{\max}=\max\{C_B(v_1),C_B(v_2),...,C_B(v_n)\}\ ;BC_{\min}=\min\{C_B(v_1),C_B(v_2),...,C_B(v_n)\}\\
CC_{\max}=\max\{C_C(v_1),C_C(v_2),...,C_C(v_n)\}\ ;CC_{\min}=\min\{C_C(v_1),C_C(v_2),...,C_C(v_n)\}\\
EC_{\max}=\max\{C_E(v_1),C_E(v_2),...,C_E(v_n)\}\ ;EC_{\min}=\min\{C_E(v_1),C_E(v_2),...,C_E(v_n)\}
\end{array} \tag{10}$$

where n represents the total number of the nodes; $DC_{\max}$, $BC_{\max}$, $CC_{\max}$ and $EC_{\max}$ represent the maximum value of the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality respectively; $DC_{\min}$, $BC_{\min}$, $CC_{\min}$ and $EC_{\min}$ represent the minimum value of the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality respectively.

Based on formula(10), the degree of support for the importance and umimportance in the frame of discernment can be expressed as follows:

$$
\begin{aligned}
m_{DCi}(H) &= \frac{DC_i - DC_{\min}}{DC_{\max} - DC_{\min} + \delta}; m_{DCi}(L) = \frac{|DC_i - DC_{\max}|}{DC_{\max} - DC_{\min} + \delta} \\
m_{BCi}(H) &= \frac{BC_i - BC_{\min}}{BC_{\max} - BC_{\min} + \delta}; \; m_{BCi}(L) = \frac{|BC_i - BC_{\max}|}{BC_{\max} - BC_{\min} + \delta} \\
m_{CCi}(H) &= \frac{CC_i - CC_{\min}}{CC_{\max} - CC_{\min} + \delta}; \; m_{CCi}(L) = \frac{|CC_i - CC_{\max}|}{CC_{\max} - CC_{\min} + \delta} \\
m_{ECi}(H) &= \frac{EC_i - EC_{\min}}{EC_{\max} - EC_{\min} + \delta}; \; m_{ECi}(L) = \frac{|EC_i - EC_{\max}|}{EC_{\max} - EC_{\min} + \delta}
\end{aligned}
\tag{11}
$$

where δ is an adjustable parameter which aims to avoid zero denominator; $m_{DCi}(H)$, $m_{BCi}(H)$, $m_{CCi}(H)$ and $m_{ECi}(H)$ represent the degree of support for the importance in the frame of discernment by the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality respectively; $m_{DCi}(L)$, $m_{BCi}(L)$, $m_{CCi}(L)$ and $m_{ECi}(L)$ represent the degree of support for the unimportance in the frame of discernment by the degree centrality, betweenness centrality, closeness centrality and eigenvector centrality respectively.

The degree of support for the unknownness in the frame of discernment can be calculated by

$$
\begin{aligned}
m_{DCi}(\Theta) &= 1 - (m_{DCi}(H) + m_{DCi}(L)) \\
m_{BCi}(\Theta) &= 1 - (m_{BCi}(H) + m_{BCi}(L)) \\
m_{CCi}(\Theta) &= 1 - (m_{CCi}(H) + m_{CCi}(L)) \\
m_{ECi}(\Theta) &= 1 - (m_{ECi}(H) + m_{ECi}(L))
\end{aligned}
\tag{12}
$$

Then the evaluation evidence of node i can be obtained by

$$
\begin{aligned}
M_{DC}(i) &= [m_{DCi}(H), m_{DCi}(L), m_{DCi}(\Theta)] \\
M_{BC}(i) &= [m_{BCi}(H), m_{BCi}(L), m_{BCi}(\Theta)] \\
M_{CC}(i) &= [m_{CCi}(H), m_{CCi}(L), m_{CCi}(\Theta)] \\
M_{EC}(i) &= [m_{ECi}(H), m_{ECi}(L), m_{ECi}(\Theta)]
\end{aligned}
\tag{13}
$$

4.3.3. *Evidence fusion via ER rule*

(1) Calculation of fusion parameters.

When using the ER rule, an important task is the calculation of fusion parameters (i.e., the weight of evidence w_j and the reliability of evidence r_j).

The weight of evidence w_j is the relative importance of evidence e_j compared with the other pieces of evidence. It can be determined by the degree of support by the other pieces of evidence. In this paper, evidence similarity is used to calculate the degree of support. The higher the similarity between one piece of evidence and other pieces of evidence, the higher the degree of support of the piece of evidence by other pieces of evidence, and thus the greater the weight.

For a frame of discernment Θ, each piece of evidence can be regarded as a point or a vector in a high-dimensional space. Suppose that m_i and m_j are two pieces of evidence in Θ, and can be represented as vectors, then the *Jousselme* distance of m_i and m_j can be calculated by

$$
\begin{aligned}
d_{BPA}(m_i, m_j) &= \sqrt{\frac{1}{2}(\vec{m}_i - \vec{m}_j)^T D (\vec{m}_i - \vec{m}_j)} \\
&= \sqrt{\frac{1}{2}\left(\left\|\vec{m}_i\right\|^2 + \left\|\vec{m}_j\right\|^2 - 2 < \vec{m}_i, \vec{m}_j >\right)}
\end{aligned}
\tag{14}
$$

The evidence similarity of m_i and m_j can be calculated by

$$
sim(m_i, m_j) = 1 - d_{BPA}(m_i, m_j) \tag{15}
$$

Then the degree of support of m_i can be obtained by

$$
\sup(m_i) = \sum_{\substack{j=1 \\ j \neq i}}^{n} sim(m_i, m_j) \tag{16}
$$

After normalization, the weight of evidence can be obtained by

$$
w_j = \frac{\sup(m_i)}{\sum_{j=1}^{n} \sup(m_j)} \tag{17}
$$

The reliability of evidence r_j is the inherent attribute of evidence, which represents the ability to provide accurate assessment of a given problem. The specific calculation is as follows:

$$
r_j = \frac{T_{\max} - A_{\max}}{T_{\max}} \tag{18}
$$

where $T_{\max}$ is the theoretical maximum value of the attribute derived from the evidence e_j; $A_{\max}$ is the actual maximum value of the attribute derived from the evidence e_j.

(2) Evaluation evidence fusion.

According to the evaluation evidence obtained by the global network and the local networks, the ER rule is used for evidence fusion. The belief degree distribution functions of node importance in the global network and local networks can be obtained as $M^{global}(i)=(p_{\theta,e(K)}{}^{global}(H)$, $p_{\theta,e(K)}{}^{global}(L)$, $p_{\theta,e(K)}{}^{global}(\Theta))$ and $M^{local}(i)=(p_{\theta,e(K)}{}^{local}(H)$, $p_{\theta,e(K)}{}^{local}(L)$, $p_{\theta,e(K)}{}^{local}(\Theta))$, respectively. Among them, $p_{\theta,e(K)}{}^{global}(H)$, $p_{\theta,e(K)}{}^{global}(L)$ and $p_{\theta,e(K)}{}^{global}(\Theta)$ represent the belief degree of the node i in the global network is important, unimportant and uncertain, respectively; $p_{\theta,e(K)}{}^{local}(H)$, $p_{\theta,e(K)}{}^{local}(L)$ and $p_{\theta,e(K)}{}^{local}(\Theta)$ represent the belief degree of the node i in the local sub-networks is important, unimportant and uncertain, respectively.

4.3.4. *Importance ranking strategy*

Based on the belief degree distribution functions of node importance M^{global} and M^{local} obtained above, the uncertainty is distributed by an average distribution strategy to obtain the node importance evaluation values I_{global} and I_{local}, as shown below:

$$
\begin{aligned}
I_{\text{global}}(i) &= p_{\theta,e(K)}^{\text{global}}(\mathrm{H}) - p_{\theta,e(K)}^{\text{global}}(\mathrm{L}) \\
I_{local}(i) &= p_{\theta,e(K)}^{local}(H) - p_{\theta,e(K)}^{local}(L)
\end{aligned}
\tag{19}
$$

Then the final importance of node i can be calculated by

$$
I(i) = \alpha I_{global}(i) + \beta I_{local}(i) \tag{20}
$$

where α and β represent the weight of global network and sub-networks, respectively.

According to the elaboration in the above sections, the node

Table 2
Node importance evaluation algorithm.

Input: Adjacency matrix of global network A, Adjacency matrix of local network $M=\{A_1,A_2,\ldots,A_h\}$, node *ID*
Output: *I*(*ID*)
$Temp \leftarrow \{A,A_1,A_2,\ldots,A_h\}$
FOR $k = 1$ to $h+1$ do
$N = getSize(temp[k])$; //obtain the node number of the selected network
FOR $i = 1$ to N do
$[C_D[\mathrm{ID}],C_E[\mathrm{ID}],C_B[\mathrm{ID}],C_C[\mathrm{ID}]] = centralityCalculate(temp)$; //according to formula(1)-(4)
END FOR
FOR $ii = 1$ to N do
$[M_{DC}[\mathrm{ID}],M_{EC}[\mathrm{ID}],M_{BC}[\mathrm{ID}],M_{CC}[\mathrm{ID}]] = evidenceGenerate(C_D,C_E,C_B,C_C)$;//according to formula(10)-(13)
END FOR
FOR $j = 1$ to N do
$w[ID] = weightCalculate(M_{DC},M_{EC},M_{BC},M_{CC})$; //according to formula(14)-(18)
$r[ID] = reliabilityCalculate(M_{DC},M_{EC},M_{BC},M_{CC})$; //according to formula(19)
END FOR
FOR $jj = 1$ to N do
$M[ID] = fusionER(M_{DC}[ID],M_{EC}[ID],M_{BC}[ID],M_{CC}[ID],w[ID],r[ID])$; // according to formula(7)-(9)
$I[ID][k] = getNodeimportance(M[ID])$;
END FOR
IF k > 1 then
$I_{module}[ID] = addResult(I[ID][k])$;
ELSE
$I_{system}[ID] = addResult(I[ID][k])$;
END IF
END FOR
$I[ID] = getFinalimportance(\alpha,\beta,I_{module}[ID],I_{system}[ID])$; // according to formula(20)

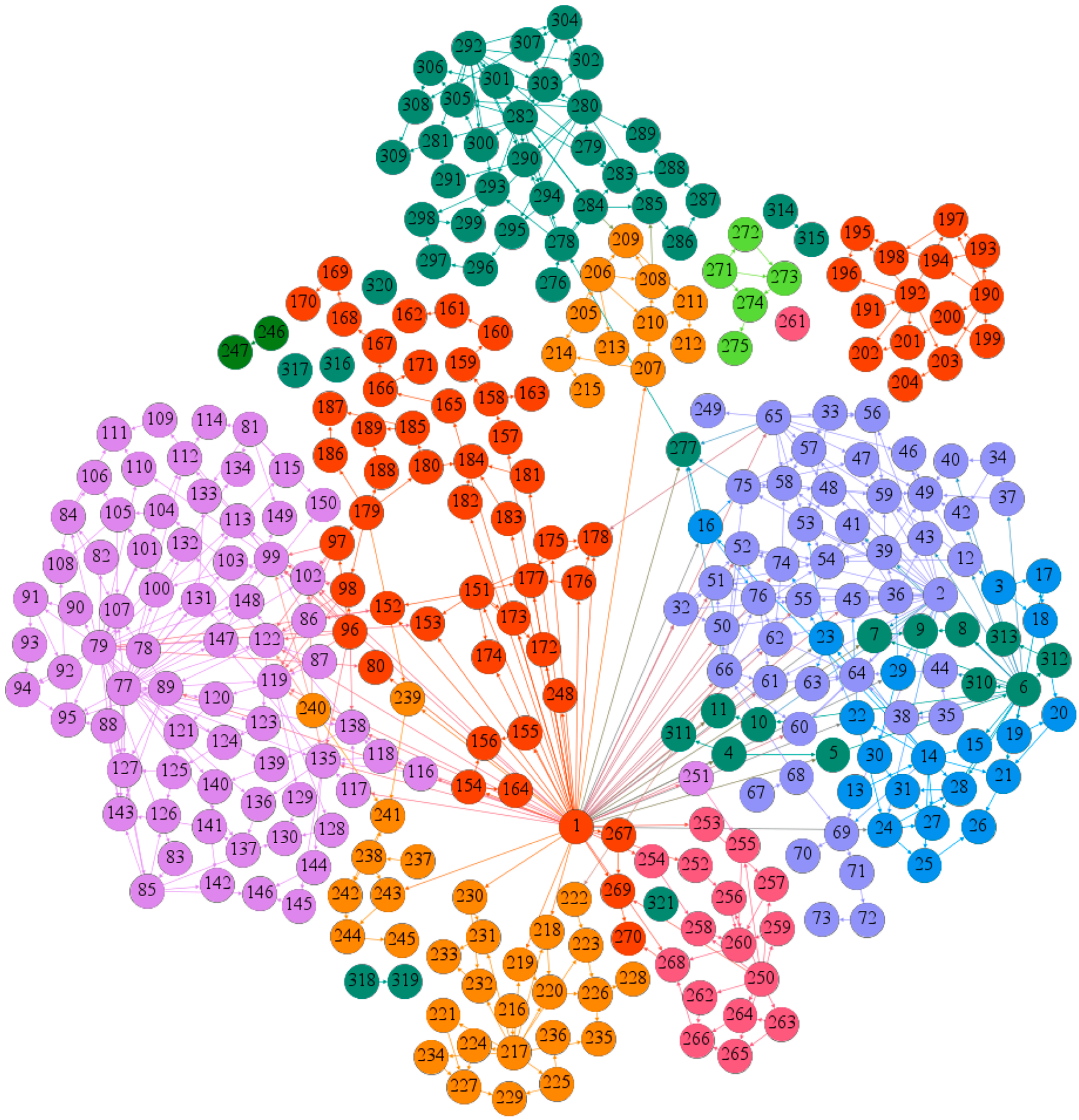


Fig. 3. The DoCMSCN of elevator design.

importance evaluation algorithm is shown in Table 2.

5. Case study

To verify the effectiveness and superiority of the proposed approach, the complex network about vertical elevator design is taken as an example. It has been divided into 9 sub-networks (Zhang, Zhang, Lu, Gao, & Xiao, 2020). According to the elaboration in section 3, the corresponding DoCMSCN of elevator design (i.e., global network) is constructed, as shown in Fig. 3. Different colors represent different sub-networks (i.e., local networks).

The DoCMSCN of elevator design contains 321 nodes representing abstract elevator design services and 625 edges representing logical dependency relationships of abstract elevator design services. Specifically, each node expresses the functional attributes of the elevator design service instances with the same function in the MSC. The details of abstract elevator design services is shown in Table 3. For example, node 1 represents “Basic performance parameters design” and node 2 represents “Traction ratio design”. Besides, the non-functional attributes of the elevator design service instances in the MSC has no effect on the functional importance evaluation results. Therefore, the non-functional attributes will not be considered in the experiments.

5.1. Compared with existing approaches

Three algorithms are selected for comparison. Algorithm 1 is the Leader-Rank value (LRV) based algorithm (Wu, Peng, Huang, & Zhang, 2019; Jiang, Zhang, & Cao, 2019). Essentially, it is a kind of single indicator based evaluation algorithm. Algorithm 2 is the DS based algorithm in which the traditional DS theory is used to evaluate the importance of nodes in the global network (Wang, Shan, Zhao, Dong, Ren, & Liu, 2019; Mo & Deng, 2019). Algorithm 3 is our algorithm proposed in this paper. It is an ER based algorithm which considers the importance of the nodes in the global network and local networks simultaneously.

Table 3
The details of abstract elevator design services.

ID	Name	ID	Name
1	Basic performance parameters design	245	Composite stress check of standing beam of car frame
2	Traction ratio design	246	Calculation of ground force in the machine room
3	Traction size parameters design	247	Calculation of permissible ground force in the machine room
…	………	…	………
13	Type selection of traction wire rope	250	Structural parameters design
14	Technical parameters query of traction wire rope	251	Calculation of the minimum guidance stroke of the guide rail at car side
…	………	…	………
31	Pressure ratio check of wire rope and groove	260	Minimum height design for the top floor
…	………	…	………
65	Mass design of counterweight	273	Average velocity calculation of car door
66	Mass design of accompanying cable	274	Kinetic energy calculation of car door
…	………	…	………
77	Basic parameters design of the guide rail	280	Technical parameters query of material of load-bearing beam of traction machine
78	Type selection of guide rail	281	Permissible disturbance calculation of load-bearing beam of traction machine
79	Technical parameters query of guide rail	282	Installation parameters design of load-bearing beam of traction machine (direct installation)
…	………	…	………
152	Type selection of safety gear at car side	291	Maximum disturbance check of load-bearing beam of traction machine (direct installation)
153	Type selection of safety gear at counterweight side	292	Installation parameters design of load-bearing beam of traction machine (installation with bracket)
…	………	…	………
216	Type selection of lower beam of car frame	320	Type selection of band brake power supply
217	Technical parameters query of lower beam of car frame	321	Type selection of circuit breaker

5.1.1. *Verification of effectiveness*

Functional robustness (FR) of a network refers to the ability of the network to maintain its basic functions when several nodes are removed (Zhou, Zhang, Zhou, Zou, & Yang, 2012). The smaller the value of FR, the worse the connectivity of the network after removing the nodes. From the perspective of function, the removed nodes are more important. Therefore, the effectiveness of the functional importance evaluation algorithm can be verified by the change trend of the value of FR. In the experiments, two indicators namely the connectivity factor and the ratio of edges are used to evaluate the FR.

(1) Connectivity factor (*CF*). It refers to the reciprocal of the number of isolated sub-networks (including isolated nodes) after removing the target nodes. The smaller the value of *CF*, the worse the FR. It can be calculated by the following formula

$$CF_{global}(\{NR\}) = \frac{m}{m(\{NR\})}$$
$$CF_{local}(\{NR\}) = \frac{1}{p}\cdot\sum_{i=1}^{p}\frac{n_i}{n_i(\{NR\})} \tag{21}$$
$$CF(\{NR\}) = CF_{global}(\{NR\}) + CF_{local}(\{NR\})$$

where $\{NR\}$ represents the target nodes removed in the network; $CF(\{NR\})$ is the connectivity factor of the network after removing $\{NR\}$; $CF_{glocal}(\{Node\})$ and $CF_{local}(\{Node\})$ respectively represent the connectivity factor of the global network and the local networks after removing $\{NR\}$; m and $m(\{NR\})$ respectively represent the number of sub-networks in the global network before and after removing $\{NR\}$; n_i and $n_i(\{NR\})$ respectively represent the number of sub-networks in the ith local network before and after removing $\{NR\}$; p represents the number of local networks.

(2) Ratio of edges (*RE*). It refers to the ratio of the number of edges after removing the target nodes to the number of edges in the initial network. The smaller the value of *RE*, the worse the FR. It can be calculated by the following formula

$$RE_{global}(\{NR\}) = \frac{e(\{NR\})}{e_0}$$
$$RE_{local}(\{NR\}) = \frac{1}{p}\cdot\sum_{i=1}^{p}\frac{e_i(\{NR\})}{e_i} \tag{22}$$
$$RE(\{NR\}) = RE_{global}(\{NR\}) + RE_{local}(\{NR\})$$

where $RE(\{NR\})$ represents the ratio of edges of the network after removing $\{NR\}$; $RE_{global}(\{NR\})$ and $RE_{local}(\{NR\})$ respectively represent the ratio of edges of global network and the local networks after removing $\{NR\}$; e_0 and $e(\{NR\})$ respectively represent the number of edges in the global network before and after removing $\{NR\}$; e_i and $e_i(\{NR\})$ respectively represent the number of edges in the ith local network before and after removing $\{NR\}$.

According to the above two indicators, the functional robustness of the network can be calculated by the following formula

$$FR(\{NR\}) = \frac{(CF(\{NR\}) + RE(\{NR\}))}{2} \tag{23}$$

To verify the effectiveness of the evaluation approach, a certain percentage of nodes are sequentially removed based on the obtained importance ranking results. Then the change of the FR is analyzed. In the experiment, the Random algorithm in which the nodes are selected randomly is used as a reference. Fig. 4 shows the change trend of the FR after removing different proportions (5 %-30 %) of important nodes obtained by different algorithms.

As shown in Fig. 4, all of the values of FR by different algorithms show a downward trend. Generally speaking, when the same number of nodes are removed, the values of FR obtained by the three algorithms (i.e., ER based, DS based and LRV based algorithm) are smaller than the Random algorithm. It indicates that all of the three algorithms have certain effectiveness.

Then we further analyze the effectiveness of ER based, DS based and LRV based algorithms. Firstly, the ER based algorithm performs best since the values of FR are always smaller than the others. Secondly, from

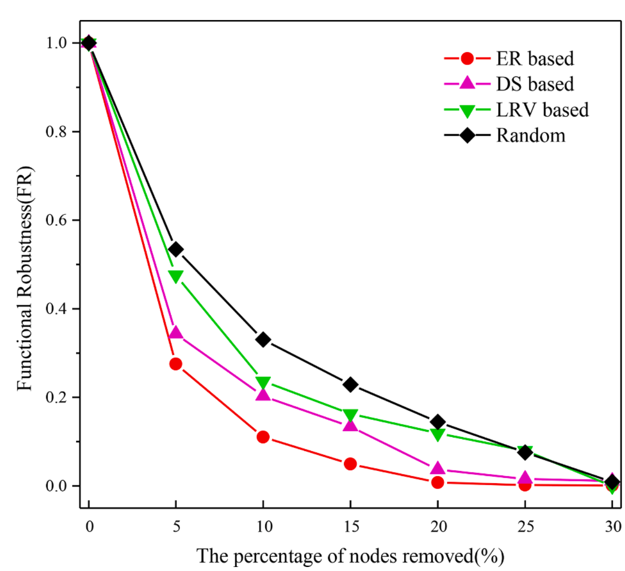
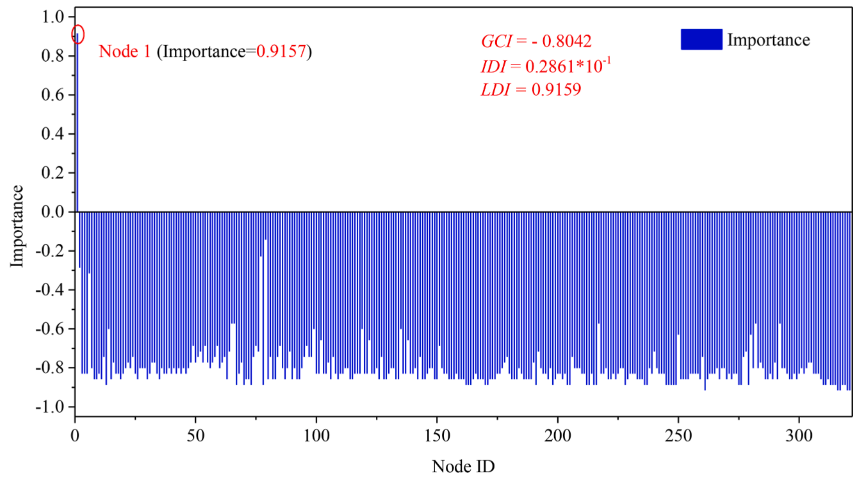


Fig. 4. The changes of functional robustness.

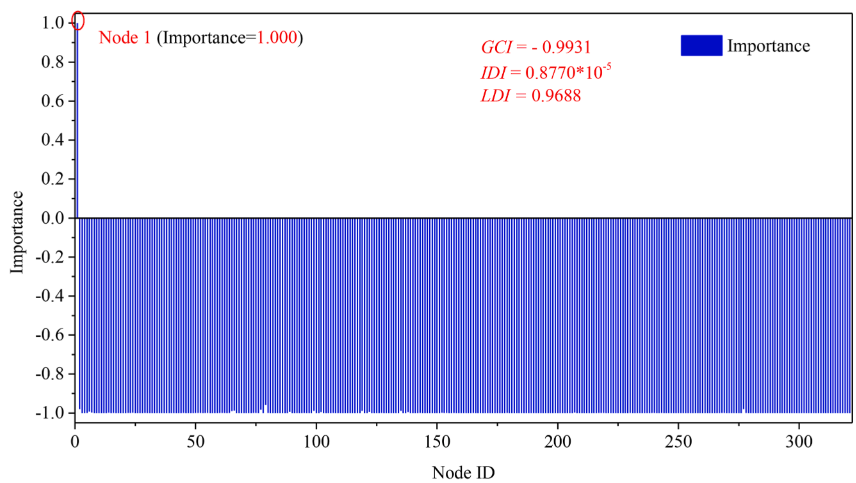
the perspective of decline rate, the curve obtained by our algorithm is the fastest. When removing 20 % of important nodes, the value of FR is close to 0. In comparison, 25 % and 30 % of important nodes are needed to remove in the DS based algorithm and LRV based algorithm, respectively. In conclusion, compared with the existing algorithms, our algorithm is more effective.

5.1.2. *Comparison of superiority*

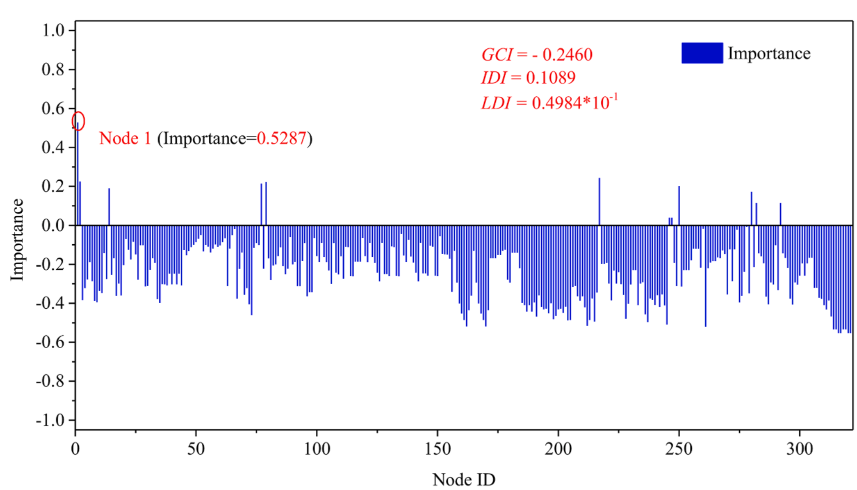
To verify the superiority of our algorithm, the global credibility index, importance difference index and community distribution index



(a) Node importance obtained by Leader-rank value based algorithm



(b) Node importance obtained by DS based algorithm



(c) Node importance obtained by our algorithm

Fig. 5. Node importance obtained by different algorithms.

are introduced to evaluate the performance of different algorithms.

(1) Global credibility index (*GCI*). It can be obtained by calculating the mean value of the importance of all nodes. The larger the value of *GCI*, the higher the overall credibility of the results obtained. The calculation formula is as follows

$$GCI = \frac{\sum_i^n I(i)}{n} \tag{24}$$

where n represents the number of nodes, $I(i)$ represents the importance of node i.

(2) Importance difference index (*IDI*). It represents the degree of importance difference of nodes. The larger the value of *IDI*, the better importance ranking results. It can be calculated as

$$ID = median(|I(i) - median(I)|) \tag{25}$$

where *median*(*) represents the median value of the sequence *.

(3) Local distribution index (*LDI*). Due to the functional granularity of the network, good evaluation results should make the important nodes more evenly distributed in each local network. The smaller the value of *LDI*, the better the importance ranking results. It can be calculated as

$$\text{LDI} = \frac{\text{Num}(\{\text{Node}\}_{pre})}{n},\ \forall i \in p,\ \exists\{\text{Node}\}_{pre} \cap \{Node\}_{Net(i)} \neq \varnothing \tag{26}$$

where the $\{Node\}_{pre}$ represents a set which contains the selected nodes according to ranking results; $Num(\{Node\}_{pre})$ represents the number of the node set $\{Node\}_{pre}$; $\{Node\}_{Net(i)}$ represents a set which contains the nodes in the ith local network; p is the number of the local networks.

The experimental results obtained by the above algorithms are shown in Fig. 5. It can be seen from the figures that the global credibility index (*GCI* = -0.2460), importance difference index (*IDI* = 0.1089) and community distribution index (*LDI* = 0.04984) obtained by our algorithm is the best. In our algorithm, four evaluation indicators in both global network and local networks are comprehensively used. Meanwhile, the weight and reliability of the evaluation evidence in the fusion process are considered. However, in the LRV based algorithm, only a single indicator (i.e., Leader-Rank value) of the global network is used which leads to poor evaluation results. Although multiple indicators of global network are fused in the DS based algorithm, the weight and reliability of the evidence obtained by these indicators are ignored. As a result, the effect is not as expected. Therefore, our algorithm is better than the existing algorithms.

It is worth noting that the result obtained by the traditional DS based algorithm is worse than the result obtained by the LRV based algorithm. It indicates that inappropriate fusion of multiple indicators may lead to poor result. For this reason, further analysis is conducted to verify the superiority of the proposed approach.

5.1.3. Further analysis

In this section, the four indicators namely degree centrality(CD), betweenness centrality(CB), closeness centrality(CC) and eigenvector centrality(CE), and three algorithms, namely single indicator algorithm, DS based algorithm and ER based algorithm are used to generate different evaluation plans. For example, using the indicator CD can be seen as a single indicator algorithm. Also, using the ER algorithm to fusion the two indicators CD and CB is one of the combination plans. Totally, there are 52 different combination plans.

To give comprehensive comparison results, we assign a suitable weight to each index (i.e., *GCI*, *IDI* and *LDI*) to get a final value. The larger the value, the better the performance of the algorithm. Therefore, a weight assignment method combining objective information and subjective information is used (Xu & Da, 2002). In the method, the entropy method is used to obtain objective weights and analytic hierarchy process (AHP) method is used to obtain subjective weights. In this paper, when using the AHP method, all of the indexes are considered to be equally important. Table 4 is the comprehensive values obtained by different single indicators.

As shown in Table 4, when a single indicator is used for evaluation, the result obtained by considering both global network and local

Table 4
Comprehensive values obtained by different single indicators.

Granularity Indicator	Global network	Global network +Local network
CD	0.3252	0.6392
CB	**0.5434**	0.6458
CC	0.0251	0.3934
CE	0.3529	**0.6779**

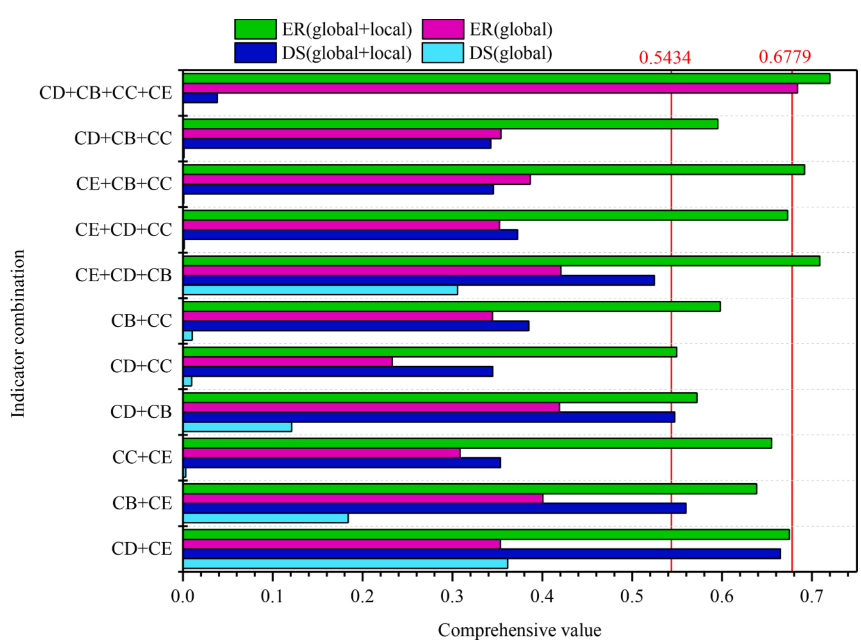


Fig. 6. Comprehensive values obtained different combination plans.

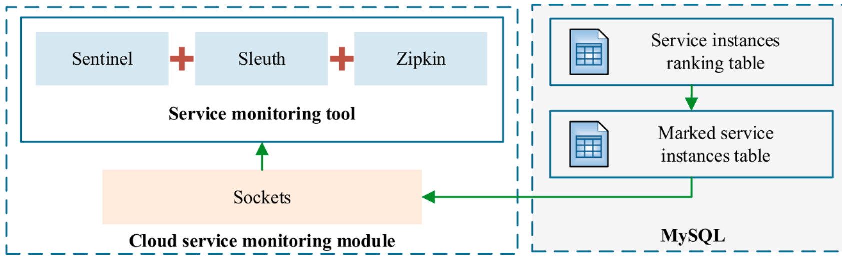


Fig. 7. Elevator design services monitoring process.

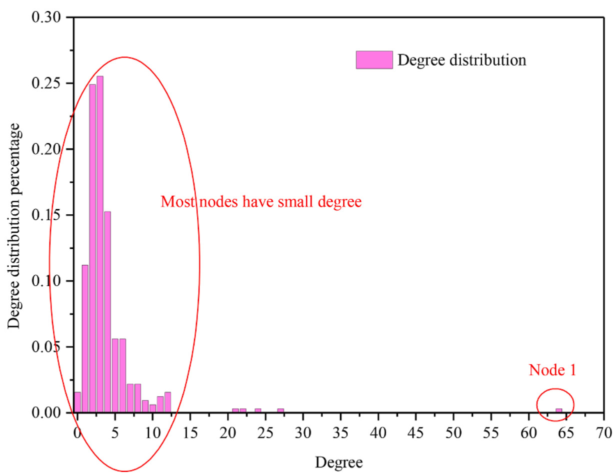


Fig. 8. Degree distribution of the vertical elevator design service network.

networks is better than that obtained by only considering global network. The optimal result is 0.5434 and 0.6779, respectively. The two optimal values are used as the referential values to compare with results obtained by different combination plans in the fusion algorithms. Fig. 8 gives the comprehensive values obtained.

As shown in Fig. 6, for both the DS based algorithm and the ER based algorithm, the results obtained by comprehensive consideration of the global network and local networks are significantly better than that obtained only by the global network. It demonstrates that the functional granularity of the network should be taken into consideration. Meanwhile, the ER based algorithm is much better that the DS based algorithm, whether in two indicators, three indicators or four indicators. Moreover, along with the increasing of evaluation indicators, the results obtained by ER based algorithm is getting better and better. In contrast, the DS based algorithm achieves counterproductive effects. It is attributed to the fusion parameters (i.e., the weight w_j and reliability r_j). At the same time, all of the comprehensive values obtained by the DS algorithm are worse than the optimal value (0.6779) obtained by the single indicator algorithm. In our algorithm, a better result can be found in three indicators and four indicators fusion solution. In summary, the fusion algorithm proposed in this paper is more advanced.

5.2. Implementation of the proposed algorithm in monitoring

5.2.1. Development of elevator design service monitoring system

The proposed algorithm has been proven to be effective and advanced in evaluating the importance of nodes in the DoCMSCN of elevator design. It has been integrated into an elevator design service system, which contains three main modules, namely cloud design service management module, cloud design service operation module and cloud design service monitoring module. The management module is responsible for the management of elevator design services including service registry, service update, service delete, service query and so on.

Table 5
Development technologies and environment.

Name	Specific information
Development framework	SSM(Spring, SpringMVC, Mybatis), SpringBoot
Development language	Java
Database	MySQL
Service registry tool	Nacos
Service monitoring tool	Sentinel + Zipkin + Sleuth
Operation environment	Linux
Service invocation tool	RestTemplate

The operation module is responsible for the invocation and execution of the elevator design services. The monitoring module is responsible for the configuration of the monitoring resources. The development technologies and environment of the system are shown in Table 5.

Based on the SSM and SpringBoot framework, the elevator design activities can be encapsulated into Restful cloud services instances. Each service is registered in the service center in the Nacos and assigned an URI (i.e., unique resource identifier). In the system, there are 321 service clusters. In each service cluster, several number of design service instances are registered. Then the service users can invoke a design service through the URI by RestTemplate. The elevator design services monitoring process is shown in Figure 9.

As shown in Fig. 7, the importance ranking results are stored in MySQL database. When a monitoring request arrives, the design service instances with higher priority are marked and the sockets of these services are formed. Then the sockets are sent to the services monitoring tool (i.e., Sentinel + Zipkin + Sleuth) and the monitoring resources are allocated.

5.2.2. Monitoring strategy based on importance ranking results

According to the functional importance ranking results, the monitoring priority of the elevator design services can be determined. For example, the design service instances in the MSC of “Basic performance parameters design” has the top priority since the node 1 is the most important node in the network. Based on the priority, the monitoring strategy can be made from the functional perspective. The strategy can minimize the risk of the system functionality being compromised by monitoring a small number of services.

In this section, we give an example to illustrate the design services monitoring strategy in conditions of limited resources. Suppose that the monitoring resources could only cover 5 % of the design service instances in the MSCs (i.e., 321*5%≈16 MSCs).

Firstly, the top 5 % important nodes (AMSs) namely node 1, node 217, node 2, node 79, node 77, node 250, node 14, node 280, node 282, node 292, node 246, node 247, node 278, node 260, node 66 and node 274 should be selected. As shown in Fig. 4, when removing the top 5 % important nodes, the function of the network is most affected. Secondly, based on the mapping relationship of AMS and MSC, the design service instances in the corresponding MSCs are marked and monitored. For example, the design service instances in the MSCs of “Basic performance parameters design” should be monitored.

5.3. Discussion

Through the analysis of the above experimental results, it can be seen that the algorithm in this paper can improve the accuracy of the node importance evaluation of DoCMSCN by using multi-indicator evidence fusion and multi-granularity evaluation strategy. Compared with the existing algorithms, our algorithm is more effective and advanced. At the same time, it indicates that the multi-indicator fusion method is not always better than the single-indicator algorithm, and the contribution of each indicator needs to be fully considered during the evaluation process.

Meanwhile, it should be noted that the most important node obtained by the the DS-based algorithm and Leader-Rank algorithm are all node 1. And the importance values of the two algorithms are much larger than that of our algorithm. One possible reason is that the degree of node 1 is relatively large. Fig. 8 shows the degree distribution of the DoCMSCN of vertical elevator design.

As shown in Fig. 8, most of the nodes have relatively low degrees while there are a small number of nodes with high degrees. Therefore, the network has scale-free characteristic. Among them, the degree of node 1 is sixty-four, which is much larger than other nodes. Consequently, the effect of the centrality indicators of node 1 is exaggerated in the importance evaluation process. In our algorithm, the evidences generated by the centrality indicators are discounted to a certain extent by considering the weight and reliability of the evidence. So different evaluation indicators can be effectively fused and thus the results obtained are more reasonable.

Besides, the service monitoring strategy is made based on the functional importance ranking results. It considers the service monitoring problem from a new perspective. Therefore, it acts as a complement to the existing approaches. In the above section, we just give one feasible monitoring strategy. In practical engineering, the monitoring scenarios and requirements are usually different. More complex monitoring strategies can be evolved based on our approach.

6. Conclusion

Based on the idea of multi-granularity and multi-indicator, a novel approach for evaluating the functional importance of cloud manufacturing services based on complex network and evidential reasoning rule is proposed in this paper. Through experimental results of the vertical elevator design cloud services, the effectiveness and superiority of the proposed approach are proved. Moreover, it also indicates that multi-indicator fusion is not always better than the single-indicator algorithm if the contribution of each indicator is not fully considered. According to the functional importance ranking results, the monitoring priority of the cloud manufacturing services can be determined. Then the monitoring strategy can be made based on the monitoring priority. Our research can facilitate the decision-making of monitoring strategy in conditions of limited resources from the functional perspective. Especially, for the cloud manufacturing platform manager, cost-effective strategy in monitoring the cloud manufacturing services can be developed. It can minimize the risk of the system functionality being compromised by monitoring a small number of services with high priority. Therefore, it is of great significance for the rational allocation of monitoring resources and the effective reduction of maintenance costs.

Our future work mainly carried out from the following aspects: firstly, the non-functional features of manufacturing services (e.g. QoS) as well as the customization requirements of users need to be further studied to improve the importance evaluation theory of manufacturing services; secondly, the more complex monitoring strategies for manufacturing services based on the importance ranking results are also worthy of study.

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CRediT authorship contribution statement

Zhenjie Zhang: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Jiahao Hu:** Investigation, Software. **Xiaobin Xu:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Guodong Wang:** Software, Investigation. **Schahram Dustdar:** Investigation, Writing – review & editing. **Shenghua Chen:** Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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