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Quantitative study of correlation strength of mechanical parts based on weighted complex network model

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Abstract. In order to better calculate the correlation strength of mechanical parts, a new calculation method based on weight complex network model is designed. A complex product system module partition method based on the weighted complex network community discovery technology is proposed. In order to construct a complex product system, the component weight complex network model is used to map the parts into network nodes. The relation and intensity between components are mapped into weighted edges and edges of complex networks. The quantitative method of relation strength between function and structure is studied. The experimental results show that a number of module partitioning schemes are obtained to form a scheme set through the different values of network modularity. Based on the above finding, it is concluded that the improved GN algorithm can be used to realize the complex structure of complex product system and the community structure of the complex network.

Key words. Weight, complex network model, intensity, association.

1. Introduction

With the progress of science and technology, the evolution of technology related to subsystems has been accelerated in complex product systems. Emerging customer demand continues to emerge, and current customer demand continues to change. Objectively, the efficiency of R & D of complex product systems needs to be improved continuously to cope with the complex and changeable market environment [1]. The research of existing complex product system mainly focuses on the concepts, characteristics, interpretation, innovation mechanism exploration and research and development, operation management and other factors related to the new research and development of complex product systems [2]. It lacks the research on the basis of several variants. Design knowledge reuse and redesign are developed to improve R & D efficiency [3]. Modular design is widely used in the field of mass

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customization. It is an effective way to improve the efficiency of product development through the standardization of product structure and design variables [4]. Compared with traditional mass customization products, complex product system has high complexity and obvious heterogeneity, but the traditional modular design theory is difficult to deal with these characteristics effectively [5]. There are many reasons for the heterogeneity of complex product systems [6]. First of all, changes in customer demand require complex product systems to constantly add new features or to improve existing functions, which can easily lead to functional heterogeneity [7]. Secondly, due to the adoption of integrated product development in complex product systems, there is a lack of effective communication between product research and development projects [8]. At present, the flow of core research and development personnel is very large, and it is easy to produce the same functions and principles with different physical structure, forming structural heterogeneity [9]. To solve the above problems, matrix analysis method is used to realize the homogenization reduction of the function and structure heterogeneity of the existing complex product system. A weighted complex network model is introduced to study the module partitioning problem of complex product systems [10].

2. Introduction of relevant concepts

2.1. Complex network concepts

A complex network can be represented as a graph $G = (V, E)$ consisting of a set of nodes, V, and an edge set E. Among them, the element in formula $V = (v_1, v_2, ..., v_n)$ represents the node in the network, and the elements in formula$E = (e_1, e_2, ..., e_m)$ represent edges in a network. The graphical representation of a complex network is shown in Fig. 1.

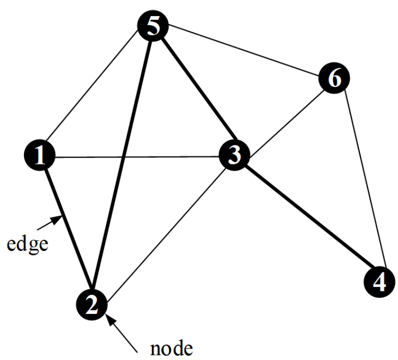


Fig. 1. Graphical representation of complex networks

If it is not specified, the weight of the complex network edge is generally 1. This network can be expressed in binary matrix A, which is called adjacency matrix. The matrix A is made up of elements A_{ij}, and A_{ij} follows the following rule:

$$A_{ij} = \begin{cases} 1, & \text{if the node } i \text{ is connected to the node } j\,, \\ 0, & \text{other}\,. \end{cases} \tag{1}$$

Then, the adjacency matrix shown in Fig. 1 can be represented as

$$A = \begin{bmatrix} - & 1 & 1 & 0 & 1 & 0 \\ 1 & - & 1 & 0 & 1 & 0 \\ 1 & 1 & - & 1 & 1 & 1 \\ 0 & 0 & 1 & - & 0 & 1 \\ 1 & 1 & 1 & 0 & - & 1 \\ 0 & 0 & 1 & 1 & 1 & - \end{bmatrix} . \tag{2}$$

The adjacency matrix of complex networks requires attention to the following two points: First, the autocorrelation between the nodes of a complex network is not considered, so the diagonal elements of A do not exist. Second, if it is not otherwise specified, A is a symmetric matrix and complex networks are undirected networks. When the topology of a complex network is established, a series of parameters used to characterize its properties can be calculated. Several complex network parameters related to the research are introduced below [11].

In a complex network, the degree of node (degree) can be expressed as k_i, which refers to the number of edges connected to the node i, and is a positive integer [12]. For a complex network with n nodes, the degree of the node can be calculated by summing the elements of the adjacency matrix

$$k_i = \sum_{j=1}^{n} A_{ij}\,. \tag{3}$$

In the formula, A_{ij} represents the elements of the adjacency matrix A.

In a complex network, the number of nodes (between two nodes) is the shortest path through the node: in next text this will be denoted as betweenness. Assuming that the shortest path between the nodes s and t is through the node i, then $n_{st}^{i} = 1$, and vice versa, if $n_{st}^{i} = 0$, then the betweenness of the node i can be expressed as

$$b_i = \sum_{s,t}^{n} n_{st}^{i}\,. \tag{4}$$

A community in a complex network (community) can be defined as a set of closely linked nodes. It has a close connection between the nodes within the community, and the connection between the communities is sparse [13]. Figure 2 shows a complex network instance with three communities.

Modularity is a quantitative index to measure the degree of structure of a complex network community [14]. Through this indicator, a good community structure can be obtained. The most widely used modular computing method is proposed by

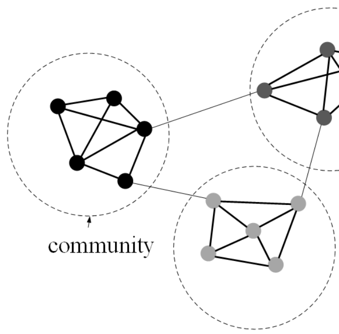


Fig. 2. Structure diagram of complex network group theory

Newman:

$$\lambda = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta \left(C_i, C_j \right) . \tag{5}$$

In the formula, m stands for the total number of edges in the network. If $s = t$, then the function $\delta(st)$ is valued at 1, and vice versa is 0. Symbols C_i and C_j represent the communities in which nodes i and j are located, respectively. The value of a lambda is a natural number between 0 and 1. Different modularity can be used to obtain different community structures.

2.2. Weighted complex network concepts

The weighted complex network can also be represented by an adjacency matrix, which is similar to the ordinary complex network. Figure 3 shows an example of a weighted complex network.

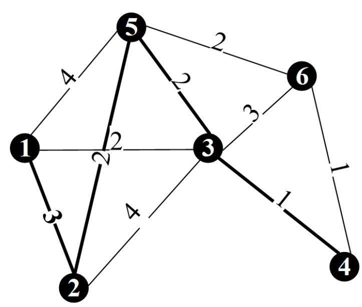


Fig. 3. Weighted complex network example

Its adjacency matrix is

$$A = \begin{bmatrix} - & 3 & 2 & 0 & 4 & 0 \\ 3 & - & 4 & 0 & 2 & 0 \\ 2 & 4 & - & 1 & 2 & 3 \\ 0 & 0 & 1 & - & 0 & 1 \\ 4 & 2 & 2 & 0 & - & 2 \\ 0 & 0 & 3 & 1 & 2 & - \end{bmatrix} . \tag{6}$$

The length of a path can be expressed as

$$L = \sum_{i,j}^{p} A_{ij} , \ i \neq j . \tag{7}$$

In the formula, A_{ij} represents the element of the adjacency matrix A, and P represents the number of nodes on the path. Obviously, the length of path $1-2-5-3-4$ in Fig. 3 is 15. The node betweenness, community structure and modularity in weighted complex network are similar to those of the complex networks.

3. Methods

In order to find a more efficient and appropriate way to solve the problem of complex network communities, Girvan and Newman designed the GN algorithm. By identifying the edges between the communities in the network and removing them one by one, the community structure of the complex network is finally obtained through this iterative process. The flow of the GN algorithm is shown in Fig. 4.

The betweenness of all edges in a complex network is calculated by using breadth first rules.

One of the largest edges (possibly more than one) is removed. If the shortest path between two nodes is more than one, the same weight is assigned to them, and then one of them is removed at random.

The betweenness of all remaining edges is calculated.

Step (2) and (3) are repeated until all edges are removed to obtain a community structure of a complex network. If there is a particular degree of modularity constraint, the algorithm ends when the iteration satisfies the module degree constraint.

4. Results and discussion

4.1. Standard analysis of module division

A functional modeling method is used by researchers in the field of product design. For example, as shown in Table 1, the lower the functional level of the two components realizes, the closer the relationship should be. On the basis of the above research, the quantitative evaluation of functional correlation between components

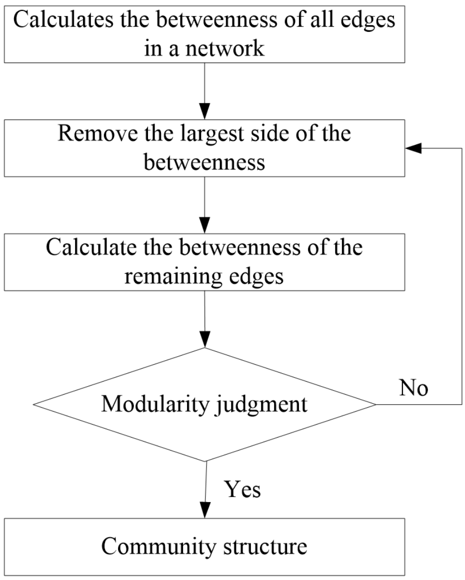


Fig. 4. Algorithm flow

is realized.

Taking the parts of the crawler crane track (Fig. 5) as an example, the above quantization standard is analyzed by example, and the result is shown in Table 2. Taking the gray background cell as an example, "2" means that the drive wheel and the track rack weld together to achieve the same main function. That is to say, the supporting track provides power and support for the whole machine. "10" means that the drive wheel and reducer work together to accomplish a sub function, that is to say, to provide walking power for the whole vehicle. "6" means that the guide wheel and the bracket respectively perform the function of walking, guiding and tensioning, and the guiding function is the subsidiary function of the tensioning function.

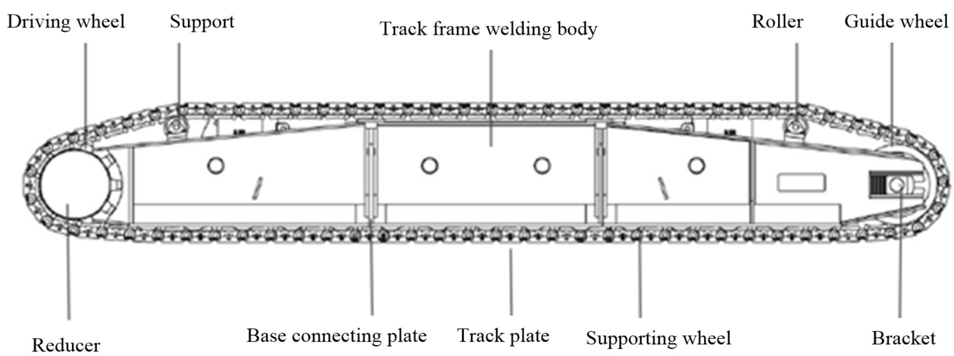
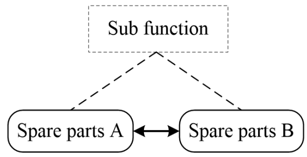
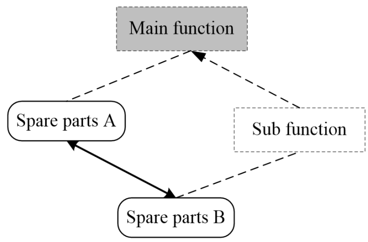
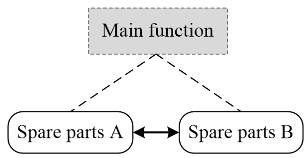
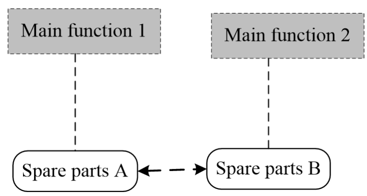


Fig. 5. Sketch map of crawler frame

Table 1. Relative strength of parts function

Relative strength	Score	Description	Graphic
Strong	10	Two components realize the same sub function together	
Common	6	One component is used to implement the main function, and the other is used to implement the sub function under the main function	
Weak	2	Two components are used to achieve the same main function	
Nothing	0	Two components are used to implement different main functions or sub functions	

5. Conclusion

The weighted complex network theory is introduced into the problem division of complex product system modules. Meanwhile, the problem of module partitioning is abstracted into the community discovery problem of weighted complex networks. Firstly, the relation and intensity between components are mapped to edge and edge weights of weighted complex networks. Secondly, because of the complexity of complex product systems, the core elements of product design are considered. That is to say, the function and the structure relation between components are used as the basis of the module division, and the quantitative method of the correlation strength is put forward. Thirdly, the improved GN algorithm can efficiently realize the component weight of complex product system and find out the community structure of complex network. At the same time, this algorithm avoids the fact that the traditional clustering algorithm and heuristic algorithm cannot obtain the optimal solution because of the large number of parts. Finally, through the different values of network modularity, several module partitioning schemes can be obtained to form a scheme set, which provides a data base for the subsequent module partitioning scheme evaluation.

Table 2. Correlation strength evaluation data of function of crawler frame parts

No.	1	2	3	4	5	6	7	8	9	10
1		2	2	2	10	0	2	2	2	2
2			2	2	2	0	2	2	2	2
3				2	2	0	2	2	2	6
4					2	0	2	2	6	2
5						0	0	0	0	6
6							0	0	0	0
7								2	2	2
8									0	0
9										0
10										

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