

Analysis on Refinery System as a Complex Task-resource Network^{*}

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Abstract Refinery system, a typical example of process systems, is presented as complex network in this paper. The topology of this system is described by task-resource network and modeled as directed and weighted graph, in which nodes represent various tasks and edges denote the resources exchanged among tasks. Using the properties of node degree distribution, strength distribution and other weighted quantities, we demonstrate the heterogeneity of the network and point out the relation between structural characters of vertices and the functionality of corresponding tasks. The above phenomena indicate that the design requirements and principles of production process contribute to the heterogeneous features of the network. Besides, betweenness centrality of nodes can be used as an importance indicator to provide additional information for decision making. The correlations between structure and weighted properties are investigated to further address the influence brought by production schemes in system connectivity patterns. Cascading failures model is employed to analyze the robustness of the network when targeted attack happens. Two capacity assignment strategies are compared in order to improve the robustness of the network at certain cost. The refinery system displays more reliable behavior when the protecting strategy considers heterogeneous properties. This phenomenon further implies the structure-activity relationship of the refinery system and provides insightful suggestions for process system design. The results also indicate that robustness analysis is a promising application of methodologies from complex networks to process system engineering.

Keywords complex network, refinery system, structure-activity relationship, heterogeneity, robustness

1 INTRODUCTION

In the field of Process System Engineering (PSE), modeling, optimization, process control and decision making for plant or unit operations have been in the major domain of research for years [1]. As pointed out by Biegler *et al.* [2], the studying of PSE has expanded from unit level up to supply chain level where the whole process of product development is regarded as an interactive and integrity system. Such industrial processes are complex systems [3] and a new breakthrough will be made in engineering by adopting physical and mathematical tools from the study of complex systems [4].

During the past decade, the structure and organization of components interdependence in both natural and artificial complex systems are studied by a new approach, complex network [5, 6]. Some ubiquitous properties such as ‘small-world’ [7] and ‘scale-free’ [8] bring a new perspective in understanding complex systems. Venkatasubramanian *et al.* [9] propose that problems in chemical engineering can be better explained by concepts and tools used in complex network. Some researchers model the systems from process industry as complex networks and study their topological features from a perspective of network theory. Andrade *et al.* [10] describe the complex topology of flowsheets of oil refinery plants. Jiang *et al.* [11] present an Ammonia process flow diagram network. Both of the above works model the process on a fine level of observation, where components of networks are equipment items, such as towers, reactors or pumps.

However, the upper level of the system which is more closely related to planning, scheduling and operations of the whole supply chain is not considered in previous work. Besides, the relations between structural features and processing properties are not discussed and the underlying principles of the emerged organizations still remain to be investigated further.

In this work, we model a refinery system as a task-resource network on the supply chain level. In the production process, many tasks need to be fulfilled successively [12] before the final products are obtained. A group of equipment is regarded as one plant to accomplish one task. Resources of materials and information are required to complete the tasks. The resources consumed by one task are usually from multiple predecessor tasks and the produced resources are delivered to different subsequent tasks. In the refinery task-resource network (RTR network), tasks are viewed as nodes and edges are assigned if resources are exchanged between two tasks. The network representation provides an efficient tool to study the complexity of refinery systems by concentrating on interactions and interdependence between different components. By studying the topological properties of the RTR network, we show the heterogeneity of the network through node degree distribution, strength distribution and other weighted quantities. Meanwhile, we propose that the processing principles and production schemes contribute to the connectivity properties of the RTR network. The robustness analysis of the system is carried out by simulating cascading failures on the RTR network and the network performance

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under two capacity assigning strategies is compared.

2 REFERINEY TASK-RESOURCE NETWORK

The system studied here is abstracted from a real refinery system in Jiujiang, China. The operation scale of this system is 5 million tons per year. The refinery task-resource network is based on the production schemes which describe the operations of functional units and pipelines within the factory. In the RTR network, nodes represent the tasks and edges denote the resources transferred from one task to the others. One task may be composed of several equipment and different tasks have different functions. For instance, processing tasks can consume several feed-in resources and produce multiple outcomes for successor tasks. Processing tasks such as Crude oil Distillation Unit, Fluidized Catalytic Cracking Unit and Catalytic Reforming Unit are all composed of different towers, reactors and pumps to perform treatment of crude oil or intermediate products. Tasks responsible for inventory store raw materials and different products. Mixture tasks collect resources from multiple tasks and deliver them to processing tasks. At the same time, outlet streams are separated by split task for further processing or storage. There are also peripheral tasks defining the boundary of the system, including unload of crude oil as well as upload of final petroleum products. Materials, utilities and other information shared between tasks are all generally defined as resources and quantified by production schemes. For example, the resources generated by one task are assigned to successive tasks proportionally according to certain scheme and this proportion may be changed in different schemes. In this work, the most commonly used production scheme is applied to each task. The resources exchanged between tasks of storage are missing in our model because they are assigned heuristically according to actual production process other than production schemes. Fortunately, such exchanges are often avoided during production so the missing part will not affect the whole network. Besides, the electricity, gas or other energies that may be consumed during the production are not considered. It is assumed that the amount of feed-in resource to one task is equal to that of the resource discharged by the same task.

According to the above definitions, the network is regarded as directed and weighted network. The directions of edges are defined by the flows of resources and the weights indicate the amount of corresponding resources. Totally, there are 248 vertices and 760 edges in the network. The network can be described as $G = (V, E, W)$, consisting of a vertices set $V = \{i | i = 1, 2, \dots, N\}$, an edge set $E = \{e_{ij} \in \{0, 1\} | i, j = 1, 2, \dots, N, i \neq j\}$, and a set of weights $W = \{w_{ij} \geq 0 | i, j = 1, 2, \dots, N, i \neq j\}$ attached to the edges. If there is one edge pointing to node j from node i , $e_{ij} = 1$, otherwise

$e_{ij} = 0$. The outgoing degree k_i^{out} of node i , defined as $k_i^{\text{out}} = \sum_{j \in \Omega_i} e_{ij}$, counts the number of edges going out from i , where Ω_i is the set of downstream neighbors of node i . The incoming degree k_i^{in} , defined as $k_i^{\text{in}} = \sum_{j \in \Psi_i} e_{ji}$, denotes the number of edges from other nodes to i , where Ψ_i is the set of upstream neighbors of node i . The average outgoing and incoming degree are defined as $\langle k_{\text{out}} \rangle = \sum_{i \in V} k_i^{\text{out}} / N$ and $\langle k_{\text{in}} \rangle = \sum_{i \in V} k_i^{\text{in}} / N$ respectively. In this network, the edge weight w_{ij} represents the amount of resources coming from i to j under certain production scheme. The total amount of outgoing resource flow of node i is defined as $W_i^{\text{out}} = \sum_{j \in \Omega_i} w_{ij}$ and the overall amount of incoming resource flow of node i is calculated by $W_i^{\text{in}} = \sum_{j \in \Psi_i} w_{ji}$. Because of the mass conservation, the feed-in flow of node i is equal to its output flow, so $W_i = W_i^{\text{out}} = W_i^{\text{in}}$, and this measurement is defined as node strength $S_i = W_i$.

Our refinery task-resource network is different from other network-based representations of processing systems, such as state-task network (STN) [13] or resource-tasks network (RTN) [14], both of which regard resources as individual nodes. In their work, state or resource nodes are linked to task nodes *via* edges if states or resources are consumed or produced by tasks. However, in our RTR network, only groups of physical units are defined as nodes and all the resources exchanging among tasks are represented by edges. Besides, the resources are delivered through pipelines, so the edges also represent the physical connections between different units. Compared with other network models, our approach provides better description of the real topology of the physical connections among units and equipment. Such representations are more suitable for exploring the topological properties of the system while dynamical process such as planning, scheduling or other operations may be affected or restricted by these characters.

3 HETEROGENEITY OF THE REFINERY TASK-RESOURCE NETWORK

Gimenez *et al.* describe the structural complexity of multi-purpose facilities in process engineering from five aspects [12] and these characters are also adequate for refinery system. The complex functionality of one task is easily influenced by changing input resources, boundaries or coupled patterns with other tasks. The multiple processing routes of chemical products contribute to the complexity of the system and make several significant topological properties emerged. Some

basic statistical characteristics of the task-resource network are given in Table 1, in which N is the number of nodes, E is the number of edges, $\langle W \rangle$ is the average weight of edges, $\langle S \rangle$ is the average strength of nodes, $\langle k_{in} \rangle$ is the average incoming degree of nodes, $\langle k_{out} \rangle$ is the average outgoing degree of nodes, $\langle L \rangle$ is the average shortest path length between any pair of nodes in the corresponding directed unweighted network.

Table 1 Basic characteristics of the RTR network

N	E	$\langle W \rangle$	$\langle S \rangle$	$\langle k_{in} \rangle$	$\langle k_{out} \rangle$	$\langle L \rangle$
248	760	5.62	18.41	3.06	3.06	8.82

We will first investigate the heterogeneity of the RTR network. Heterogeneity has been reported in many real-world networks. This property reveals the structural variations of the network and implies that the importance of different components in network is not identical. Typically, heterogeneous network are defined by heavy-tail distributions of nodes degree, betweenness centrality and other weighted quantities [15].

3.1 Degree and betweenness centrality distributions of the RTR network

Degree distribution is one of the most investigated properties of networks. Node degree is defined as the number of edges linking to a given node. Degree distribution illustrates the probability of one node to gain a certain degree. In random network, every vertex has the same possibility to obtain edges and the node degree presents Poisson distribution [16]. Thus random network is referred as homogeneous network. In contrast with random network, some networks are with heterogeneous degree distribution, in which there exist a few vertices, whose degree is pretty high while most of the nodes are comparatively poorly connected [8]. It is obvious that the nodes which better connected with others are more influential as they can affect more vertices directly. These nodes are usually referred to as 'hub' in network theory. The existence of hub is reported

in many real-world networks, such as scientific collaboration network [17], airport network [18] and protein-protein interaction network [19], and the degree distribution often displays power-law behavior.

For the directed RTR network, the incoming and outgoing degree distributions are shown in Fig. 1. A few hubs with large degree exist while a large number of vertices are less connected. Both of the incoming and outgoing degree distribution can be approximately described as power-law, *i.e.*, $p(k_{in}) \sim k_{in}^{\gamma_{in}}$ and $p(k_{out}) \sim k_{out}^{\gamma_{out}}$, with the exponents $\gamma_{in} = 1.78$ and $\gamma_{out} = -1.62$, respectively.

For the function of tasks with large incoming degree and outgoing degree, we find that the topological properties of tasks are related to the production process. The nodes with large incoming degree are usually responsible for storage and large outgoing degree always belongs to tasks of separating materials. This phenomenon is consistent with the production principles of refinery processing. For example, the requirements of a broad spectrum of chemicals determine the multiple processing routes of refinery systems. Before transferred to the processing units or qualified as final products, the intermediate products are composed of different chemicals. Storage vessels collect all of the necessary chemicals from multiple tasks and mix them completely. Thus the incoming degree of some inventory tasks is higher than that of other tasks in the system. Meanwhile, the separation tasks lead chemical products into different processing routes and thus obtain the large outgoing degree.

Heterogeneity of the RTR network is also exhibited by betweenness centrality of vertices. Betweenness centrality of vertex m describes the number of shortest paths between all of the pairs of vertices that going through m and thus can indicate how influential a node is in communication [20]. If there are c_{ij} shortest pathways between node i and j , among which $c(m)_{ij}$ are through m , the betweenness centrality $bc(m)$ is defined by the fraction $c(m)_{ij}/c_{ij}$ over all pairs of vertices as shown in $bc(m) = \sum_{i \neq j} c(m)_{ij} / c_{ij}$.

It has been reported that the distributions of node

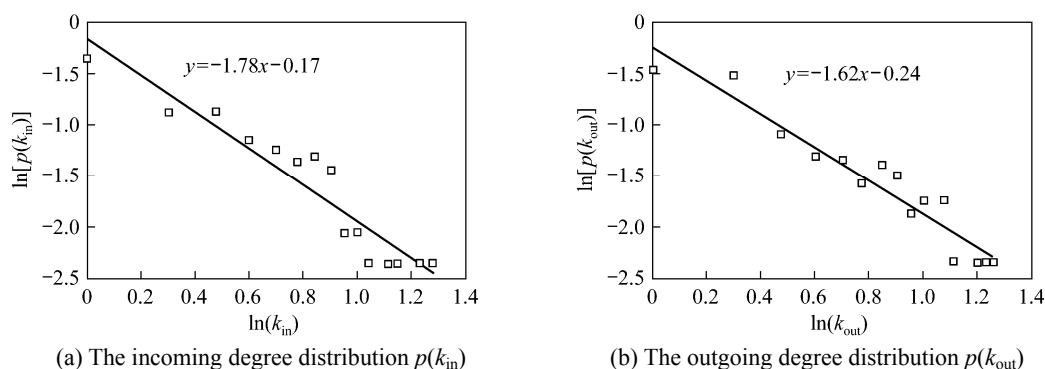


Figure 1 Degree distributions of the RTR network

betweenness centrality in many complex networks are scale-free [21]. This heterogeneous character is strongly related to the network efficiency of communication and stability under attacks or disturbance. By analyzing our network, we find that the node distribution of betweenness centrality in the RTR network also displays the heterogeneous feature. As shown in Fig. 2, we plot the probability $p(bc)$ that a vertex having betweenness centrality of bc in the RTR network. A power-law relation between $p(bc)$ and bc is observed and the linear fit shows that $p(bc) \sim bc^{-1.09}$.

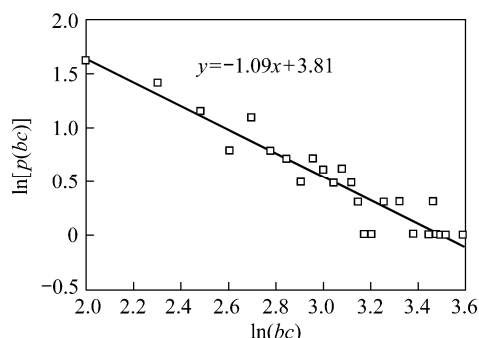


Figure 2 The node betweenness centrality distribution $p(bc)$ of the RTR network

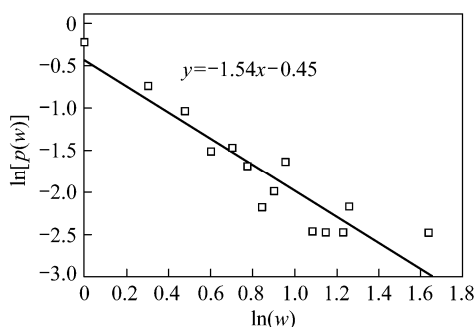
By exploring the functionality of tasks with high betweenness centrality, we find that unlike tasks with high degrees, these nodes are not restricted within one type of function. Tasks of processing materials, tasks of material separation or tasks responsible for inventory are all possible to gain high value of betweenness centrality. In the processes of communication or transportation, nodes with high betweenness centrality are more likely to be visited in order to get high efficiency. Therefore betweenness centrality is regarded as a quantitative description of the importance of a given vertex [22]. By adopting this criterion, betweenness centrality may also provide information for the importance of tasks in the RTR network. For instance, the average betweenness centrality of tasks relating to chemical processing is the highest among all the tasks with different kinds of functions. This phenomenon coincides with the fact that processing units are the

most important components in the refinery system. Thus we believe that the betweenness centrality of vertices reveals the importance of individual task.

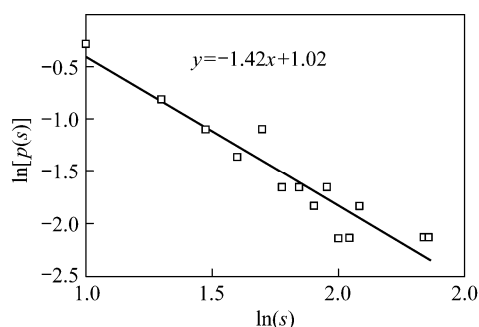
3.2 Edge weight and node strength distributions of the RTR network

Here we investigate the weighted properties of the RTR network through distributions of edge weight and node strength. In this work, edge weights w represent the amount of resources transferred between two tasks and node strength s represents the resource flows that one task is handling. As shown in Fig. 3 (a), the edge weight distribution $p(w)$ is heavy-tailed and can be approximated by the power-law behavior $p(w) \sim w^{\gamma_w}$ with the exponent $\gamma_w = -1.54$. The node strength distribution displays similar phenomenon in Fig. 3 (b), in which $p(s) \sim s^{\gamma_s}$ with the exponent $\gamma_s = -1.42$.

The distributions of edge weight and node strength indicate strong heterogeneity of the RTR network, *i.e.*, some tasks require much more resources to complete while most of the other tasks can only handle limited amount of resources. Such node strength phenomenon has also been found in other complex networks. For world-wide airport network, the vertex strength indicates the total traffic handled by one airport [23]. In the case of telephone network, the strength accounts for the accumulative duration of one's phone calls [24]. In all of these networks, node strength integrates the information of node degrees as well as the edge weights and thus provides more general picture of the complexity of network other than solely individual weight or structural features. Thus the strength of vertex is regarded as one of the significant measures in the statistical analysis of weighted network and indicates the importance or centrality of the vertex in the network. For the RTR network, this behavior of node strength matches the production process in refinery system. After being unloaded from the vehicles, the crude oil is first transmitted to Crude oil Distillation Unit (CDU) for preparation and separation, then the out-streams are delivered for multiple processing tasks, such as treatments in Fluidized Catalytic Cracking Unit and Catalytic Reforming Unit, storage



(a) Edge weight distribution $p(w)$ of the RTR network



(b) Node strength distribution of $p(s)$ of the RTR network

Figure 3 Edge weight distribution and node strength distribution of the RTR network

or other different tasks. Thus CDU needs to process all of the raw materials and other processing units or tanks only handle part of the materials. The production principles characterize the RTR network, in which some of the tasks, especially the ones closer to the first treatment of raw materials, require more resources while others are only with few resources. The situation is the same for weights of edges.

Besides, the analysis on edge weight and node strength reveals the bottlenecks of the network and provides additional information. For example, different capacities of pipelines or communication bandwidth can be assigned according to the amount of resources exchanged between two tasks. The resources can be better utilized and the efficiency of the system at limited cost is improved.

3.3 Origins of topological properties of the RTR network

One of the key questions discussed in the domain of complex network is the explanations and predictions of certain topological properties. In the above analysis, we found that the heterogeneity of the network is related to the functions of tasks and the resources exchanged among them. Meanwhile, it is well known that the configuration and operations of tasks and resources are restricted by processing principles of the refinery system. Therefore, it is highly possible that the underlying processing rules lead to the emergence of certain structural properties. An example of task-resource network obeying the same design principles as the one abstracted from real refinery system is proposed to demonstrate this point.

In the refinery system, resources delivered from one task to another are usually determined by processing principles. The processing principles contain not only chemical specifications, but also the operational conditions, market requirements and other factors that may influence the integrated processing systems. For

example, tasks of mixture streams usually collect resources from different tasks of inventory and transmit them to processing tasks for further treatments. The outgoing resources of processing tasks are usually delivered to successive tasks, like inventory or another round of treatment through tasks of split. In one word, the resource connections between different tasks are all defined by processing principles to fulfill the production targets.

According to this configuration, we provide a simplified example of refinery task-resource network. The number of tasks responsible for processing, mixture, split and storage is one, two, five and seven respectively. Besides, three peripheral tasks form the boundary of the RTR network. The example is illustrated in Fig. 4. In the figure, plant represented processing task, mixer performed mixture task, splitter indicated task of splitting and tank meant task of storage. The number of different tasks and connections between any two kinds of tasks were proportional to the real data set of the refinery system, while the particular lines were assigned randomly. The exchanging patterns of resources between any two kinds of tasks are designed according to processing principles. The number of links e_{ij} and their weights w_{ij} are proportional to the real data set of refinery system, while the particular lines are assigned randomly. The example network has 18 nodes and 50 edges. By calculating this example, we find that tasks responsible for storage get the highest average incoming degree 4.2 and separation tasks gain the highest average outgoing degree 5.8, while the average incoming and outgoing degree over all nodes is only 2.7. The tasks responsible for processing obtain the largest betweenness centrality 124 while the average value is 21. Besides, the largest strength is with the processing task and the others are all with a relatively small value of strength. All of the aforementioned behavior of degree, betweenness centrality and strength are the same as what we find in the original refinery system task-resource network.

This example illustrates that the processing

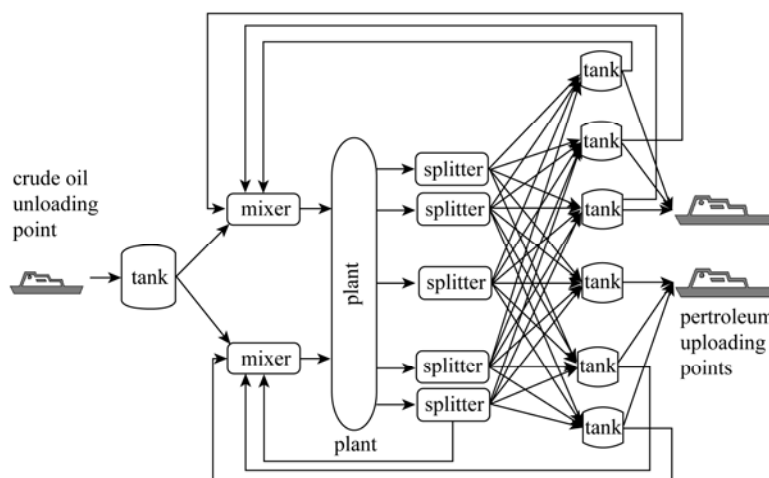


Figure 4 A simplified example of refinery system (each box indicates a task of different functionality)

principles of the refinery system contribute to the structural features of the RTR network. The functions of different tasks in the system determine the local properties of individual nodes. The interactions among these elements lead to the emergence of certain features and eventually generate the global behavior for the whole system.

4 CORRELATIONS BETWEEN NETWORK TOPOLOGY AND WEIGHTED PROPERTIES

In this part, we explore the correlations between structural features and weighted properties. It is obvious that weights of edges and nodes bring lots of information about the network. However, one needs to further investigate how the weighted features influence the system topology and describe the actual system better than the pure structural information. Here, the behavior between node degree and strength is analyzed to suggest the relations between system structure and resource weights. In addition, another measurement weighted average nearest neighbors degree is employed to investigate how weighted features influence the overall network properties. Generally, the topology of refinery system determines the overall resource flows, yet the weighted features defined by the flows may react and generate new topological properties.

4.1 Correlations between node degree and strength

From the definition of node strength, it is easy get the conclusion that in the absence of correlation between edge weight and node degree, node strength and degree have following relationship: $S_i = \sum_{j \in \Omega_i} W_{ij} = \langle W \rangle k_i / 2$ where $\langle W \rangle$ is the average weight of edges connected to node i and k_i is the degree of node i defined as $k_i = k_i^{\text{in}} + k_i^{\text{out}}$. In this work, we investigate the dependence of $s(k)$ on k where $s(k)$ is the average strength of all the vertices with degree k . Fig. 5 shows that $s(k) \sim k^{\lambda_k}$ with exponent $\lambda_k = 0.83$, while this value is supposed to be 1 in non-correlation situation.

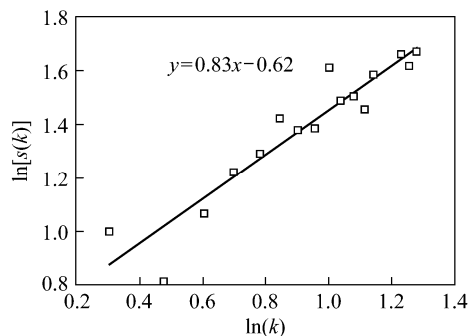


Figure 5 The correlation between node degree k and strength $s(k)$ of the RTR network

This phenomenon implies that the strength of nodes grows slower than their degrees, *i.e.*, the weight of edges belonging to highly connected vertices tends to have a value smaller than that corresponding to a random assignment of weight. This behavior may be explained by protection strategy that tasks which are intensively exchanging resources with other tasks try to protect themselves from heavy load and thus limit the amount of resource handled.

4.2 Weighted average nearest neighbors degree

In random networks, nodes connect to the others without any preferential rules, so there is no specific connection pattern. However, evidence from empirical networks shows that there exist two connection patterns in complex networks [25]. One is called ‘assortative’, in which nodes sharing similar property or type are more likely to be connected together. The other pattern, on the contrary, is referred to as ‘disassortative’, in which nodes tend to link the others with different properties. Node degree is one of such properties that usually is employed to investigate the structural connection patterns in complex networks [26, 27]. The correlations between degree of node i and its average nearest neighbors degree, defined as $k_{\text{nn},i} =$

$\frac{1}{k_i} \sum_{j \in \Omega_i} k_j$, provide a quantitative description of the connection patterns [28]. For all the nodes with degree k in the network, the average nearest neighbors degree is $k_{\text{nn}}(k) = \frac{1}{N_k} \sum_{i \in \Pi_k} k_{\text{nn},i}$ where Π_k is the set of

nodes with degree k and N_k is the number of elements in this set. If $k_{\text{nn}}(k)$ is an increasing function of k , the network presents assortative behavior while a decreasing behavior of $k_{\text{nn}}(k)$ indicates a disassortative connection pattern. If there is no relation, for any values of k , $k_{\text{nn}}(k)$ should be equal to the average degree of all nodes $\langle k \rangle$. Both assortative and disassortative patterns are commonly found in complex networks from natural and artificial systems [25, 26, 28]. It is pointed out that for weighted network, the above definition may be insufficient because it does not consider the weight of edges [23]. The inclusion of weights and their correlations might change the statistic properties of solely topological structure. For instance, high-degree node may be connected to a majority of high-degree nodes while distributes most proportion of its strength to nodes of small degree. Then the connection pattern is better described by disassortative rather than assortative. The weighted average nearest neighbors’ degree is thus introduced as $k_{\text{nn},i}^w = \frac{1}{S_i} \sum_{j \in \Omega_i} w_{ij} k_j$. We

display the relations of $k_{nn}(k) \sim k$ and $k_{nn}^w(k) \sim k$ in Fig. 6. For all values of degree, $k_{nn}^w(k) > k_{nn}(k)$, which means that edges with large weights are more likely to point to the nodes with larger degree. Besides, weighted analysis shows a more definite assortative pattern when $k > 4$ because vertices of high degree concentrate most of their strength on the high-degree nodes. However, this tendency is less obvious in solely topological approach.

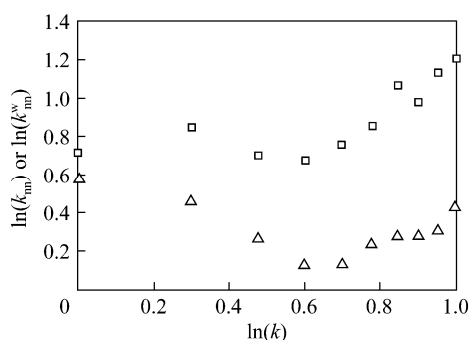


Figure 6 Variation of unweighted k_{nn} and weighted k_{nn}^w average nearest neighbors degree with node degree k
 $\triangle \ln(k_{nn})$; $\square \ln(k_{nn}^w)$

The difference between unweighted and weighted average nearest neighbors degree as well as relations between node strength and degree imply strong interactions between weight and structural features of the RTR network. By the definition of the task-resource network, the structural features of the network are mainly decided by processing principles while the weights of edges are more related to the production scheme. The relations between weight and structural features imply that there exist some underlying rules for the design of production schemes.

5 ROBUSTNESS ANALYSIS OF THE RTR NETWORK

One of the key performance measures of industrial systems is robustness under disturbance or some kind of uncertainties. In the domain of complex network, the robustness is analyzed by measuring the network performance under random removals or targeted attacks of nodes and edges [29, 30]. Random removals refer to the deletion of nodes or edges randomly without specific criteria. Targeted attacks, on the contrary, tend to remove vertices or links based on certain rules, such as in the descending order of node degree or betweenness centrality [31]. The network performance of connectivity and functionality are measured to quantify the network robustness under disturbance. Lots of researches have demonstrated that many complex networks are resilient to random breakdowns while vulnerable to targeted attacks [32]. Generally, there are two approaches to investigate the

network robustness, static and dynamical. In static way, removals of nodes or edges would only bring topological impact such as distance between nodes or size of largest connected component [33]. However, if dynamical properties and detailed technical aspects of the system are considered, deletion of one edge might trigger the reconfiguration of the whole network. Motter and Lai [34] first studied the cascading failures on complex network by taking the dynamics of flows into consideration. For normal situation, each node is with certain load and the maximum load one can handle is defined as capacity. The fail of one node or edge leads to the redistribution of loads on the whole network and results in progressive damage that more nodes and edges might exceed their capacities and fail to work. Such phenomenon is called cascading failures and could bring about large scale failures on the whole network. Catastrophe brought by cascading failures can be found in the cases of internet and power grid.

5.1 Cascading failures model on the RTR network

In this work, we explored the topological robustness of RTR network through dynamical properties of cascading failures under targeted attack.

For each node in the network, the load of node i is its strength $L_i(t) = S_i(t)$, which represents the amount of resource one task is handling at time t . The capacity of the node is defined as $C_i = (1 + \alpha)S_{i_initial}$, in which $S_{i_initial}$ is the initial load of node i under normal condition without attack, and α is the tolerance parameter. If the load of one node exceeds the corresponding capacity, this node will fail to work. The failure of one node will lead to the malfunction of all the edges attached to it and further trigger the redistribution of load among the neighboring nodes.

Following previous work [35], we propose the redistribution strategy as showed in Fig. 7. The broken of one edge starting from node i will change all of the other edges coming out from i . Among i 's neighbors, the higher w_{ij} one edge used to have, the larger extra weight it will have after the reconfiguration. If the edge between i and j is broken, the new w_{ij} will be zero. The share of resources w_{ij} which supposed to go to node j will be redistributed to other nearest neighbors

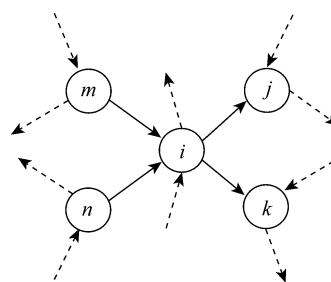


Figure 7 Schematic illustration of reconfiguration of the RTR network

of node i . Thus all of the outgoing edges of node i will deliver an extra share of resource Δw_{ik} , which is proportional to their original share to the neighbors:

$$\Delta w_{ik} = w_{ij} \frac{w_{ik}}{\sum_{k \in \Omega_i, k \neq j} w_{ik}}, \text{ where } \Omega_i \text{ is the set of}$$

neighboring nodes of i . Following this reconfiguration, flows on the network will be redistributed and some vertices will receive more resources than that can be handled. This may result in the situation that more vertices fail for overloaded and all of the edges connected with them will be broken, leading to another round of reconfiguration. The iteration will continue until loads on all the remaining nodes are within their capacity. The survived nodes represent tasks with normal functionality. The size of the largest connected component after cascading failure is usually used to indicate the robustness of the network. Adopting this concept to the RTR network, the ratio of survived nodes after cascading failures is used to quantify the network robustness. This measurement defines the robustness of network as $R = N_s/N$, where N and N_s are the numbers of functional nodes before and after the cascading failures respectively.

At last, we introduce the notion of cost. Cost spent on protecting the system is usually relevant to robustness. The more you spend the better performance you get. Without including the cost associated with individual nodes or edges, only extra costs related to node protections are considered in this work. This cost can be approximated by the amount of extra capacity allocated, defined as: $\text{cost} = \frac{1}{N} \sum_{i \in N} \alpha_i$ [36, 37].

In present model every node had the same tolerance parameter $\text{cost} = \alpha$.

In the following part, we try to find the relations between cost and network robustness. Fig. 8 depicts the robustness performance R after cascading failures with different value of tolerance parameter α . The cascading failures are triggered by attacking the edge with the largest load. It is shown that the impacts of cascading failures experience several phases with the

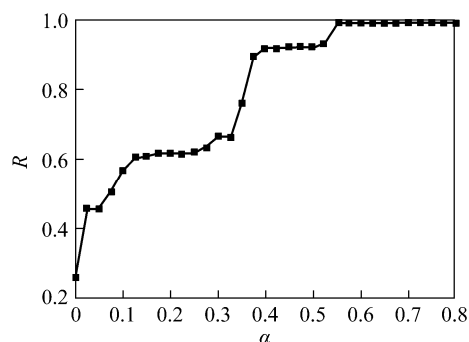


Figure 8 The robustness performance R of the RTR network as function of tolerance parameter α

increase of α . When $\alpha < 0.18$, augment of node capacity can improve the network robustness effectively. As α increases from 0.18 to 0.32, the number of nodes survived from cascading failures only increases 5%. However, as α increase from 0.32 to 0.4, the portion of survived nodes exhibits a step change from 66% to 90%. Then the robustness of the network remains the same until α gets 0.58 when nearly all the nodes run steadily. It is obvious that larger capacity will guarantee better robustness performance of the network. However we see that not every penny spent will improve the overall robustness. In practical situation, the redundancies are often limited by finical considerations. From the above analysis, it can be concluded that the damage of cascading failures on the RTR network can be controlled by choosing appropriate capacities for nodes. A proper α will provide efficient support for network robustness while reduce the cost as much as possible.

5.2 Improved strategy for capacity assignment

Recently, different strategies of protection under cascading failures have been provided to improve the network robustness [38, 39]. A lot of work focuses on adjusting the capacity for different vertices based on nodes properties. In this work, we adopt the idea from Wang-Kim model [36] and redefine the concept of load by node strength instead of betweenness centrality. The result shows this model can improve the network performance at the same cost when cascading failures happen.

The capacity of nodes is redefined as $C_i = (1 + \alpha_i)S_{i_initial}$ in which tolerance parameter α_i is different according to different properties of node i . In this model, $\alpha_i = \alpha \Theta(S_{i_initial}/S_{\max_initial} - \beta)$ where $\Theta(x) = 0(1)$ for $x < 0(>0)$, $S_{\max_initial} = \max_i(S_{i_initial})$. The parameter of β guarantees that one node will get extra protection only if its strength is large enough. The distribution of node strength suggests that a great many nodes in the RTR network are with the small value of strength while a few important nodes are with relative larger strength. The definition of α_i takes the heterogeneous property of node strength into consideration so nodes with higher importance are better protected. The rule of load redistribution is the same as previous model.

In this work, we tend to choose the optimal pair of α and β for limited cost to obtain the most robust network structure. We first investigate the robustness performance R as a function of β for different values of α , as show in Fig. 9. The robustness decreases as β increases with several flat ranges, in which the robustness performance is not sensitive to the change of β . As both α and β are closely related to the cost of network, it is possible that these flat ranges bring better robustness-cost performance. Actually, this has been proved by the relations of robustness and cost of network at given value of α in Fig. 10.

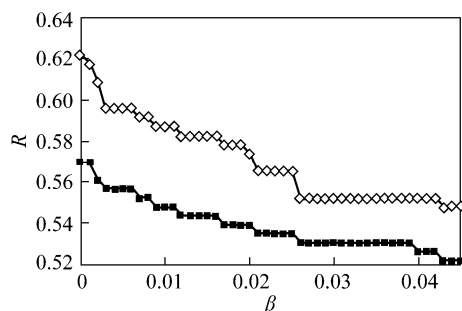


Figure 9 The robustness performance R of the RTR network as function of β with certain values of α
 ■ $\alpha = 0.1$; ◇ $\alpha = 0.24$

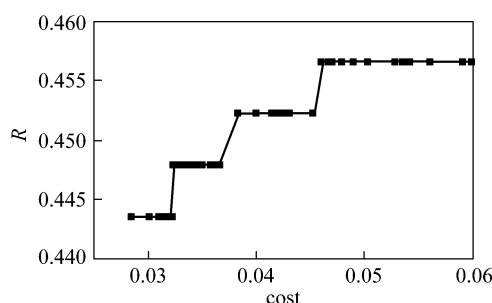


Figure 10 The robustness performance R of the network as function of cost with ($\alpha = 0.06$)

It is obvious that the more you spend, the better the robustness of network. However, as shown in Fig. 10, in some phases, the increase of investment will not improve the robustness performance of the network effectively. This is the same as what we have found in previous model.

The above analysis gives us the clue that there exists optimal pair of (α, β) , which can provide the best robustness performance at certain cost. Fig. 11 reports the comparison of robustness performance provided by aforementioned two strategies. The robustness performance with improved strategy is obtained using the optimal pair of (α, β) for each cost. It shows clearly that for most of given cost, the improved strategy provides better robustness performance than the previous one. The improvement is as high as 15% which means a big profit for the whole refinery system. This result indicates that the capacity assignment

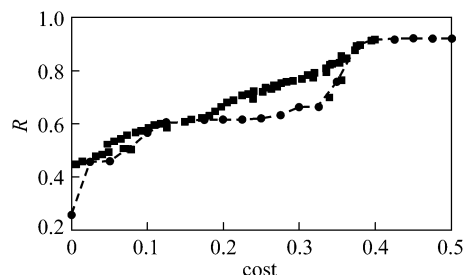


Figure 11 The best robustness performance R in the RTR network under two capacity assignment strategies with variation of cost

● former strategy; ■ improved strategy

strategy considering the heterogeneity of network structure can provide better protection to the RTR network.

6 CONCLUSIONS

In this work, the topological properties of a complex refinery task-resource network are investigated. The RTR network is formulated according to real production schemes and it contains a variety of information about processing principles in refinery system. We demonstrate the heterogeneous nature of the network using several structural and weighted properties. Incoming and outgoing degree distributions depict the network characters purely structurally. Edge weight and node strength take weighted information into consideration and describe the network properties more thoroughly. It is worthy to notice that all of the distribution behaviors is related to the functionality of tasks in the system and provide additional information about the system. Generally, large incoming degrees belong to the tasks responsible for inventory while tasks of stream separation are with large outgoing degrees. Node strength and edge weight are employed to detect the bottlenecks of the system. Behavior of node betweenness centrality shows that this measurement indicates the importance of individual task in the whole system. All of the aforementioned phenomena imply that there exist a strong relation between system functionality and network organization. Thus we propose that the design principles and production processing requirements of the refinery system contribute to the heterogeneity of the task-resource network. To further discuss the relations between network topology and weighted properties, we analyze the correlations between network structures and weighted properties. In this context, weighted properties are mainly quantified by production schemes while the topologies of the system are decided by processing principles. The behavior of node strength with its degree indicates that the strength grows slower than that of degree. The weighted average nearest neighbors degree shows assortative behavior of the network. Both of above features predict a strong correlation between the weighted and topological properties in the RTR network and demonstrate the influence of processing schemes on system connectivity pattern. The underlying principles of this influence may inspire the future development of production schemes.

The robustness of the RTR network under targeted attack is investigated using cascading failures model. We formulated the cascade failures model based on mass conservation and load redistribution. The malfunction of one component will lead to the successive failures of a great many other parts in the system. Thus, system structure and protecting strategies become the key factors determining the robustness performance of the system. One of the crucial issues in this domain is how to improve the system robustness while keeping the cost at a low level. For the RTR network, robustness performance under two

different strategies of capacity assignment is compared. We find that the strategy considering the heterogeneity of the network provides better protection to the system at the same running costs. This cascading failures approach provides an example how local properties of network structure would determine the overall performance of the system and introduces a new perspective of robustness analysis for industrial systems.

In summary, the task-resource network of refinery system has significant topological characters. The close relations between structural properties and production principles can help better understanding the structure-activity relationship of the refinery system. The robustness analysis that employs the structural information provides a new approach to investigate the reliability of the system and suggests possible ways to improve system performance under disturbance. There are still lots of open questions worth to be discussed in the future, such as how the topological properties are related to the dynamic process of refinery system, how the local properties of individual elements and interactions among them lead to the emergence of global behavior, how connectivity properties are determined by processing principles and conversely benefit the development of production schemes. It is promising that the methodologies from domain of complex network will have future applications in Process System Engineering and other engineering areas.

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