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Network structure analysis based on embodied energy of the Australian economy

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A R T I C L E I N F O

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A B S T R A C T

Energy and economic growth are closely linked and have negative impacts on the environment. Both environmental protection and economic development are significant global focal points of concern. Australian economic growth has slowed but energy consumption has increased. The relationship between economic growth and energy consumption has changed significantly. However, existing methods for accounting energy transfers between industries overlook the role of embodied energy, making them insufficient to fully capture the actual energy usage in both domestic and international trade. This study investigates the structural changes in embodied energy in the Australian economy. The paper integrates sectors as the section nodes for a network and constructs a two-layer network model to analyze energy flows both between and within nodes. The results show that the Australian embodied energy network exhibited significant variations in efficiency and interconnectedness over time, with a trend toward shorter, more interconnected paths from 2015 to 2019, enhancing overall network efficiency. The Australian embodied energy network currently faces significant funding constraints. The findings show that the Australian economic sectors have increased energy consumption in production without contributing to economic growth due to the concentration of resources within the network.

1. Introduction

Global economic development needs the strong support of energy resources, indicating the close relationship between energy consumption and economic growth. Besides the influences on economic growth, energy consumption also contributes to environmental deterioration. Both environmental protection and economic development are significant global focal points of concern. Energy utilization has contributed to a range of environmental problems, including global warming and air pollution, as noted by Shi et al., (2017). In recent academic research, energy consumption, import/export data, carbon emissions, and labor statistics have been listed as indicators of economic performance to examine the influences of various sectors on energy consumption (Tran et al., 2022; Yang et al., 2023; Zhang et al., 2023).

As one of the world's largest primary energy emitters, in 2021 Australian direct energy consumption was 6014 PJ with average growth 0.7% higher than in 2019. However, the Australian economy contracted by 0.3% in 2019 to $1.9 trillion (ABS, 2021). Despite the deceleration of economic growth, energy consumption has not decreased. The increase in energy consumption has not had a positive effect on economic growth, showing that the relationship between economic growth and energy consumption has changed significantly. However, most approaches to accounting for energy transfers between industries fail to consider the importance of embodied energy, leading to an incomplete representation of actual energy consumption in both domestic and international trade. A more comprehensive analytical framework is needed to fully elucidate the complex nature of energy interchanges in the economy (Chen et al., 2017).

Exploring the changes in energy consumption in economic development has positive implications for the relationship between energy structure and economic development at national and global levels. Embodied energy is the best medium to shows the transfer based on input–output analysis and life-cycle assessment (Guan et al., 2016; Lam et al., 2019; Liu et al., 2020; Pakdel et al., 2021). Energy embodied in goods or services flows among different sectors in international trade, forming a huge network system with complex inflows and outflows

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between numerous sectors. These sectors can be seen as the nodes of the network. The embodied energy transmission among industries, regions, or international trade-offs have been discussed in some studies (Liang et al., 2023; Liu et al., 2022; Shepard and Pratson, 2020), while the characteristics from the perspective of the network have been neglected. Hence, the complex network method is selected here to analyze the properties of the Australian economic network. The related variables can measure the network characteristics. The relationship between energy structure and economic growth can also be explored. The relationship betweenness of a network means the proportion of the number of paths passing through a node on all shortest paths in the network to the total number of shortest paths, which describes the influence of energy flows of a specific sector on an economic network.

The purpose of this study is to investigate the structural changes in embodied energy in the Australian economy. A hybrid method based on the complex network approach is suitable to analyze the network questions based on the support of input–output data sources. To analyze the relationships between energy and economy, the embodied energy networks are created by integrating data from the Australian Input–Output Tables and energy statistics for the different economic sectors. This research integrates sectors as the section nodes for the network and constructs a two-layer network model to analyze energy flows both between and within nodes. Based on the complex network method, multiple analysis categories are selected as the first step. Then, the variable indicators are computed to quantify the characteristics of the embodied energy network, attempting to reveal the changes and influences of the energy structure. Finally, the key sections are identified and policy-relevant insights are supplied for improving network efficiency and sustainability.

The contributions of this study include: (1) it establishes the Australian embodied energy network and measures the characteristic properties of the Australian energy structure from the perspective of the network; and (2) it quantifies the influence of changes in the energy structure on the Australian economy at the section level. The findings from this study provide insights into the energy consumption patterns and interrelationships among the various economic sectors in Australia.

2. Literature review

2.1. Complex networks

Complex networks are systems composed of a large number of interconnected components where the interactions between these components lead to emergent behaviors that cannot be easily predicted from the properties of individual elements alone (Barabási, 2016). Newman and Girvan (2004) developed algorithms for detecting community structures in networks, revealing the presence of densely connected subgroups. This work has had significant implications for understanding social networks, protein interactions, and other complex systems. Recent research has focused on extending network analysis to multilayer and interdependent networks, where multiple networks interact with each other. Buldyrev et al. (2010) demonstrated that interdependent networks can be more vulnerable to cascading failures than single networks, highlighting the importance of considering network interdependencies in critical infrastructure. Their model showed that in a system of two interdependent networks, the failure of nodes in one network can lead to failures in the other, potentially resulting in a cascade of failures that can destroy both networks entirely. Gao et al. (2011) introduced a framework for analyzing the robustness of interdependent networks under random attacks and found that interdependent systems are more fragile and can collapse abruptly. The concept of multilayer networks, which provides a more general framework than that of interdependent networks, has been extensively developed by Kivela et al. (2014). They discuss various aspects of multilayer networks, including their structure, dynamics, and applications across different fields. Zakariya and Teh (2023) provided a comprehensive review of the modeling and analysis of interdependent critical infrastructure systems. Zhu et al. (2023) studied the cascading failures in coupled power grids and communication networks, demonstrating how failures in the power grid can impact the communication network and vice versa, leading to more severe and widespread outages. Researchers have also investigated potential strategies to enhance the resilience of interdependent networks. Schneider et al. (2013) proposed a method for identifying the minimum set of nodes that need to be protected to prevent cascading failures in interdependent networks. Moreover, the study of interdependent networks has extended beyond infrastructure to other domains such as assessment of energy system reliability (Pan et al. (2022). For example, Wunderling et al. (2022) applied the concept to climate networks, showing how the interdependencies between different climate variables can lead to more abrupt and severe climate events. In the realm of social systems, Alvarez-Rodriguez et al. (2021) explored the dynamics of opinion formation in multilayer social networks, demonstrating how the interaction between different social contexts can influence the spread and persistence of opinions.

As the world becomes increasingly interconnected, understanding the behavior of multilayer and interdependent networks becomes crucial. This field of study has significant implications not only for critical infrastructure but also for financial systems, ecological networks, and socio-technological systems. Future research directions may include developing more sophisticated models that capture the complexity of real-world interdependent systems, designing strategies to enhance the resilience of these systems, and exploring the interplay between network structure and dynamics in multilayer contexts.

2.2. Network analysis of energy in economic development

The application of network analysis to energy systems and their role in economic development has gained significant traction in recent years. This approach provides valuable insights into the complex relationships between energy infrastructure, consumption patterns, and economic growth. Researchers have increasingly recognized the importance of viewing energy systems as complex networks. Bale et al. (2015) argued that network theory offers a powerful framework for understanding the intricate relationships within energy systems, particularly in the context of transitioning to more sustainable energy sources. Pfenninger et al. (2014) highlighted the critical role of energy system modeling in informing policy decisions. Chen et al. (2019) applied network analysis to study the synergies and trade-offs between energy transitions and sustainable development goals, providing valuable insights for policymakers. By applying this concept to the subsystem within the larger group of seven sectors, it was possible to examine how the nodes within the system are connected and the extent to which they are able to communicate with one another efficiently (Zhu and Milanović, 2021). This analysis provided valuable insights into the structure and functioning of the subsystem, which can inform decision-making and improve overall system performance. Network analysis has emerged as a powerful tool for understanding the complex relationships between energy systems and economic development. By capturing the intricate interdependencies within and between energy and economic systems, this approach offers valuable insights for policymakers and researchers alike. As the global energy landscape continues to evolve, network-based studies will likely play an increasingly important role in shaping our understanding of sustainable economic development pathways.

2.3. Research gap

The above review of the literature describes the research on energy networks and national economies. The research gap can be described as follows: (1) Few scholars have focused on the role of energy based on industry composition in the sections of a national economic system, especially in the field of city development. The dynamics and complexities of modern interconnected networks are important to study, particularly as embodied energy networks become increasingly integrated and critical to societal operations, while the complexity of networks is reflected in their numerous nodes and uncertain node relationships. Revealing the hidden interdependencies within subsystems is necessary in exploring flexibility and adaptability for analyzing complex systems. (2) The existing literature lacks in-depth analysis of cascading failures in coupled and evolving networks in real-world scenarios. The current studies have primarily focused on dynamic analysis of static or individual networks. The research on interaction between the networks is insufficient, especially in the context of medium-transfer flow models. Many studies have emphasized the failure mechanisms within isolated systems or examined the interdependencies between two independent infrastructures, such as construct message networks (Pauget and Wald, 2013), human life networks (An et al., 2016), and social systems networks (Nelson et al., 2013). (3) Current models often oversimplify complex interdependencies, leading to incomplete understanding of systemic collapses. There is an urgent need to develop more refined medium-transfer flow models that systematically consider the temporal evolution of networks and their interactions in order to deeply analyze cascading failures in interconnected systems. This research gap highlights the need for further studies to develop analytical models. Therefore, this study employs the complex network analysis method to examine the structural roles of sectors in the Australian embodied energy network.

3. Method

A hybrid method is constructed based on the similar relationship structure. Both the input–output approach and the complex network approach display the direct and indirect relationships between the sectors or nodes (Barabási, 2016; Liu and He, 2016). The input–output table also supplies the data, while the complex network approach reveals the characteristics of the network. So, this hybrid method is suitable to analyze the network questions. Fig. 1 shows the research framework of this study. Input–output tables and data on energy consumption have been built into a new complex energy network with two layers. The characteristics of important sections and sectors are then analyzed based on this network, indicating the changes in energy consumption and its influences on the economic system.

3.1. Embodied energy flows in an economic system

In a conventional input–output table of an economic system with m sectors, let X_{ij} represent the direct monetary transfer from sector i to sector j and $\boldsymbol{X}$ represents a corresponding transfer matrix ($n \times n$). $\boldsymbol{Q}$ denotes a diagonal matrix ($n \times n$) and its element Q_{ii} is the total monetary input or output of sector i. The direct energy consumption (input) of sector j is expressed as Z_j and $\boldsymbol{Z}$ represents the direct energy consumption matrix ($1 \times n$). Therefore, the embodied energy intensity matrix ($1 \times m$) of the economic system, $\boldsymbol{E}$, can be constructed in the following equation (Liang et al., 2021; Liu et al., 2018):

$$\boldsymbol{E} = \boldsymbol{Z} \times (\boldsymbol{Q} - \boldsymbol{X})^{-1} \tag{1}$$

The embodied energy intensity of an economic sector j, E_j, represents its comprehensive energy consumption amount embodied in the exchange of each unit of monetary value in an economic system and is then used to determine the embodied energy flow from another sector, such as sector i, to sector j, f_{ij}, as follows:

$$f_{ij} = X_{ij} \times E_j \tag{2}$$

Then the multiplication of the embodied energy intensity and the total output (X_{ij}) of each sector means the embodied energy flows for each sector.

3.2. Establishment of an embodied energy network

Based on the embodied energy flows between sectors, an embodied

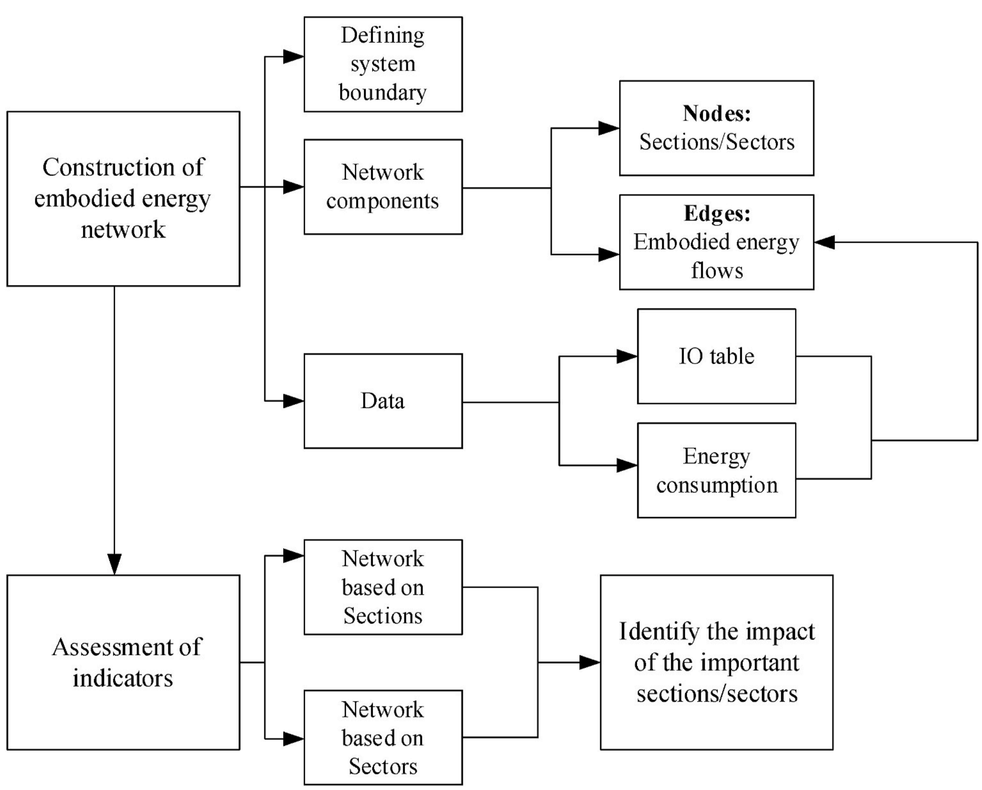


Fig. 1. The research framework of this study.

energy network can be established to examine the impact on both inter-section and inter-sector embodied energy, as illustrated in Fig. 2. This network is constructed with two distinct layers, each capturing different aspects of the energy flow dynamics within and between sections and sectors.

In Layer 1, each section is composed of multiple interrelated single sectors. These sections are connected to one another through the embodied energy that flows between them. This layer highlights a macroscopic view of energy interactions at the section level, showing how energy consumption and exchange occur across broader economic or geographical boundaries. The connections between these sections represent the volume of embodied energy exchanged, indicating the intensity and significance of their energy relationships.

In Layer 2, the focus shifts to the internal structure of each section. Here, the single sectors within each section are interconnected through embodied energy flows. This layer provides a detailed microscopic view, revealing how individual sectors within a section contribute to and depend on the energy dynamics of their immediate environment. The connections within each section signify the embodied energy shared among sectors, emphasizing the intra-section dependencies and interactions.

Notably, the single sectors in different sections are not directly connected to each other in this framework. Instead, their interaction is mediated through their respective sections in Layer 1. This distinction ensures a clear separation between inter-section and intra-section energy flows, allowing for a more nuanced analysis of energy dependencies and impacts. The lines connecting sectors and sections represent the volume of embodied energy exchanged, serving as a quantitative measure of the energy flow. Thicker lines indicate higher volumes of embodied energy, reflecting stronger energy ties and potentially greater mutual dependencies. Conversely, thinner lines suggest lower volumes and weaker connections. By examining both layers of the embodied energy network, researchers can gain comprehensive insights into the energy landscape. This dual-layer approach facilitates the identification of key sectors and sections that play pivotal roles in energy distribution and consumption. It also helps in understanding the ripple effects of energy policy changes, technological advancements, or economic shifts on both macro and micro scales.

A common way to model an embodied energy network is through

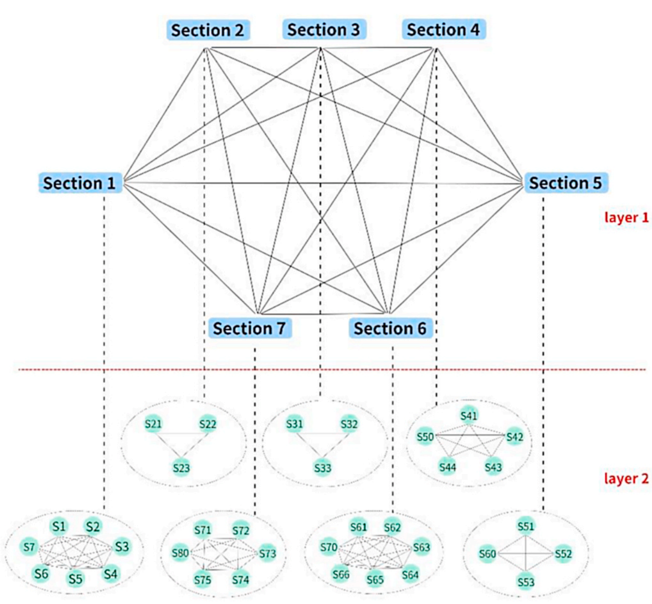


Fig. 2. The structure of the Australian embodied energy network within two layers. Note: Layer 1 is the embodied energy network contributed by the sections. Layer 2 is the embodied energy network contributed by the sectors of each section.

direct links representing the relationships between nodes. In this network, the sectors are the nodes and the embodied energy flows among sectors are the edges. By representing an embodied energy network as a graph, it is possible to analyze and visualize the relationships between nodes in a mathematical and structured way (Jing and Wang, 2020). In this study, the embodied energy flow matrix can be constructed based on Equations (1) and (2). The sectors contribute the network nodes and the embodied energy flows among sectors are the edges. In order to study the relationship between nodes, we determined that the network F in this study is an embodied energy network.

$$F=\begin{bmatrix} 0 & f_{1,2} & f_{1,3} & \cdots & f_{1,n} \\ f_{2,1} & 0 & \cdots & \cdots & f_{2,n} \\ f_{3,1} & \vdots & \ddots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & f_{n-1,n} \\ f_{n,1} & f_{n,2} & \cdots & f_{n,n-1} & 0 \end{bmatrix}$$

3.3. Complex network analysis method

In weighted networks, the evaluation of average path length, betweenness, and closeness depends on identifying and measuring the shortest paths connecting nodes. Consequently, a crucial initial step involves devising a generalized approach for determining these shortest distances and defining their lengths. Given that weighted networks assign specific numerical values to edges, representing the strength of node connections, the concept of shortest paths transcends traditional topological distances. Instead, it incorporates the cumulative impact of edge weights along the traversed route (Opsahl et al., 2010).

In this study, d_{ij} denotes the shortest distance between nodes i and j, and n is the number of nodes in the network. When considering the distance between a node and itself, such as when $i=j$, the distance d_{ij} is invariably taken to be 0, representing the absence of any intermediate nodes or links on a path. In the weighted network, a larger embodied energy flows volume indicates a closer relationship, then the weighted flow f_{ij} should be inversed to acquire the shortest path in the network, shown as Equation (3):

$$d_{ij}=\min\left(\frac{1}{f_{ik}}+\cdots+\frac{1}{f_{lj}}\right) \tag{3}$$

where f_{ik} and f_{lj} are the embodied energy flows from node i to node k and node l to node j, respectively. If $k=l$, then d_{ij} is only go through one intermediate node from node i to node j. If $k\neq l$, then the intermediate node from node i to node j is ≥ 2.

The average path length represents the mean value of each pair of nodes' distance. The longest shortcut is the diameter of the network (Watts and Strogatz, 1998). The symbol l equals the average number of all the shortest paths length from a given node to all other nodes. Thus, the average path length is defined as in Equation (4):

$$l=\frac{1}{n(n-1)}\sum_{i=1}^{n}\sum\nolimits_{j=1}^{n}d_{ij} \tag{4}$$

The betweenness is commonly used in network analysis to evaluate the importance of nodes. It is calculated based on the number of shortest paths that pass through a particular node (Brandes, 2001; Sun et al., 2023). When a node has high betweenness, this implies that it plays a crucial role in connecting other nodes in the network and thus can be considered a key mediator of information or resources. In the context of the present study, high betweenness of a node in the network can be interpreted as an indication of its strong embodied energy capability. This is because a node with high betweenness would likely have a significant influence on the flow of energy within the network, as either a supplier or a consumer of energy. Therefore, measuring the betweenness of nodes can provide insights into the capability of nodes in the network with respect to embodied energy. The betweenness (b_i) can be calculated by Equation (5):

$$b_i = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} g_{jk}(i)/g_{jk}}{(n^2 - 3n + 2)/2}, j \neq k \neq i, j < k \tag{5}$$

where, $g_{jk}(i)$ is the number of the shortest path from node j to node k pass through node i and g_{jk} is the number of shortest paths from node j to node k.

The closeness in a network is typically defined as the reciprocal of the average length of the shortest paths to or from all other nodes in a complex network. In a complex network, closeness-in represents the minimum number of steps needed for a node to access other nodes, while closeness-out characterizes the minimum number of steps required to access all other nodes from a given node. In this study, we employ the closeness to evaluate the transfer speed of embodied energy between different nodes. To be more precise, closeness-in (CC_i^{in}) and closeness-out (CC_j^{out}) of node i are computed according to the formulas originally proposed by (Freeman, 2002), shown in Equations (6) and (7):

$$CC_i^{in} = \left(\frac{1}{n-1} \sum_{j=1}^{n} d_{ji} \right)^{-1} \tag{6}$$

$$CC_i^{out} = \left(\frac{1}{n-1} \sum_{j=1}^{n} d_{ij} \right)^{-1} \tag{7}$$

The strength of a node in a complex network represents the aggregate weights of the edges connected to that node (Gao et al., 2018). Within this research, the concept of node strength encompasses two distinct aspects: strength-in and strength-out. Strength-in corresponds to the total import volume of embodied energy for a specific node. It quantifies the cumulative influx of embodied energy by summing the weights of all incoming edges connected to the node. Each incoming edge represents the embodied energy associated with the imports received by the node. Strength-out, on the other hand, captures the total export volume of embodied energy for the node. It is calculated by summing the weights of all outgoing edges connected to the node. Each outgoing edge represents the embodied energy related to the exports generated by the node. Strength-in and strength-out are calculated by Equations (8) and (9), respectively.

$$S_i^{in} = \sum_{j=1}^{n} f_{ji} \tag{8}$$

$$S_i^{out} = \sum_{j=1}^{n} f_{ij} \tag{9}$$

where the S_i^{in} and S_i^{out} denote the strength-in and strength-out. S_i stands for the point strength of node i, which is equal to the sum of strength-in and strength -out of sector i.

In the complex network analysis method, nodes that possess numerous neighboring nodes often exhibit a heightened capacity for exchanging information with other nodes. Given that the network under investigation in this study is direct, the degree metric must be subdivided into degree-in and degree-out. Specifically, within the context of this study, the degree-in of a given node represents the number of nodes that contribute embodied energy to it and can be viewed as a measure of the node's import partners. Similarly, the degree-out is defined as the number of nodes to which a given node exports its embodied energy and can be regarded as a measure of the node's export node (Jiang et al., 2019). Degree-in $\left(D_i^{in}\right)$ and degree-out $\left(D_j^{out}\right)$ of node i are calculated by Equations (10) and (11), respectively:

$$D_i^{in} = \sum_{j=1}^{n} a_{ji} \tag{10}$$

$$D_i^{out} = \sum_{j=1}^{n} a_{ij} \tag{11}$$

An adjacency matrix **A** represents the neighboring relationships between nodes. The symbol a_{ij} is the component in the adjacency matrix **A** of the complex network. If there is a connection between node i and node j, then $a_{ij} = 1$, otherwise $a_{ij} = 0$. D_i is the degree of node i, which is equal to the total of degree-in and degree-out.

The clustering coefficient serves as a metric for assessing the likelihood of the neighboring nodes of a given node being interconnected. In the present study, a high clustering coefficient in a particular node indicates a substantial level of proximity between its partners. Therefore, the clustering coefficient can be viewed as a measure of the extent to which a node is connected to its collaborating counterparts. c_i is the node's clustering coefficient of node i and can be used to expresses how the two adjacent nodes are linked (Jiang et al., 2019). The clustering coefficient is calculated using Equation (12):

$$c_i = \frac{1}{S_i(D_i - 1)} \sum_{j=1,k=1}^{n} \frac{\left(f_{ij} + f_{ki}\right)}{2} a_{ij} a_{jk} a_{ki} \tag{12}$$

where f_{ik} represent the embodied energy of node i to node k and a_{ij}, a_{jk}, and a_{ki} indicate whether a triangle is formed by nodes (i, j, k). A value of 1 signifies that a triangle is indeed formed, indicating that nodes i, j, and k are connected in a triangular relationship. Conversely, a value of 0 indicates that the three nodes do not constitute a triangle.

The average clustering coefficient of the network represents the complex network's clustering characteristics, which are similar to the node's clustering coefficient, shown in Equation (13):

$$C = \frac{1}{n} \sum_{i=1}^{n} c_i \tag{13}$$

3.4. Data

The economic system is used as a prototype to establish an embodied energy network to reflect the embodied energy which is transferred among economic sectors. In the embodied energy network, economic sectors are defined as its nodes, while the embodied energy transferred from one sector to another is defined as the flow. An embodied energy input–output table is then constructed to capture the energy flows described by the inflows and outflows of economic sectors. Table 1 shows the structure of multi-levels embodied energy input–output table of an economic system with m sections and n sectors. In this table, one section contains n sectors. Detailed classification of different sections is listed in the Appendix.

This study is conducted using Australia's input–output tables from 2012 to 2019. These tables provide detailed information on the supply and use of products in the Australian economy and the structure of its economy (ABS, 2023). The data on energy consumption are taken from the Australian energy statistics from 2012 to 2019 (ABS, 2021). Based on data from these two sources, the authors developed eight annual embodied energy input–output tables and make use of these tables in the remainder of this paper.

Because the data on energy consumption only include seven major economic sectors, the authors aggregated 114 sectors in the monetary input–output table into seven sections, which are Agriculture, Forestry and Fishing; Mining; Manufacturing; Electricity, Gas, Water, and Waste Services; Construction; Commercial Services; and Transport, Postal, and Warehousing, as shown in the Appendix (ABS, 2013).

4. Results and key findings

4.1. Small-world nature of Australian embodied energy network at section level

In Section 4.1, we analyze the network structure of the Australian embodied energy network by using the complex network analysis method. The nodes in the network are each sector and the edges of the network are energy transfers between each pair-wise sector. Some

Table 1
Illustrated structure of multi-level embodied energy–based input–output table.

<table>
<tr><td colspan="3" rowspan="3">Output
Input</td><td colspan="17">Intermediate demand</td><td rowspan="3">Final demand</td></tr>
<tr><td colspan="5">Section 1</td><td rowspan="2">…</td><td colspan="5">Section j</td><td rowspan="2">…</td><td colspan="5">Section m</td></tr>
<tr><td>Sector 1</td><td>…</td><td>Sector j</td><td>…</td><td>Sector n</td><td>Sector 1</td><td>…</td><td>Sector j</td><td>…</td><td>Sector n</td><td>Sector 1</td><td>…</td><td>Sector j</td><td>…</td><td>Sector n</td></tr>
<tr><td rowspan="17">Intermediate input</td><td rowspan="5">Section 1</td><td>Sector 1</td><td colspan="5" rowspan="5"></td><td rowspan="5"></td><td colspan="5" rowspan="5"></td><td rowspan="5"></td><td colspan="5" rowspan="5"></td><td rowspan="5"></td></tr>
<tr><td>…</td></tr>
<tr><td>Sector i</td></tr>
<tr><td>…</td></tr>
<tr><td>Sector n</td></tr>
<tr><td colspan="2">…</td><td colspan="5"></td><td></td><td colspan="5"></td><td></td><td colspan="5"></td><td></td></tr>
<tr><td rowspan="5">Section i</td><td>Sector 1</td><td colspan="5" rowspan="5"></td><td rowspan="5"></td><td colspan="5" rowspan="5">Indirect energy flow
f i j</td><td rowspan="5"></td><td colspan="5" rowspan="5"></td><td rowspan="5">FDi</td></tr>
<tr><td>…</td></tr>
<tr><td>Sector i</td></tr>
<tr><td>…</td></tr>
<tr><td>Sector n</td></tr>
<tr><td colspan="2">…</td><td colspan="5"></td><td></td><td colspan="5"></td><td></td><td colspan="5"></td><td></td></tr>
<tr><td rowspan="5">Section m</td><td>Sector 1</td><td colspan="5" rowspan="5"></td><td rowspan="5"></td><td colspan="5" rowspan="5"></td><td rowspan="5"></td><td colspan="5" rowspan="5"></td><td rowspan="5"></td></tr>
<tr><td>…</td></tr>
<tr><td>Sector i</td></tr>
<tr><td>…</td></tr>
<tr><td>Sector n</td></tr>
<tr><td colspan="3">Direct energy input</td><td colspan="5"></td><td></td><td colspan="5">Zj</td><td></td><td colspan="5"></td><td></td></tr>
</table>

indicators are calculated by Ucinet 6 (Borgatti et al., 2002).

The total embodied energy of the Australian embodied energy network, average path length, and average clustering coefficient from 2012 to 2019 based on Equations (2), (4) and (13) are shown in Table 2. The total embodied energy of the Australian economy showed a continuous increase from 2012 to 2017. However, it experienced a significant decline of more than 50% in 2018, followed by an increase in 2019 to 449,113 PJ. The temporal trend of average path length exhibited an inverse relationship with that of embodied energy due to its calculation based on the reciprocal of embodied energy. Notably, the maximum average path length was observed in 2014, reaching a value of 678, whereas the minimum value occurred in 2017, decreasing to 111. The average path length values from 2012 to 2014 were significantly higher compared to those from 2015 to 2019, indicating a tendency toward shorter and more interconnected direct paths within the industry. The observed variations in average path length underscore the changing efficiency and interconnectedness of the industry network during the specified time period. A decrease in average path length implies a reduction in the average number of links required to connect different nodes, facilitating more direct and efficient pathways for information or resource transfer. Conversely, the higher average path length in 2012–2014 suggests a comparatively more fragmented network structure characterized by longer routes between nodes, potentially leading to delays and inefficiencies in information dissemination and resource allocation. The inverse correlation between average path length and embodied energy signifies the interplay between network structure and resource allocation efficiency. As average path length decreases, embodied energy tends to increase, indicating a concentration of resources within the network. Conversely, as average path length rises, embodied energy diminishes, reflecting a more distributed resource allocation pattern.

Table 2
Embodied energy, average path length, and average clustering coefficient.

Year	Embodied energy (PJ)	Average path length	Average clustering coefficient
2012	77,041.729	540.969	6.570
2013	67,794.198	603.520	5.867
2014	94,008.191	677.938	7.874
2015	239,067.404	205.202	19.037
2016	385,278.081	204.387	30.376
2017	449,113.236	110.954	35.293
2018	200,811.677	287.744	16.079
2019	346,999.380	209.609	27.385

Table 2 also shows the average clustering coefficient of the Australian embodied energy network from 2012 to 2019, calculated by using Equation (13). In this table, the average clustering coefficient exhibited a gradual decline from 2012 to 2014, followed by a significant increase from 2014 to 2017, reaching its peak value of 35.293. However, from 2017 to 2019, the average clustering coefficient showed fluctuations in its value. The highest average clustering coefficient was recorded as 35.293 in 2017, while the lowest value was observed as 5.867 in 2014. The gradual decline in the average clustering coefficient from 2012 to 2014 suggests a weakening tendency for nodes to form tightly interconnected clusters during that period. This could indicate a decrease in the level of local cohesion and interconnectedness within the network. However, the substantial increase in the average clustering coefficient from 2014 to 2017 indicates a significant enhancement in local clustering patterns within the network. This implies that nodes started to form denser clusters, indicating a higher level of interconnectedness among neighboring nodes and the formation of more cohesive subnetworks. The fluctuations observed in the average clustering coefficient from 2017 to 2019 suggest variations in the network's local connectivity and cluster formation during that period. These fluctuations could have been influenced by changes in the network structure, connection patterns, or the distribution of edges among nodes during this time frame.

In Layer 1, each section acts as a node inside its aggregated section network to form a section network with other sectors, as shown in Layer 2 of Fig. 1. The level of embodied energy of each section reflects the size of the section volume. Fig. 3 shows the embodied energy of each section from 2012 to 2019. In this figure, all sections experienced an increasing trend in their energy consumption from 2012 to 2017, with S2 reaching its minimum value of 486 PJ in 2013 and S5 reaching its maximum value of 775,658 PJ in 2017. The increase trend indicates all sections experienced an increasing trend in energy consumption from 2012 to 2017. This could be attributable to various factors, such as economic growth, population increase, and industrial expansion. The steady growth in energy consumption indicates a rising demand for energy resources within these sections during this period. However, from 2017 to 2019,

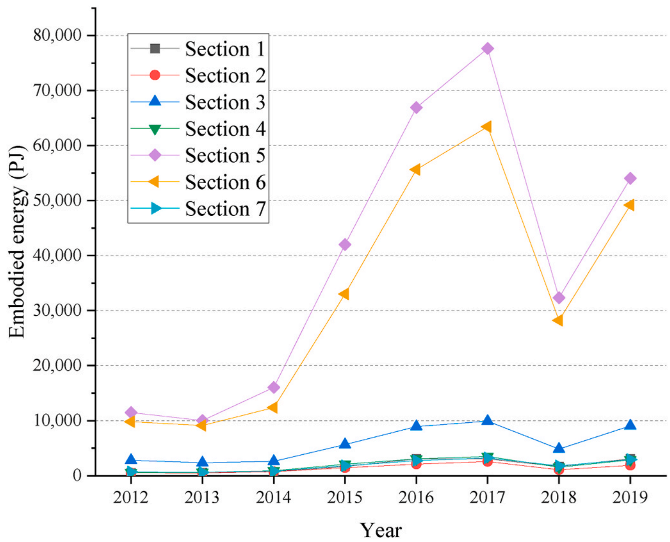


Fig. 3. Embodied energy of each section from 2012 to 2019.

there was a noticeable fluctuation in energy consumption across all sections. This result indicates that, after 2017, there was a period of fluctuation in energy consumption across all sections until 2019. Fluctuations in energy consumption may indicate changes in economic conditions, energy prices, or policy shifts, which can affect energy demand within each section. Additionally, it is evident that S5 and S6 had significantly higher embodied energy compared to other sections, indicating a more active transfer of embodied energy among sectors within these two sections. This suggests a higher level of inter-sectoral activity in the energy transfer process within S5 and S6.

The results for average path length of each section network from 2012 to 2019 are shown in Fig. 4. In this figure, across all section networks examined, a notable commonality is observed in their average path length. However, it is worth noting that the results from the period spanning 2012 to 2014 consistently exhibited larger values when compared to those from 2015 to 2019. During the earlier time frame, the maximum average path length of 732 was identified for S7 in 2014, signifying a relatively greater degree of separation between nodes within this section. In contrast, the minimum average path length of 74 was recorded for S6 in 2017, indicating a comparatively shorter distance between nodes and a higher level of connectedness within this specific section. This trend of decreasing average path lengths from 2012 to 2019 implies a potential evolution toward increased network efficiency and reduced node-to-node distances over time. The observed variations in average path lengths between different sections and years offer valuable insights into the structural dynamics and interconnectivity patterns within the section networks under investigation. Further investigation into the driving factors behind these trends is warranted to gain a deeper understanding of the underlying mechanisms shaping the observed network behaviors.

The results for the average clustering coefficient of each section network based on Equation (13) are shown in Fig. 5. In this figure, overall, the results demonstrate an upward trend. This indicates an increasing ability to establish connections with collaborating counterparts in every network. However, there was a decreasing trend observed from 2017 to 2018. Additionally, the result for S7 also decreased from 2013 to 2014. The results derived from each section consistently demonstrate the lowest clustering coefficient when compared to other individual sectors. This finding suggests that the presence of multiple sectors within a section does not confer a higher clustering ability within a multi-sector network. The clustering coefficient is a metric that quantifies the extent to which nodes and their neighboring nodes form triangular connections, reflecting the level of local interconnectedness within a section. A higher clustering coefficient indicates a greater prevalence of interconnected clusters, indicating a tight-knit and cohesive section network structure. The results indicate where sections comprising multiple sectors exhibited lower clustering coefficients, challenging the assumption that larger sections would exhibit a higher degree of clustering. It suggests that the presence of multiple sectors within a section does not necessarily lead to a denser network of triangular connections among their constituent sectors. This finding has important implications for our understanding of section network structures and their role in network dynamics. Other factors, such as the nature of interactions, interdependencies, and the flows of embodied energy among sectors, may play more significant roles in determining the clustering patterns observed in the network.

4.2. *Centrality analysis of Australian embodied energy network at sector level*

Centrality analysis contains betweenness and closeness centralities. The significant scale-free property indicates that a few sectors played important roles in the Australian embodied energy network. Table 3

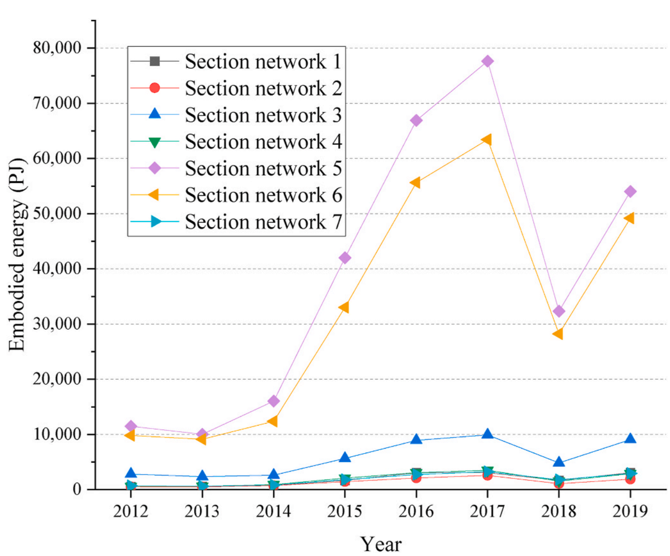


Fig. 4. Average path length of each section network from 2012 to 2019.

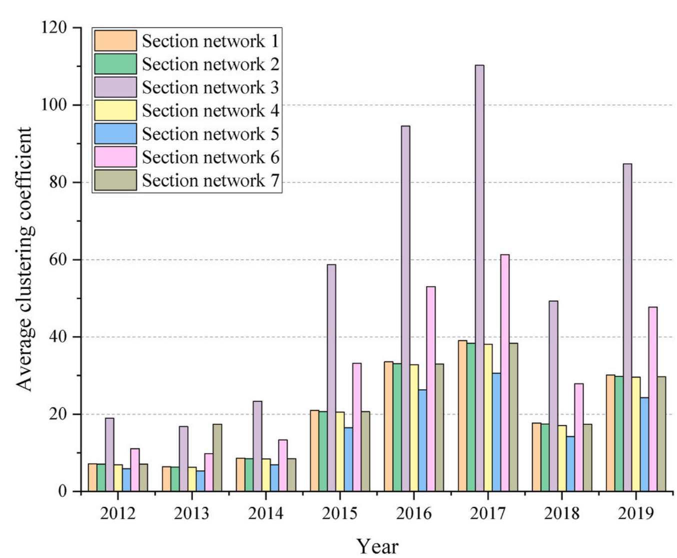


Fig. 5. Average clustering coefficient of each section network from 2012 to 2019.

Table 3
Betweenness, closeness, strength, degree, and clustering coefficient of top 10 sectors in 2019.

Rank	Between ness	Closeness-in	Closeness-out	Strength-in	Strength-out	Degree-in	Degree-out	Clustering coefficient
1	S8	S29	S94	S73	S73	S7	S1	S96
2	S58	S26	S89	S70	S96	S12	S2	S75
3	S84	S31	S29	S71	S74	S14	S6	S74
4	S26	S27	S4	S72	S90	S16	S7	S90
5	S110	S30	S103	S50	S95	S28	S18	S91
6	S3	S39	S107	S14	S92	S38	S24	S98
7	S27	S89	S27	S65	S98	S61	S39	S95
8	S6	S15	S101	S96	S78	S64	S76	S78
9	S15	S5	S2	S74	S11	S68	S88	S73
10	S24	S43	S26	S78	S70	S90	S100	S100

presents the top 10 selected sectors by various indicators in the year 2019, providing valuable insights for analyzing the most important nodes in the Australian embodied energy network. The noteworthy observation of a significant scale-free property in the Australian embodied energy network indicates that only a few sectors were pivotal in their contributions to the network's overall performance. This ranking provides valuable insights into the most influential sectors in the network which are crucial for policymakers and stakeholders to identify and target for enhancing the overall efficiency of the embodied energy system. Consequently, the identification of these key sectors can inform the formulation of effective policies and strategies aimed at improving the network's sustainability and reducing its environmental impact.

The betweenness is a network parameter that measures the bridging nature of nodes, which can help to identify bottlenecks in the entire network. The results are determined based on the top 10 results for each indicator in 2019. Due to the results of betweenness having many sectors with the same value, Fig. 6 displays the average betweenness results for selected sectors from 2012 to 2019, computed using Equation (5). The trend of betweenness centrality variation demonstrates a predominantly fluctuating pattern, with its values experiencing notable changes over time. These fluctuations in betweenness centrality signify dynamic shifts in the structural properties of the network during the respective years. In this figure, the maximum values for both S8 and S58 were recorded as 1.907 in 2016, while the minimum value was observed for S6 at 0.124 in 2013. With the exception of S84 and S15, all other sectors reached their peak values in the year 2016.

Closeness-in and closeness-out are centrality measures used in network analysis to assess the importance of nodes based on their accessibility and influence in incoming and outgoing connections, respectively. These measures focus on the proximity of nodes to other nodes in the network, considering the shortest paths that connect them. Fig. 7 displays the closeness-in and closeness-out outcomes, obtained through the application of Equations (6) and (7) respectively. Closeness-in assesses the tightness among a node's inbound neighbors. A higher closeness-in indicates that its inbound neighbors tend to form closely-knit clusters, reflecting stronger connections between them. Similarly, a higher closeness-out value implies that the node's outbound neighbors also tend to form tight clusters, denoting stronger connections between them. In both cases, a higher value suggests the node's potential significance or influence in the network. The analysis revealed substantial variations in the centrality measures across different sectors and years. Specifically, in Fig. 7(a) the highest closeness-in centrality value of 228 was observed for S29 in the year 2018, underscoring its exceptional proximity to other sectors within the network. Conversely, the smallest value of 163 was attributed to S45 in 2015, indicating comparatively limited closeness to other sectors during that period. S26 and S89 demonstrated stable trends in their closeness-in centrality values over the observed time frame, suggesting consistent levels of connectivity

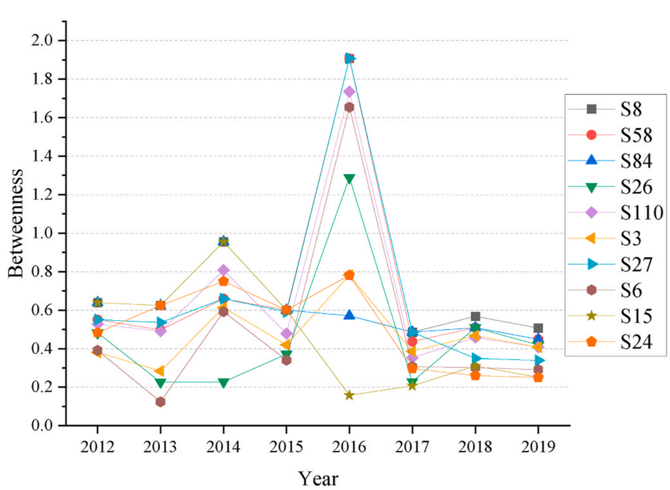


Fig. 6. Top 10 sectors of betweenness of the Australian embodied energy network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

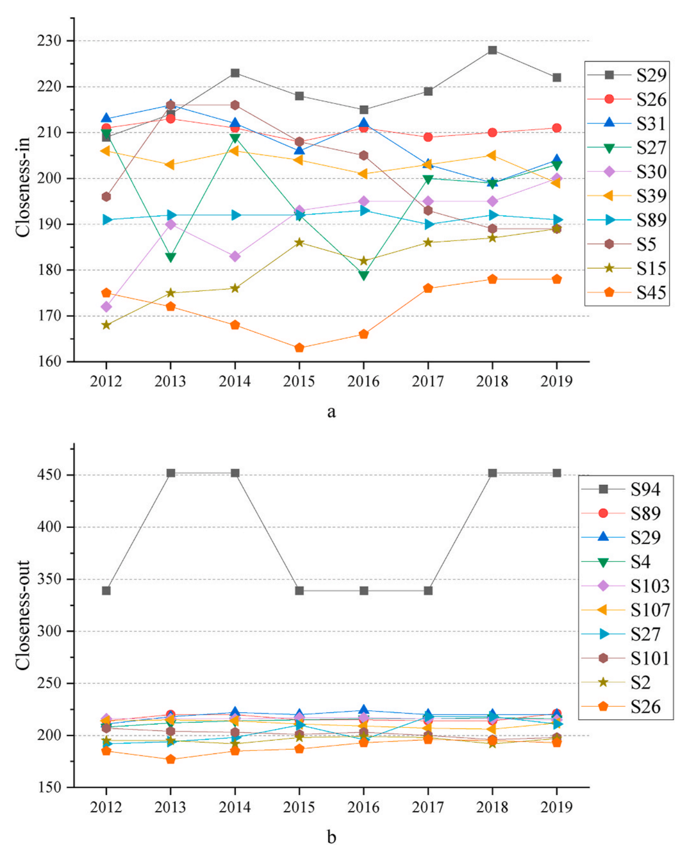


Fig. 7. Top 10 sectors of closeness-in and closeness-out of the Australian embodied energy network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

and accessibility to the wider network. In contrast, several other sectors exhibited considerable fluctuations in their closeness-in centrality scores, implying less stable patterns of inbound connections and indicating varying degrees of ease with which these sectors were reached from other nodes within the network.

Regarding the closeness-out centrality results in Fig. 7(b)–S94 stood out significantly with centrality values ranging from 339 to 452, surpassing those of other sectors by a substantial margin. This outcome suggests that S94 enjoyed stronger connections and greater reach in terms of sectoral output direction compared to its counterparts. Furthermore, the embodied energy emanating from S94 followed a shorter and more direct path to reach the rest of the sectors, underscoring its prominent position as a pivotal hub for energy dissemination within the network. The remaining sectors exhibited more consistent patterns of centrality values, with scores ranging between 156 and 224 in the context of closeness-out centrality. This stability in centrality values implies relatively balanced levels of connectivity and accessibility from these sectors to others in the network. The finding based on Fig. 7 revealed the heterogeneity of sector centrality within the network, elucidating the variations in the importance and influence of different sectors concerning both inbound and outbound energy flows. S94 emerged as a key player with dominant outbound centrality, while S26 and S89 maintained relatively stable positions with regard to their inbound centrality. These insights provide valuable implications for understanding the dynamics of energy distribution and interconnections within the network, warranting further exploration into the underlying factors driving these observed centrality trends.

In the betweenness analysis for each section network, a subset of 10

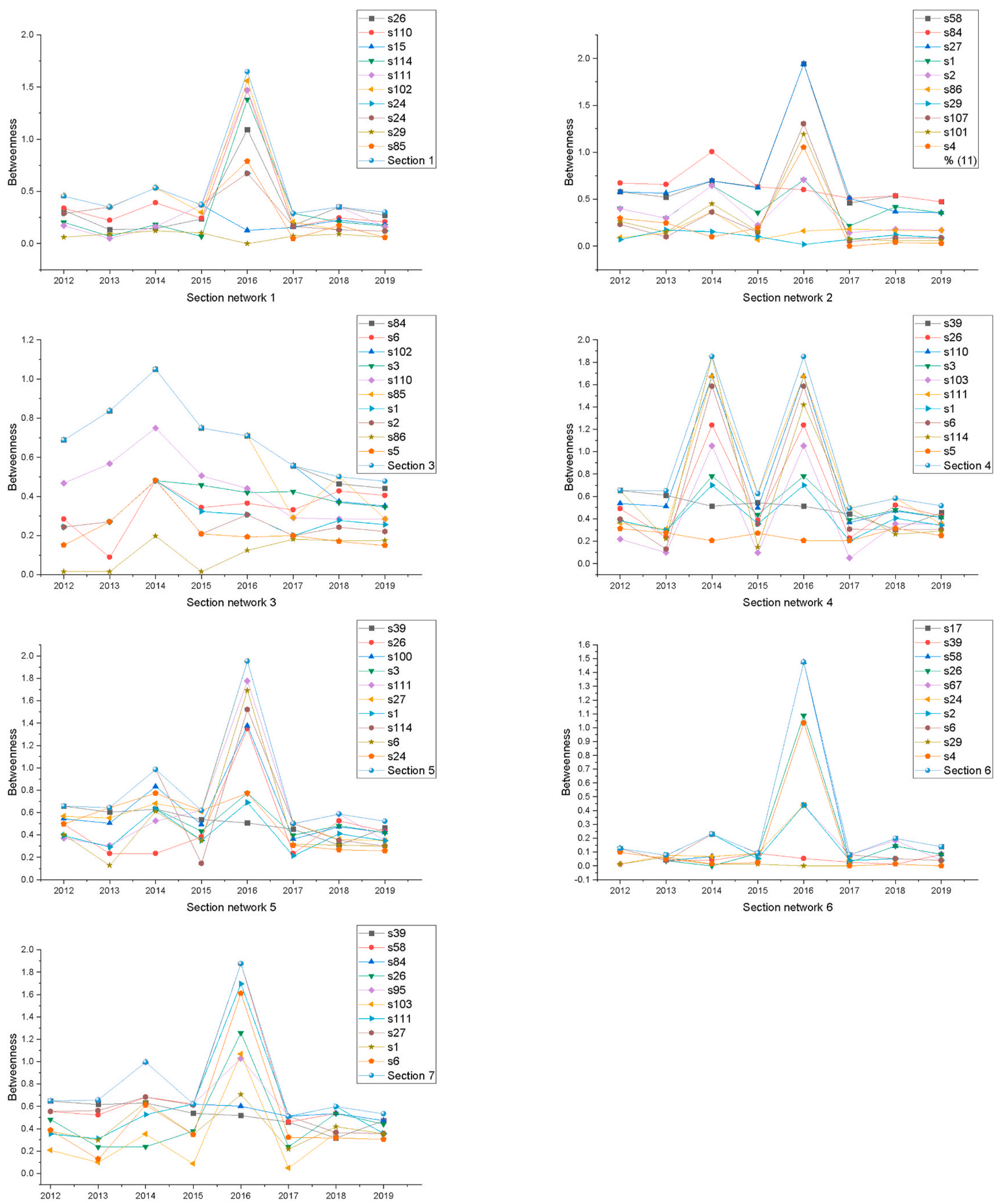


Fig. 8. Top 10 sectors of betweenness of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

noteworthy sectors was selected based on the outcomes of betweenness results within that particular network. Subsequently, an analysis was carried out on these sectors in conjunction with the outcomes specific to each corresponding section. Fig. 8 shows the betweenness results for seven section networks. In this figure, each section attained its peak value within its respective section network. Specifically, within section networks 1, 2, 5, 6, and 7, the betweenness metric achieved its maximum value in the year 2016. The observed fluctuations in betweenness exhibited a consistent pattern when compared with the Australian embodied energy network. This indicates that the impacts of sections 1, 2, 5, 6, and 7 on the betweenness of the Australian embodied energy network were relatively limited. The outcome for section network 3 exhibited an ascending trend from 2012 to 2014, followed by a gradual decline until 2019. Conversely, section network 4 not only reached its maximum value in 2016 but also attained a peak in 2014. These observations suggest that sections 3 and 4 exerted substantial influences on the betweenness outcomes of the Australian embodied energy network. Overall, these findings shed light on the dynamic interplay between different sections and their effects on the betweenness metric within the Australian embodied energy network.

While examining the outcomes of closeness-in and closeness-out within each section network, an analysis was conducted using the results of the top 10 sectors that reached their peak values in the year 2019. Fig. 9 shows the results of closeness-in for each section network from 2012 to 2019 based on Equation (6). The results indicate the minimum number of steps needed for a node to access other nodes, representing the inflow transfer speed of embodied energy between different sectors and section. A higher amount of closeness indicates a slower speed of embodied energy flows in a sector, a lower amount representing a faster speed. Nodes with high closeness-in values exert a strong influence over the network's inbound interactions, suggesting their importance in terms of attracting inputs from other nodes. In this figure, the limited fluctuations observed in the closeness-in metric can be attributed to the significant connectivity of the network. Specifically, the high degree of interconnections within the network led to relatively consistent closeness-in values. Notably, within each section, the

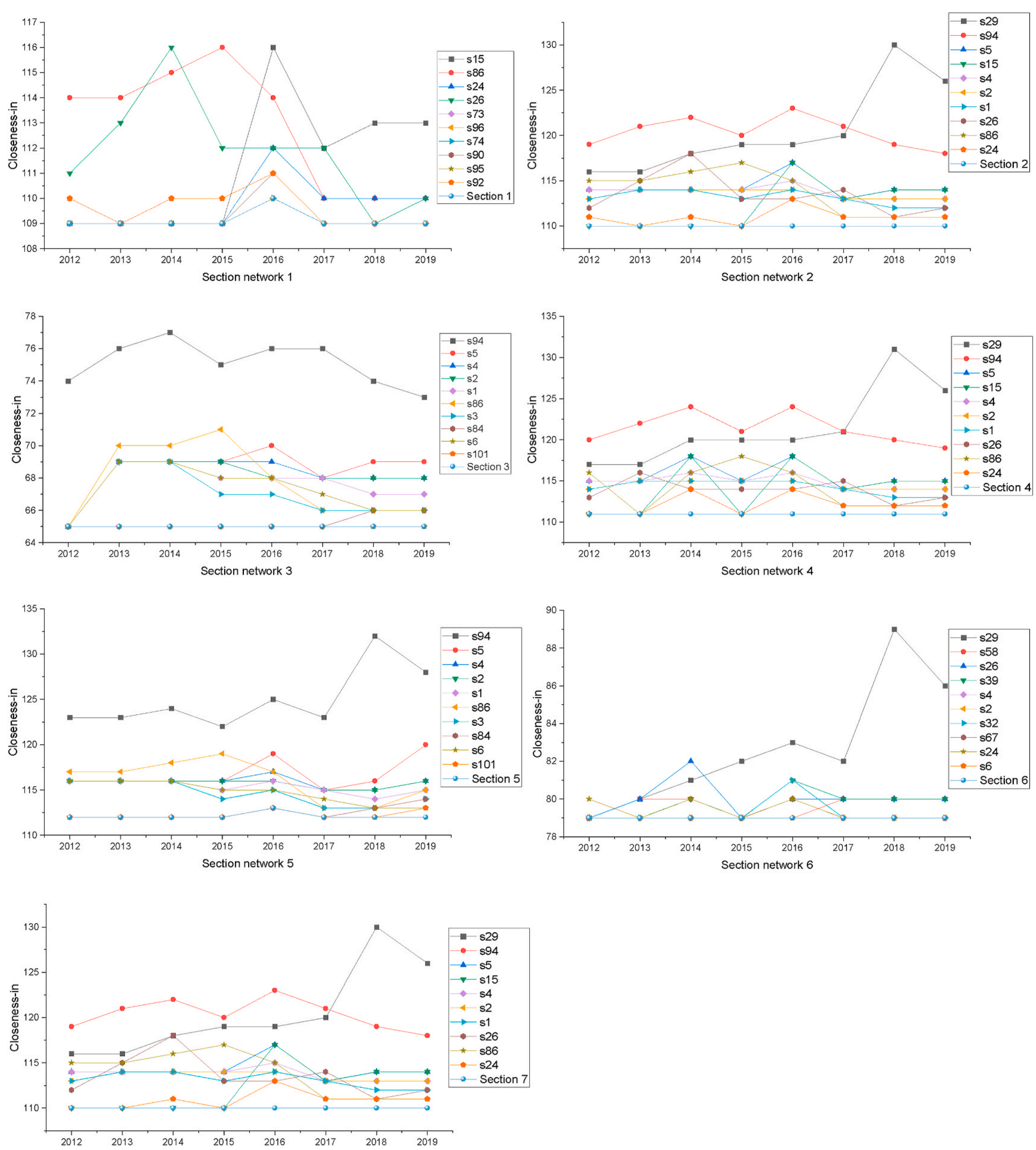


Fig. 9. Top 10 sectors of closeness-in of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

closeness-in scores exhibited consistently minimal values within their respective network aggregations. A limited number of sectors emerged as primary influencers of the closeness-in outcomes within each respective network. Specifically, within section network 1, sectors S15, S26, and S86 assumed dominant positions in shaping the closeness-in values. In section networks 2, 4, 6, and 7, S29 exhibited a leading role. Likewise, sector S94 demonstrated a pronounced influence on section networks 3 and 5. This suggests that the embodied energy flowing into these select sectors necessitated a higher number of intermediary steps for its transfer, indicating a relatively slow transmission speed. Furthermore, this pattern underscores the comparatively lower connectivity levels that these particular industries maintained with other sectors.

The results for closeness-out for each section network from 2012 to 2019 based on Equation (7) are shown in Fig. 10. The results for closeness-out indicate the minimum number of steps required to access all other nodes from a given node, representing the outflow transfer speed of embodied energy among sectors and sections. Similar to closeness-in, higher values of closeness-out indicate a lower speed of embodied energy transfer. In this figure, the observation that most sections, except for section network 1, demonstrated maximum values in their respective embodied energy networks suggests that these sections played significant roles in terms of efficient energy exchange and influence within their economic sectors. Notably, section network 5 stood out due to its substantial variation between maximum and minimum values, indicating heterogeneity in the influence of nodes within this network. The specific examples of nodes S67 in section network 5 and S48 in section network 6 showed changes in their closeness centrality over time. The increase in closeness-out centrality of S67 from 95 to 110 in section network 5 implied a heightened influence of S67 in terms of embodied energy within this network. Similarly, the change in closeness centrality of S48 from 71 to 79 within section network 6 signified an altered position of S48 in terms of its connectedness and influence.

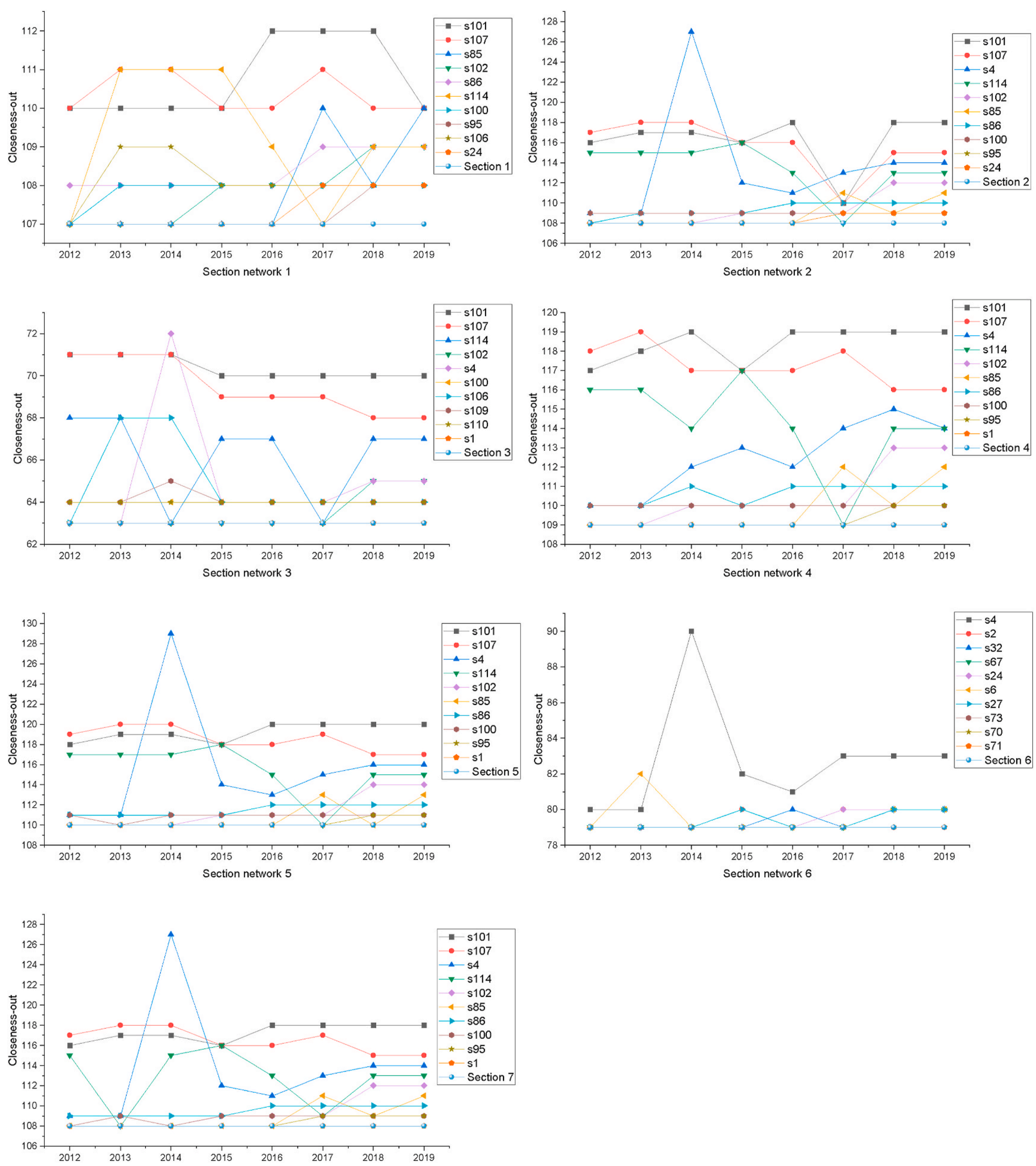


Fig. 10. Top 10 sectors of closeness-out of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

4.3. Strength analysis of Australian embodied energy network at sector level

In the complex network analysis method, node strength-in and strength-out are both metrics that quantify the importance of nodes in the network and their connectivity patterns from perspective of going into a sector and leaving a sector, respectively. These metrics can help us understand the role of nodes in a network structure and embodied energy transfer. Fig. 11 shows the strength-in and strength-out of the top 10 sectors of the Australian embodied energy network from 2012 to 2019 calculated by Equations (8) and (9). In this figure, both the strength-in and strength-out of each sector exhibited a similar pattern, showing an overall increase from 2012 to 2019, followed by fluctuations from 2017 to 2019. The observed trends in both strength-in and strength-out values suggest that the energy consumption and interconnections among sectors experienced growth from 2012 to 2019. However, the fluctuations from 2017 to 2019 indicate possible shifts in energy usage patterns and the dynamics of energy flow among the sectors during that period.

In terms of the strength-in results in Fig. 11(a)–S73 had the highest value, reaching 82,862 PJ in 2017, while S14 recorded the lowest value of 1197 PJ in 2014. In 2019, S73 retained its position as the sector with the highest strength-in value, followed by sectors S70, S71, and S72. The strength-in values for the remaining sectors were all below 10,000 PJ. It is worth noting that S73 had the most significant impact on the overall energy flow, with consistently high strength-in values, indicating a central and influential role in the network's energy transfer. On the other hand, S14 had the lowest strength-in value, suggesting relatively less significance in the energy flow of the network. In Fig. 11(b)–S73 also exhibited the highest value for strength-out in 2017 with 72,119 PJ, followed by S96. These two sectors clearly stood out with significantly higher values compared to other industries. The dominance of S73 and S96 in strength-out indicates that they had substantial energy outflows to other sectors in the network. This suggests that these sectors played crucial roles in supplying energy to other parts of the network and were likely vital components of the overall energy distribution system.

The strength-in results for each section network from 2012 to 2019, computed based on Equation (8), are presented in Fig. 12. Strength-in is used to assess the significance and influence of nodes as recipients within the embodied energy network. Higher strength-in values indicate that a node receives a greater number of external inputs, thereby signifying its heightened influence and centrality within the network. Nodes with higher strength-in values are likely to play pivotal roles in the integration and processing of embodied energy from other sectors, making them influential receivers. A common trend was observed among all the strength-in results, with values consistently increasing from 2012 to 2017, followed by a decrease from 2017 to 2018 and subsequently an increase from 2018 to 2019. This pattern suggests

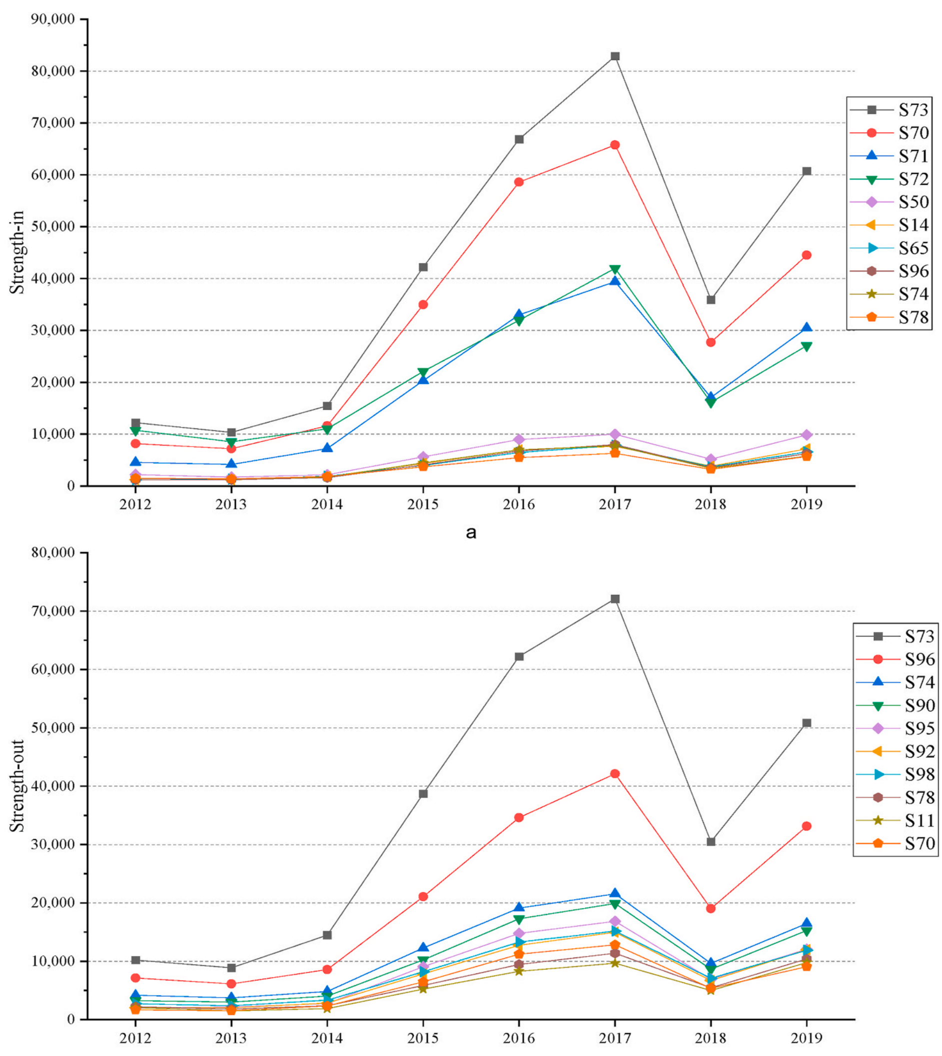


Fig. 11. Top 10 sectors of strength-in and srength-out of the Australian embodied energy network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

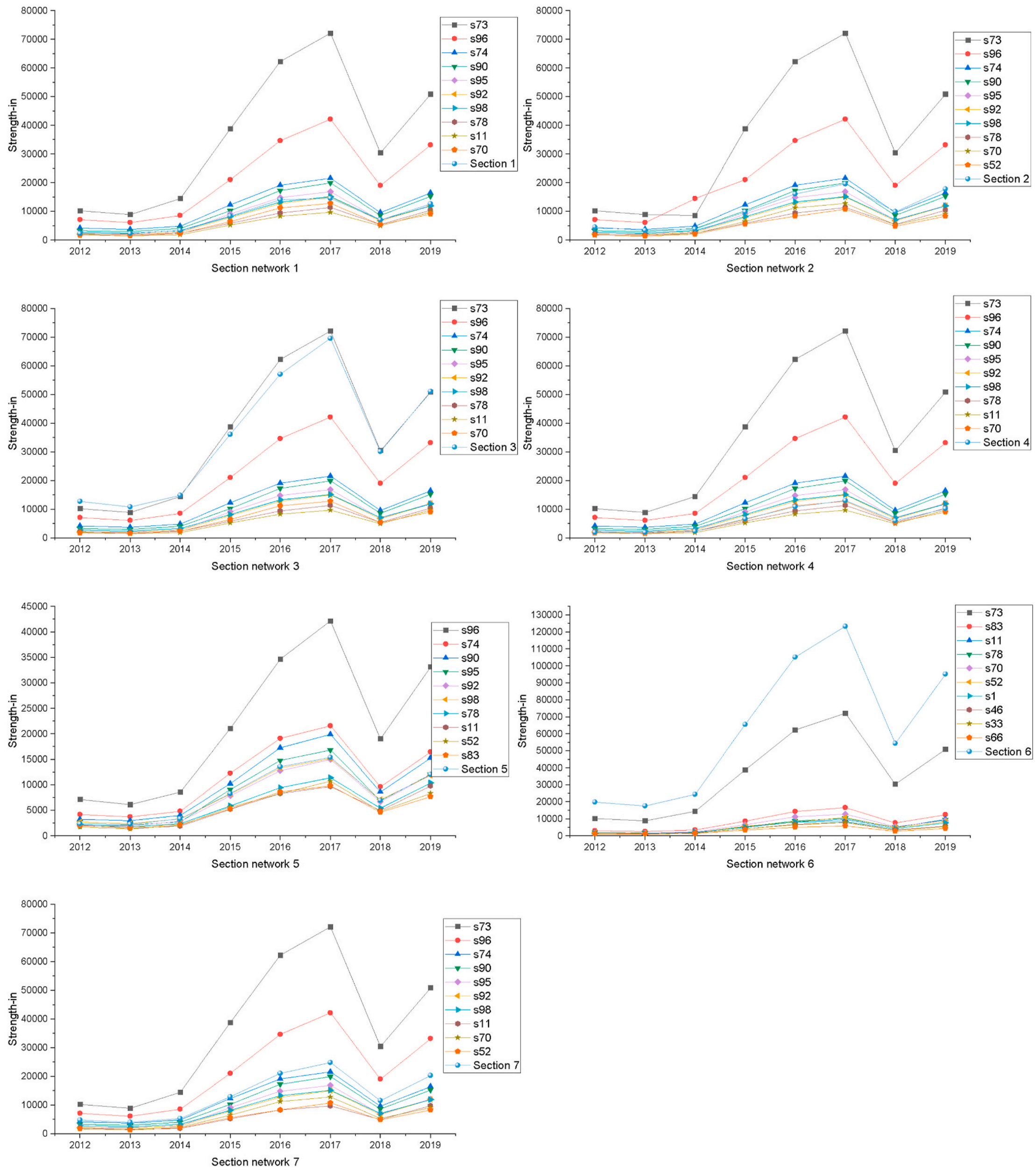


Fig. 12. Top 10 sectors of strength-in of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

evolving dynamics in the influence and centrality of recipient nodes over time, reflecting shifts in energy flow patterns and interconnections within the network. Furthermore, specific section networks 1, 2, 3, 4, and 7 consistently showed node S73 as the one with the highest strength-in values. This recurring observation underscores the paramount importance of node S73 as a recipient of embodied energy within these networks, highlighting its exceptional influence and centrality in facilitating energy reception and distribution. Additionally, an intriguing finding surfaced in the aggregated network of section 6, where the maximum strength-in value was exclusively identified. This significant result emphasizes the unmatched impact and prominence of section 6 aggregation within the entire network structure, indicating its pivotal role as a major energy recipient and a key influencer in the overall energy integration process. The observed trends and specific node behaviors in terms of strength-in values offer valuable insights into the hierarchies and energy flow dynamics within the section network.

The temporal evolution of strength-out values for each section network over the period from 2012 to 2019, computed using Equation (9), are shown in Fig. 13. Strength-out is used to quantify the significance and influence of a node as an output entity within a section network, reflecting its capacity to contribute and disseminate embodied energy or resources to other sectors. In this figure, it is observed that all the strength-out results exhibited fluctuating trends, with the highest values consistently occurring in 2017. Apart from section network 5, the remaining networks demonstrated relatively significant fluctuations in their strength-out values over time. These variations suggest dynamic changes in the output capabilities and influence of different sectors within the networks, indicating fluctuations in their respective roles as sources of embodied energy and information exchange. An interesting recurring finding is that node S73 consistently attained the highest strength-out values across six of the networks. This result highlights the exceptional influence and capacity of S73 in outputting embodied energy to other sectors within these networks. Node S73 was evidently a dominant contributor, significantly shaping the flow of resources and information in these systems.

Additionally, in the context of section network 5, section 5

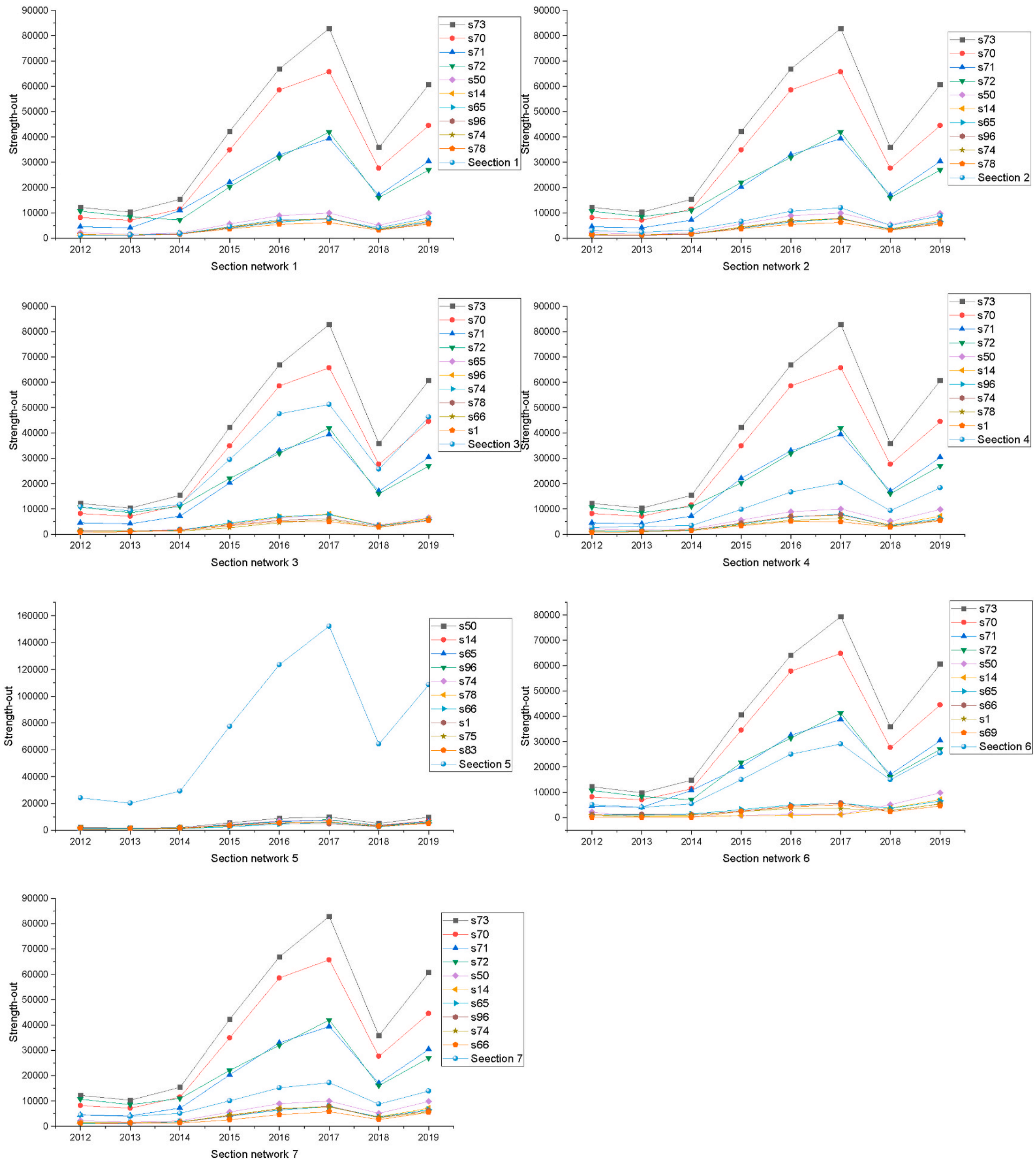
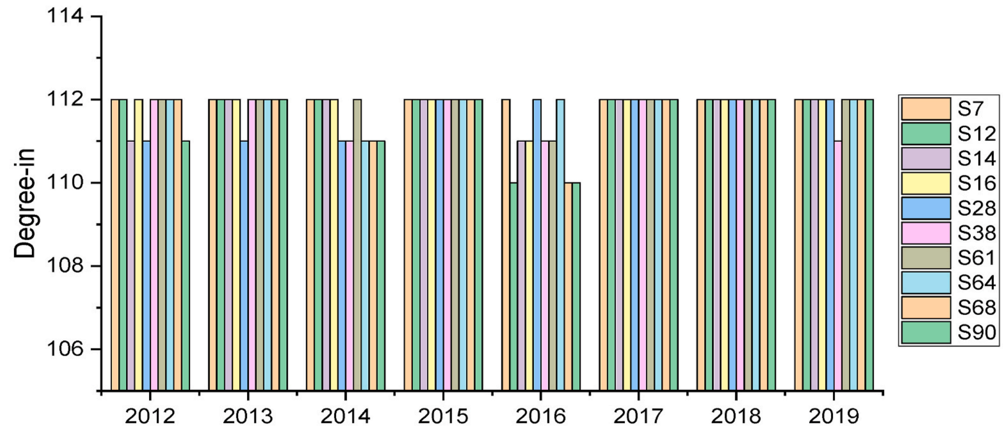


Fig. 13. Top 10 sectors of strength-out of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

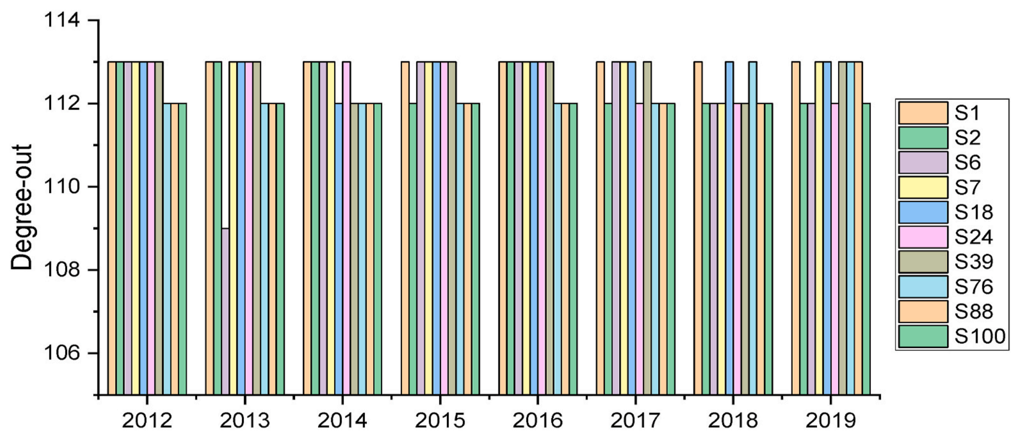
consistently exhibited notably higher strength-out values compared to other sectors in the network. This observation suggests that section 5 possessed a superior capacity for generating and disseminating outputs within the network. The substantial disparity in strength-out values emphasizes the pivotal role of section 5 in influencing the network dynamics and the flow of information and resources. Overall, the temporal analysis of strength-out values provides valuable insights into the dynamic behavior and influence dynamics of the section networks. The observed fluctuations and the recurring dominance of specific nodes underscore the complexity of energy/resource flows and the interplay of influence within these networks. These findings carry significant implications for resource management, identifying critical nodes responsible for outputting resources and for understanding the underlying mechanisms driving the observed dynamics. Further exploration and analysis are essential to gain a deeper understanding of the structural and functional implications of the strength-out patterns and to optimize the networks for enhanced efficiency and adaptability.

4.4. Degree analysis of Australian embodied energy network at sector level

The degree of a node can be utilized to measure its significance within a network. Typically, nodes with a higher degree are regarded as more central and pivotal within the network due to their direct connections to a larger number of other nodes, conferring greater influence and dissemination capacity. Based on Equations (10) and (11), the degree can be divided into degree-in and degree-out from different orientation of the node. Fig. 14(a) and (b) show the degree-in and degree-out of the Australian embodied energy network, respectively. In the results, the sectors were predominantly chosen to exhibit relatively modest fluctuations in both their degree-in and degree-out values. In the case of degree-in values, S12, S68, and S90 displayed the smallest degrees in 2016, indicating that these sectors received fewer connections from other sectors during that period. This could suggest a lower level of influence or information flow into these sectors within the network. Subsequently, S38 exhibited the lowest degree-in value in 2019,



a



b

Fig. 14. Top 10 sectors of degree-in and degree-out of the Australian embodied energy network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

implying a similar trend of limited incoming connections, potentially indicative of specific dynamics or contextual factors affecting its interactions. On the degree-out side, S6 showed the minimum degree-out value in 2013, indicating that this sector had fewer outward connections to other sectors. This could imply a lower level of influence or contribution from S6 to other parts of the network during that year. Conversely, the remaining selected sectors maintained a relatively stable degree-out range between 112 and 113, suggesting consistent engagement and dissemination of information or influence on other sectors over time.

In the context of the degree analysis conducted within each distinct section network, a subset of 10 notable sectors has been selected. This selection process was informed by the degree-in and degree-out outcomes inherent to the particular network under consideration. Fig. 15 shows the degree-in results for each section network. In this figure, each section exhibited a consistent and maximal degree-in value within its own network. Within section network 4, only S29 displayed a notable variation, with a declining trend from 2012 to 2018 followed by an increase in 2019. Furthermore, results within section network 2 exhibited relatively minor fluctuations, remaining within a range of 2 for degree-in. Conversely, degree-in results in the remaining section networks demonstrated more pronounced variations. Section networks 2 and 4 had stable degree-in values, indicating that the number of connections they received from other nodes remained relatively constant over a certain period of time. This implies that the node's incoming relationships within the network are relatively stable, meaning that the quantity of nodes connected to it does not exhibit significant fluctuations or changes in the short term.

Similar to the results for degree-in, the results for degree-out also selected 10 sectors in each section network to analyze. Fig. 16 shows the results for degree-out of each section network. In this figure, the prevailing finding is that sections 2–7 had the maximum value of degree-out, showing their predominant influence within their respective section networks by exhibiting the highest count of edges directed toward other nodes. This phenomenon underscores their prominence in terms of establishing connections and facilitating information flows within their specific network contexts. The fluctuations in the degree-in were more pronounced in each section network than for the degree-out, with S67 in section network 5 and S48 in section network 6 standing out in particular. The clear instability observed in the degree-out values indicates substantial variations in the number of connections initiated by a node with other nodes over a defined temporal interval. Such dynamic behavior suggests a certain level of unsettledness in the node's outbound relationships within the network fabric, thus alluding to potential instability in the realms of embodied energy transition and direct affiliations with other nodes.

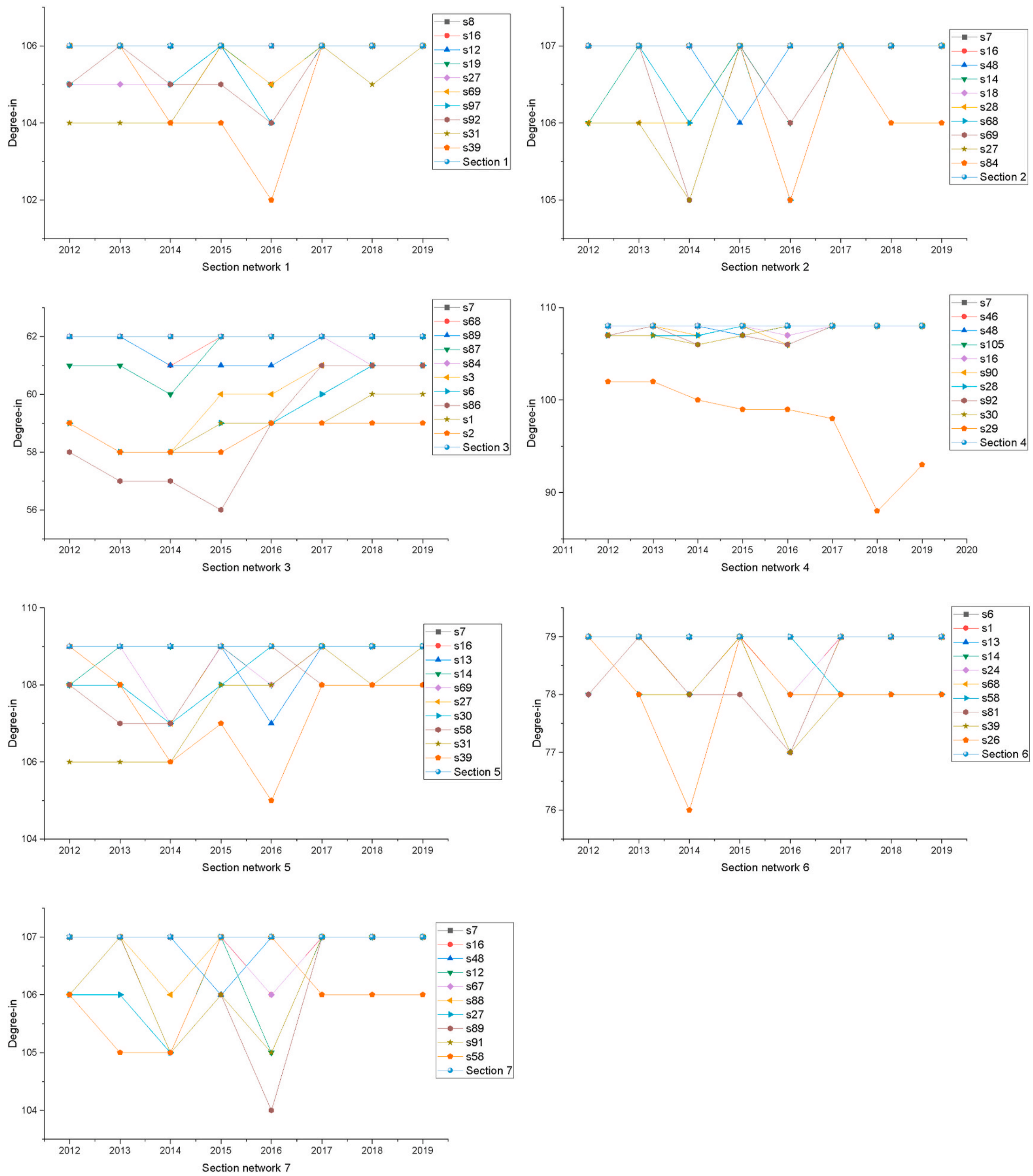


Fig. 15. Top 10 sectors of degree-in of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

4.5. Small-world nature of Australian embodied energy network at sector level

In the complex network analysis method, the clustering coefficient is closely related to the importance and influence of nodes. Nodes with high clustering coefficients often play a more significant role in information and influence propagation, such as information dissemination and influence spreading. Fig. 17 displays the top 10 sectors' clustering coefficients for the Australian embodied energy network from 2012 to 2019, calculated by Equation (12). In this figure, the overall clustering coefficient remained relatively stable from 2012 to 2014. However, starting from 2014, it experienced a substantial increase, but then decreased in 2018. The observed stability of the clustering coefficient from 2012 to 2014 suggests that the network's local connectivity and the tendency of nodes to form clusters of interconnected neighbors remained relatively constant during that period. However, the substantial increase in the clustering coefficient from 2014 onward indicates a strengthening of local clustering patterns within the network. The subsequent decrease in the clustering coefficient in 2018 could be attributable to various factors, such as changes in the network structure, alterations in connection patterns, or shifts in the distribution of edges among nodes. This reduction might indicate a decrease in the density of local clusters or a more spread-out pattern of connections in the network during that year. Within the clustering coefficient results, S94 consistently displayed a significantly higher clustering coefficient than other sectors during the same time period. S94 had a consistently higher clustering coefficient throughout the observed time period, indicating that this sector exhibited a stronger tendency for nodes to form tightly interconnected clusters compared to other sectors. This could imply a higher level of collaboration, cooperation, or interdependency among entities within S94, leading to a denser and more cohesive sub-network.

The results for the clustering coefficient of each section network based on Equation (12) are shown in Fig. 18. In this figure, overall, the results demonstrated an upward trend. This indicates an increasing ability to establish connections with collaborating counterparts in every network. However, there was a decreasing trend observed from 2017 to

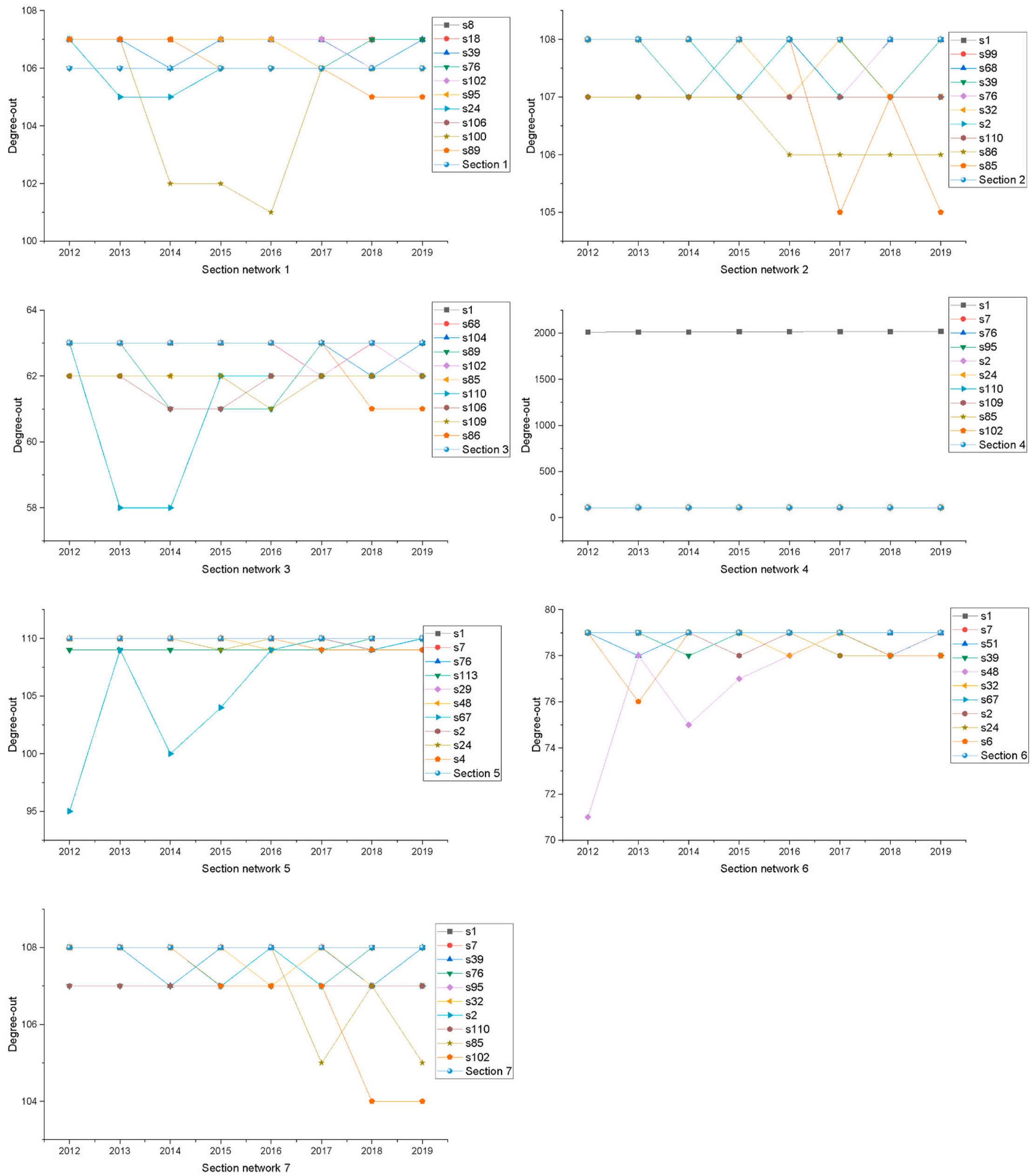


Fig. 16. Top 10 sectors of degree-out of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

2018. The results for section 7 also decreased from 2013 to 2014. The results for S94 led other sectors and sections in every section network except section network 6. The results derived from each section consistently demonstrated the lowest clustering coefficient when compared to other individual sectors. This finding suggests that the presence of multiple sectors within a section did not confer a higher clustering ability within a multi-sector network. The clustering coefficient is a metric that quantifies the extent to which nodes and their neighboring nodes form triangular connections, reflecting the level of local interconnectedness within a section. A higher clustering coefficient indicates a greater prevalence of interconnected clusters, indicating a tight-knit and cohesive section network structure. The observed pattern, where sections comprising multiple sectors exhibited lower clustering coefficients, challenges the assumption that larger sections would exhibit a higher degree of clustering. It suggests that the presence of multiple sectors within a section did not necessarily lead to a denser network of triangular connections among their constituent sectors. This finding has important implications for our understanding of section network structures and their role in network dynamics. Other factors, such as the nature of interactions, interdependencies, and the flows of embodied energy among sectors, may play more significant roles in determining the clustering patterns observed in the network. The analysis of the Australian embodied energy network revealed that only a few sectors played pivotal roles due to the network's significant scale-free property. Policymakers should focus on these key sectors to enhance the overall efficiency of the embodied energy system. By identifying and targeting the most influential sectors, interventions such as promoting energy-efficient technologies, providing sector-specific subsidies, and facilitating inter-sector collaborations can be implemented. These measures would not only improve the efficiency of energy use within these critical sectors, but also have a cascading effect on the entire network, leading to substantial reductions in overall energy consumption and environmental impact.

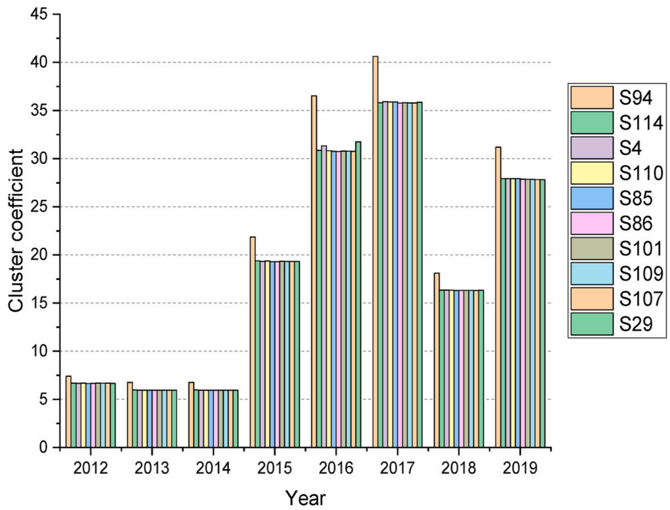


Fig. 17. Top 10 sectors of clustering coefficient of the Australian embodied energy network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

4.6. Key findings

As average path length decreased, embodied energy tended to increase, which indicates that the Australian sectors increased their energy consumption in the process of production without contributing to economic growth due to the concentration of resources within the network. In the network of the Australian economy, the significant sectors for the indicators included the following: S73 consistently held the highest strength-in and strength-out values, emphasizing its central role in receiving and disseminating embodied energy within the network; S29 had the highest closeness-in value of 228, indicating its crucial role in attracting inputs from other nodes; in section network 5, S67 showed increasing closeness-out centrality ranging from 95 to 110, highlighting its growing influence in energy distribution. S94 excelled in closeness-out values of 339–452 and consistently higher clustering coefficients. For instance, the ownership of dwellings (S94) was a pivotal hub for energy dissemination within the network as it had more direct paths to reach other sectors, indicating a boom in the real estate sector and the concentration of energy embodied in buildings, marking it as a pivotal hub for energy dissemination and local interconnectedness.

5. Conclusions and policy implications

5.1. Conclusions

In this study, our major aim was to quantify the contributions of structural changes in sectors based on embodied energy. We built an Australian embodied energy transfer network by combining input–output tables with energy consumption. Then we identified the structural roles of sectors in the embodied energy transfer network using the complex network analysis method to analyze the subsystems within the larger group of seven sections in different section networks. The detailed conclusions are as follows.

The analysis of the Australian embodied energy network from 2012 to 2019 revealed dynamic trends in energy consumption, interconnectivity, and sector/section influences. Embodied energy exhibited fluctuating patterns, with notable increases until 2017, a decline in 2018, followed by an upturn in 2019, indicating shifting resource allocation. Network efficiency improved as average path lengths shortened, showing more direct information and resource pathways. Key sectors played pivotal roles in the scale-free network structure. Section-based analysis showed rising energy consumption until 2017 due to economic growth, followed by fluctuations. Network efficiency increased over time, but larger sections did not necessarily lead to denser connections. Inbound and outbound energy flows revealed sector importance. Specific nodes like S94 and S73 displayed varying connectivity and influence. Clustering patterns challenged assumptions, suggesting that factors beyond section size shaped interconnections. These insights can guide policymakers for enhanced energy efficiency, allocation, and collaboration, fostering a sustainable energy policy for the Australian economy.

The analysis of the Australian embodied energy network and structural properties from 2012 to 2019 revealed valuable insights into the dynamics of the network and its implications for energy distribution and efficiency. Over 2012–2019, the Australian embodied energy network saw an increase in total energy until 2017, a decline in 2018, and a resurgence in 2019, indicating industry resource and consumption variability. The network's structure became more direct and efficient over 2015–2019, contrasting with the fragmented structure observed over 2012–2014. Key sectors played pivotal roles, emphasizing the network's scale-free nature. Variations were noted in sector centrality, impacting both inbound and outbound energy flows. Despite overall energy consumption growth and increased sector interconnections over the seven years, fluctuations were especially evident over 2017–2019. Finally, local connectivity strengthened over 2014–2017, as seen from the clustering coefficient analysis.

The integrated analysis of section-based embodied energy networks in the Australian embodied energy network provided valuable insights into each section's characteristics and their impacts on energy consumption and interconnectivity. Over 2012–2017, section-based embodied energy networks in Australia saw increased energy consumption due to economic and industrial growth. However, 2017–2019 experienced fluctuations, indicating changing economic conditions and energy demands. The network trended toward improved efficiency and shorter node distances, evolving its dynamics. Contrary to expectations, larger sections did not necessarily have denser connections. These insights offer policymakers a foundation to enhance energy efficiency, resource allocation, and inter-sector collaboration, aiming for a sustainable Australian energy system. Future research is essential to understand these trends further and develop optimal strategies for sustainable energy practices.

The integrated analysis of the Australian embodied energy network spanning 2012 to 2019 provided valuable insights into the dynamics of embodied energy transfer and interconnectivity among sectors and sections. The study of the Australian embodied energy network over 2012–2019 offered insights into energy transfer dynamics among sectors and sections. By analyzing network metrics, it became clear that sectors with high closeness-in values influenced inbound interactions, while those with high closeness-out values controled outbound transmissions. Nodes like S94 and S73 played significant roles in energy distribution and interconnectivity. Strength-in and strength-out analyses underscored the importance and variability of nodes in energy reception and dissemination. Contrary to assumptions, larger section-based networks did not always display denser clustering; instead, interactions and energy dynamics determined clustering patterns.

5.2. Policy implications

To improve the efficiency of the embodied energy network, policymakers should aim to reduce average path lengths and enhance local clustering. This could be achieved by fostering direct connections between sectors and encouraging the formation of tightly knit clusters. Policies could include infrastructure investments that improved connectivity, incentives for sectors to form collaborative networks, and support for regional energy hubs. Policymakers need to adopt flexible and adaptive strategies that can respond to these temporal changes. This could include continuous monitoring of network metrics and periodic reassessment of policies to ensure they remain effective under changing conditions. For instance, during periods of increased energy

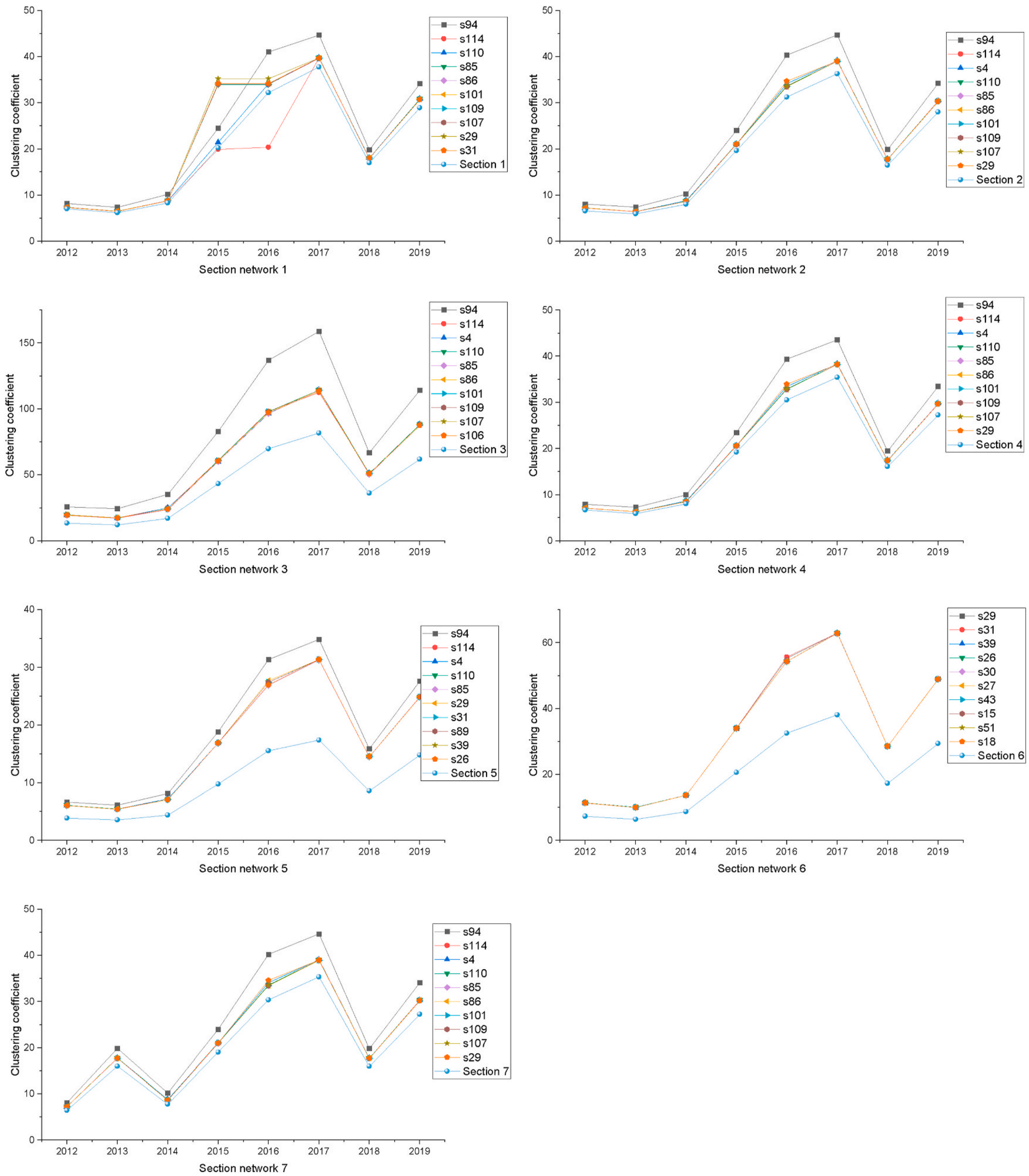


Fig. 18. Top 10 sectors of clustering coefficient of each section network from 2012 to 2019. (Note: the top 10 sectors were selected by the results ranked in 2019.)

consumption, policies could focus on demand-side management and energy conservation. Conversely, during times of reduced network connectivity or clustering, efforts could be directed toward strengthening inter-sectoral linkages and fostering collaboration. Adaptive policy frameworks would help maintain the network's efficiency and sustainability in the face of evolving economic and environmental conditions.

Policymakers should promote a more balanced and equitable distribution of embodied energy across all sectors to prevent over-reliance on a few key nodes. This could be achieved through policies that supported smaller or less connected sectors, such as providing financial incentives and technical support, and facilitating access to energy resources. By promoting sectoral balance, the network's overall stability and resilience could be enhanced, ensuring a more sustainable and robust energy system. The analysis of section networks within the Australian embodied energy network also revealed significant insights into regional energy dynamics. Policymakers should leverage these insights to inform regional energy planning and development strategies. For instance, regions with higher embodied energy and inter-sectoral activity should be prioritized for infrastructure investments and energy-efficiency programs. Additionally, understanding the unique characteristics and connectivity patterns of different sections could help in tailoring policies that addressed specific regional needs, fostering sustainable development and optimizing resource allocation at the local level.

CRediT authorship contribution statement

Lingfeng Liang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yabing Xu:** Writing – review & editing. **Bin Liu:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Chunlu Liu:** Writing – review &

editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Youquan Xu:** Supervision. **Mark Luther:** Supervision.

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.

Appendix. Classification of the sectors in different sections

Section 1: Agriculture, Forestry and Fishing

No.	Sector Name
S1	Sheep, grains, beef and dairy cattle
S2	Poultry and other livestock
S3	Other agriculture
S4	Aquaculture
S5	Forestry and logging
S6	Fishing, hunting and trapping
S7	Agriculture, forestry and fishing support services

Section 2: Mining

No.	Sector Name
S8	Coal mining
S9	Oil and gas extraction
S10	Iron ore mining
S11	Non-ferrous metal ore mining
S12	Non-metallic mineral mining
S13	Exploration and mining support services

Section 3: Manufacturing

No.	Sector Name
S14	Meat and meat product manufacturing
S15	Processed seafood manufacturing
S16	Dairy product manufacturing
S17	Fruit and vegetable product manufacturing
S18	Oils and fats manufacturing
S19	Grain mill and cereal product manufacturing
S20	Bakery product manufacturing
S21	Sugar and confectionery manufacturing
S22	Other food product manufacturing
S23	Soft drinks, cordials and syrup manufacturing
S24	Beer manufacturing
S25	Wine, spirits and tobacco
S26	Textile manufacturing
S27	Tanned leather, dressed fur and leather product manufacturing
S28	Textile product manufacturing
S29	Knitted product manufacturing
S30	Clothing manufacturing
S31	Footwear manufacturing
S32	Sawmill product manufacturing
S33	Other wood product manufacturing
S34	Pulp, paper and paperboard manufacturing
S35	Paper stationery and other converted paper product manufacturing
S36	Printing (including the reproduction of recorded media)
S37	Petroleum and coal product manufacturing
S38	Human pharmaceutical and medicinal product manufacturing
S39	Veterinary pharmaceutical and medicinal product manufacturing
S40	Basic chemical manufacturing
S41	Cleaning compounds and toiletry preparation manufacturing
S42	Polymer product manufacturing
S43	Natural rubber product manufacturing
S44	Glass and glass product manufacturing
S45	Ceramic product manufacturing
S46	Cement, lime and ready-mixed concrete manufacturing
S47	Plaster and concrete product manufacturing
S48	Other non-metallic mineral product manufacturing

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(*continued*)

No.	Sector Name
S49	Iron and steel manufacturing
S50	Basic non-ferrous metal manufacturing
S51	Forged iron and steel product manufacturing
S52	Structural metal product manufacturing
S53	Metal containers and other sheet metal product manufacturing
S54	Other fabricated metal product manufacturing
S55	Motor vehicles and parts; other transport equipment manufacturing
S56	Ships and boat manufacturing
S57	Railway rolling stock manufacturing
S58	Aircraft manufacturing
S59	Professional, scientific, computer and electronic equipment manufacturing
S60	Electrical equipment manufacturing
S61	Domestic appliance manufacturing
S62	Specialised and other machinery and equipment manufacturing
S63	Furniture manufacturing
S64	Other manufactured products

Section 4: Electricity, Gas, Water, and Waste Services

No.	Sector Name
S65	Electricity generation
S66	Electricity transmission, distribution, on selling and electricity market operation
S67	Gas supply
S68	Water supply, sewerage and drainage services
S69	Waste collection, treatment and disposal services

Section 5: Construction

No.	Sector Name
S70	Residential building construction
S71	Non-residential building construction
S72	Heavy and civil engineering construction
S73	Construction services

Section 6: Commercial Services

No.	Sector Name
S74	Wholesale trade
S75	Retail trade
S76	Accommodation
S77	Food and beverage services
S84	Publishing (except internet and music publishing)
S85	Motion picture and sound recording
S86	Broadcasting (except internet)
S87	Internet service providers, internet publishing and broadcasting, websearch portals and data processing
S88	Telecommunication services
S89	Library and other information services
S90	Finance
S91	Insurance and superannuation funds
S92	Auxiliary finance and insurance services
S93	Rental and hiring services (except real estate)
S94	Ownership of dwellings
S95	Non-residential property operators and real estate services
S96	Professional, scientific and technical services
S97	Computer systems design and related services
S98	Employment, travel agency and other administrative services
S99	Building cleaning, pest control and other support services
S100	Public administration and regulatory services
S101	Defence
S102	Public order and safety
S103	Primary and secondary education services (including pre-schools and special schools)
S104	Technical, vocational and tertiary education services (including undergraduate and postgraduate)
S105	Arts, sports, adult and other education services (including community education)
S106	Health care services
S107	Residential care and social assistance services

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No.	Sector Name
S108	Heritage, creative and performing arts
S109	Sports and recreation
S110	Gambling
S111	Automotive repair and maintenance
S112	Other repair and maintenance
S113	Personal services
S114	Other services

Section 7: Transport, Postal, and Warehousing

No.	Sector Name
S78	Road transport
S79	Rail transport
S80	Water, pipeline and other transport
S81	Air and space transport
S82	Postal and courier pick-up and delivery service
S83	Transport support services and storage

Data availability

Data will be made available on request.

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