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Sustainable Regional Straw Utilization: Collaborative Approaches and Network Optimization

Jing Tao [1,*], Wuliyasu Bai [2,*], Rongsheng Peng [1] and Ziying Wu [1]

[1] School of Business, Xinyang Normal University, Xinyang 464000, China; pengrs@xynu.edu.cn (R.P.); wziy@xynu.edu.cn (Z.W.)
[2] School of Economic and Management, China University of Geosciences, Wuhan 430074, China
* Correspondence: tjing@xynu.edu.cn (J.T.); wuliyasu@cug.edu.cn (W.B.)

Abstract: The SDGS repeatedly emphasizes the importance of reducing greenhouse gas emissions such as carbon dioxide. The strategic utilization of straw resources to curtail open-air burning not only epitomizes optimal resource deployment but also constitutes a significant stride in environmental preservation and sustainable development. Globally, the imperative of this challenge is increasingly recognized, prompting nations to enhance straw resource utilization technologies, devise regional management strategies, and extend requisite policy support. Regional straw utilization encapsulates a comprehensive concept involving an array of stakeholders including governments, farmers, corporations, brokers, and rural cooperatives, with each one of these uniquely contributing to a multifaceted network that is influenced by their respective resource utilization intentions. This heterogeneity, coupled with the diverse roles of these stakeholders, renders the identification of the pivotal participants and their specific functions within the intricate network. To navigate this complexity, this study employed text analysis and social network analysis, uncovering 30 robust associative rules within this domain. Our findings elucidate that the stakeholder network in regional straw resource utilization exhibits characteristics akin to the NW small-world network model. The key network entities identified include farmers, corporations, governments, and rural cooperatives. Furthermore, the study systematically categorizes the principal entities and elucidates the dynamics of this multi-stakeholder network. This research delineates four developmental models that are pertinent to regional straw resource utilization, which is a framework that is instrumental in pinpointing the accountable parties and optimizing the overarching benefits derived from these resources. The significance of this research lies not only in showcasing the potential of straw resources for environmental conservation but also in underscoring the importance of collaborative strategies and network optimization in order to achieve sustainable development goals.

Keywords: sustainable regional straw utilization; complex network; associate rule; waste management

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1. Introduction

As global warming intensifies, greenhouse gas emissions have become a focal point of international concern. Carbon dioxide, a primary greenhouse gas, plays a significant role in climate change, and its emission control is crucial. The reduction of CO_2 emissions from different sources is clearly highlighted in the sustainable development goals [1]. In agriculture, straw burning not only causes air pollution but is also a major source of greenhouse gas emissions. In 2016, straw burning emerged as the third-largest source of agricultural greenhouse gas emissions [2]. Hence, it is imperative to implement efficacious straw treatment methods that circumvent open-air burning, thereby ameliorating rural environmental quality and curtailing GHG emissions. In response to the biological properties of crop straw, diverse global strategies for straw valorization have emerged. Germany concentrates on integrating crop straw use into plant breeding systems, while Denmark harnesses straw for direct combustion in power generation [3]. Furthermore, nations like the United States and Brazil, as well as the European Union, are intensifying their reliance on biofuels within their energy portfolios [4]. China, which has the highest volume of straw resources, reported a theoretical straw resource of 977 million tons in 2022, with rice and wheat straws accounting for 220 and 175 million tons, respectively [5]. The country has made notable strides in straw resource utilization, achieving a comprehensive utilization volume of 662 million tons. However, the journey towards the efficient utilization of straw resources in China is long and challenging.

The concept of regional straw resource utilization encompasses a complex network of multiple stakeholders including farmers (FA), companies (COM), governments (GO), brokers (BR), and rural cooperatives (RC) [6,7]. In rural China, the decreasing agricultural workforce due to urbanization and other factors poses challenges to straw resource supply [8]. Additionally, the weak industrial base in rural areas hinders the growth and development of companies focused on straw resource utilization [9]. Although the Chinese government is gradually promoting county-level pilot policies, these external stimuli do not adequately address the marketization challenges in straw resource utilization. Other crucial but often overlooked entities include brokers, rural cooperatives, and research institutions, whose roles are vital for fostering innovation systems among farmers and comprehensive straw utilization [10].

Identifying the core entities and their interrelations within this network is essential for advancing straw resource utilization from a stakeholder perspective, thereby contributing to sustainable regional agricultural development and ecological balance. This study aims to define the multi-stakeholder cooperation network in regional straw resource utilization as a complex network. By employing the association rule mining and text mining methods, we analyze the topological structure and characteristics of the multi-stakeholder network. This approach will help identify the core entities in regional straw resource utilization and their interrelations, thereby offering policy recommendations from the perspective of these core entities to enhance the level of straw resource utilization in the region.

2. Literature Review

Regional straw resource utilization is inextricably linked to the participation and drive of various stakeholders. This multi-faceted network includes governments, utilization companies, farmers, intermediaries, rural cooperatives, and financing institutions. The interests of these entities interconnect to form a complex and vast network [11]. Research on these entities is pivotal in promoting straw resource utilization from a responsibility standpoint. Studies on regional straw resource utilization entities encompass two areas as follows: individual entity research and inter-entity interaction research. Focusing on individual entities, Quan et al. employed a multiple regression analysis to highlight factors like straw subsidies, the cost-benefit of straw utilization, awareness, technology, family farm income, and farm size as significant influencers of farmers' straw utilization and suggested enhancing farmers' comprehensive straw utilization by improving their understanding of crop straw and leveraging the exemplary role of village cadres [12]. Guo et al. constructed a Structural Equation Model (SEM) based on the Theory of Planned Behavior (TPB) to investigate the main driving factors of farmers' straw resource utilization behavior in Jilin Province. The findings revealed that the farmers' behavioral attitudes and subjective norms directly influence their actual behavior through behavioral intentions. Notably, subjective norms and moral obligation are critical in influencing the willingness to utilize straw resources in Jilin Province [13]. For an example in Thailand, Sereenonchai and Arunrat employed integrated behavioral theories such as TPB, Value–Belief–Norm (VBN), and the Health Belief Model (HBM). They concluded that enhancing group-level action knowledge and self-efficacy, coupled with self-awareness and commitment, can effectively promote the non-burning management of straw and stubble [14]. Li et al. revealed that farmers' decisions to return straw to fields are subject to conformity effects, which are influenced by village cadres, neighbors, relatives, and environmental effect perceptions [15]. Overall, the factors influencing farmers' willingness for resourceful straw utilization are multifaceted, encompassing psychological, individual, and external environmental factors.

Extensive research on straw resource utilization companies primarily revolves around analyses of operational costs and benefits. Jia notes that the assets of most Chinese straw resource utilization companies are generally below CNY 5 million, indicating a trend towards smaller enterprise scales and lower levels of operational efficiency [16]. Shen et al. observe that companies, as key market players in straw transactions, often engage in contracts with farmers, villages, or towns to organize centralized mechanical harvesting, bundling, and the transportation of straw. However, the high costs of raw material procurement and transportation lead to lower profit margins, thereby posing challenges to developing scalable commercial models for straw utilization [17]. Kaur et al. suggest that using straw as a raw material in the pulp and paper industry presents a dual-benefit choice for both farmers and companies [18]. Moreover, Sun and Hou argue that internal competition for straw raw materials could decrease the likelihood of coexistence in the biomass industry [19]. Therefore, the escalating costs of raw materials and logistics are detrimental to companies' large-scale utilization of straw, impeding the development of a straw economy.

Investigating the role of government in regional straw resource utilization, Del Valle et al. emphasized the government's crucial influence through setting straw utilization goals, regulating the straw market, and implementing broader agricultural policies. These initiatives are pivotal in fostering farmers' active engagement in straw utilization [20]. Concerning the policy content that the government should adopt, Bentsen et al. explored policy measures and found that Denmark's incentive policies have resulted in more advanced straw energy utilization compared with that of Switzerland [21]. Wang et al. analyzed the current comprehensive utilization policies, focusing on aspects such as technical training, project subsidies, and the development of collection, storage, and transportation systems. They point out an over-reliance on environmental policies and a lack of sufficient supply and demand-oriented policies [22]. Additionally, Wang et al. examined the fiscal support policies for various stakeholders in Jilin Province's straw utilization industry chain, including subsidies, tax and fee concessions, and economic rewards. They suggest intensifying financial support for the collection, storage, and transportation phases and developing fiscal policies to support consumption [23].

Beyond government initiatives, entities such as banks, rural cooperatives, and brokers play a significant role in the regional utilization of straw resources. In Japan, expenses beyond subsidies for the acquisition of agricultural return-to-field machinery are addressed through low-interest loans provided by governments or banks. Furthermore, the government leverages farmers' associations to offer farmers a suite of socialized services including credit for agricultural machinery, technical training, and maintenance [24]. The key participants in the straw logistic network encompass farmers, cooperatives, brokers, companies, and the government [25]. Wu et al. highlight the pivotal role of intermediaries in China's "Farmer-Middleman-Enterprise" straw supply model [26]. These middlemen serve as crucial connectors between farmers and factories, facilitating the entire straw supply chain. Their responsibilities extend from straw collection, storage, and transportation to processing. This comprehensive approach by middlemen ensures a seamless and efficient flow in the straw supply chain, bridging the gap between rural agricultural practices and industrial demands. Straw brokers, often farmers themselves, are driven by economic interests to join the straw supply chain, yet they frequently lack standardized training and management [25]. Research institutions and agricultural management departments develop high-efficiency technologies for the utilization of agricultural waste, achieving technological innovations and breakthroughs in the resource utilization of agricultural waste [26]. The involvement of agricultural research institutions, universities, and other societal entities in technical training for farmers significantly fosters the comprehensive utilization of straw [27]. Government agencies can amplify the adoption of mechanized straw utilization through media-driven public opinion and by creating an environment rich in promotion and awareness [28]. While the critical roles of these entities in the straw utilization process are widely recognized in both the domestic and international literature, research focusing on them remains limited.

Regional straw resource utilization forms a multifaceted system, where its effective implementation is not dependent on a singular or a handful of actors but rather requires a concerted effort from all the relevant stakeholders. Bhattacharyya et al. reviewed the specific challenges in India and the subsequent initiative taken by the government and related stakeholders [29]. Del Valle et al. demonstrated the interest relationship among different stakeholders of straw utilization through a qualitative investigation [20]. As Zheng and Shen suggest, developing a synergistic system for comprehensive straw utilization hinges on the alignment of objectives among various participating subjects [30]. Yet, the present scenario paints a less optimistic picture. By evaluating the actual benefits accrued from recent applications and promotions, it is evident that there is marked reluctance among market participants and farmers exhibiting a notable "negative psychology". This has led to a situation characterized by the governmental enthusiasm of "hot" in stark contrast to the tepid response from the involved subjects, which is "cold" [31].

It is evident that there exists a misalignment in the objectives among different entities engaged in straw resource utilization, which is marked by inherent contradictions and internal game conflicts [32]. To address these issues, current research delves into the behavioral interactions between key players, employing game theory to dissect the strategies and internal discord. Specifically, by focusing on the "government-enterprise-farmers" nexus in straw resource management, Zhang et al. developed a tripartite evolutionary game model involving the government, farmers, and straw power generation companies [33]. Similarly, Wang et al. formulated an evolutionary game model for the development of straw baling service stations. They highlighted the crucial role of government incentives in this tripartite strategy and provided a quantitative analysis of the profit distribution limits [34].

In exploring the intricate dynamics of "enterprise-farmer-middleman" within the realm of straw resource utilization, Wang et al. introduced both decentralized and centralized decision models to capture the nuanced interactions within a Stackelberg game framework involving farmers, companies, and brokers [35]. Furthermore, Wen and Zhang advanced this understanding by constructing a sequential game theory model specific to China's straw supply chain [36]. Complementing these studies, Wang and Cai advocated for leveraging professional cooperatives to orchestrate a robust system for straw collection, storage, and transportation, thereby integrating the roles of farmers, brokers, and others [37]. While these investigations have been pivotal in dissecting the functional aspects of straw utilization and logistics, a comprehensive regional approach necessitates both identifying and understanding the core entities and their interrelationships. Currently, there is a noticeable gap in research focusing on the identification of these pivotal subjects and the intricate web of interactions that define regional straw resource utilization.

The architecture of a network in a complex system is a critical determinant of its overall operational efficiency. To effectively map out the interactions within such a system, it is imperative to identify the core entities and unravel the intricate web of relationships between them. With the evolution of complex network theories, an increasing number of researchers are applying these principles to examine participant behaviors in complex systems [38,39]. Building on this momentum, this study utilizes complex network theory and web crawler data to construct a comprehensive network model of regional straw resource utilization. Through meticulous topological structure analysis, this research elucidates the system's architecture, offering insights into its functionality that is derived from the structure itself. This approach enables the identification of key responsible entities in regional straw resource utilization and their interconnections, fostering multi-entity collaboration in rural waste management. Our findings aim to contribute to the development of a green countryside and the advancement of ecological agriculture, emphasizing the interplay among multiple stakeholders.

3. Data Sources and Methodology

3.1. Data Sources

The China Agricultural Information Network, an authoritative and influential national agricultural portal under the Ministry of Agriculture and Rural Affairs of China, serves as the foundational data source for this study. In this research, by leveraging Python, we homed in on "straw" as a pivotal keyword to systematically mine data from news articles published on the designated portal spanning from January 2016 to September 2023. In the preliminary phase of our investigation, we deployed advanced web-scraping algorithms to autonomously traverse a predetermined volume of web pages. For each page, a bespoke URL was constructed, embedding the term "straw" to ensure the alignment of the extracted content with our thematic research focus. Subsequently, we meticulously accessed links preserved in our repository to retrieve textual content from news articles. In instances where the initial scraping did not yield the desired content, we revisited the links, thus reinforcing the comprehensiveness and integrity of our data collection. Furthermore, capitalizing on the data thus gleaned, we embarked on a scrupulous keyword matching endeavor grounded in entities like "government" and "farmer", as identified from our extensive literature review. In this matrix, a news article mentioning "government" was algorithmically ascribed a value of 1, while its absence entailed a value of 0. This systematic approach was replicated across all the pertinent entities, culminating in the transformation of each news article into a discrete row within our data matrix, thereby effectively capturing a binary representation of the presence or absence of diverse entities. To ensure accuracy, different expressions referring to the same entity, such as "Government" and "policy," were consolidated under a single category (e.g., all references were counted under "Government"). This methodological approach led to the creation of a matrix database encompassing 32,121 news articles and 10 key entities as follows: Government, Company, Farmer, Research Institution, Broker, Bank, Media, Rural Cooperative, Community Resident, and Consumer.

Building upon the amassed dataset, this study employed Python to intricately analyze and derive associative rules among the 10 entities involved in regional straw resource utilization. Subsequently, utilizing Gephi software and based on the association matrix, a complex network model of regional straw resource utilization was constructed and thoroughly evaluated. This approach not only illuminated the dynamic interplays among various entities but also revealed their relative positions and roles within the network. This comprehensive analysis offers novel insights into optimizing the integrated use of straw resources, significantly contributing to the advancement of ecological agriculture and sustainable rural development.

3.2. Methodology

The methodology of this study is structured into three distinct phases as shown in Figure 1, which are as follows: Initially, text mining was employed to construct a "News-subject" matrix database. This was followed by the application of the Apriori algorithm for association rule mining, focusing on metrics such as Support, Confidence, and Lift. Leveraging this association database, a complex network was then established to conduct a detailed analysis of its characteristics. This analysis is pivotal in discerning the most influential nodes and their interconnections within the network, which holds substantial importance for the effective management and optimization of resources.

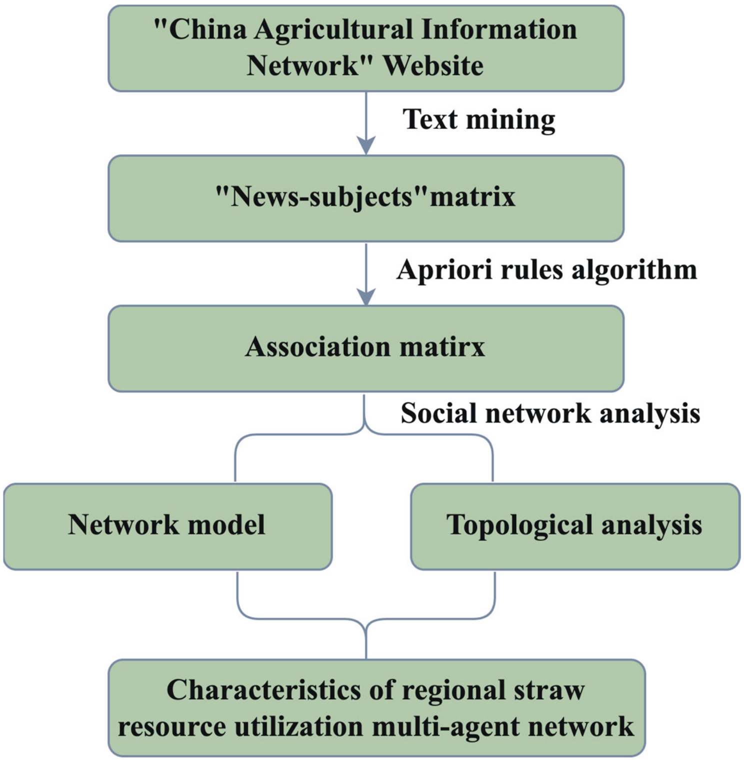

Figure 1. Methodology framework.

(1) Text mining approach

Text mining, often referred to as text data mining or knowledge discovery from textual databases, entails the extraction of significant and non-obvious patterns or knowledge from textual documents [40]. This field synergistically combines methodologies from data mining, machine learning, natural language processing, information retrieval, and knowledge management. This integration is key in addressing the challenge of information overload in the contemporary world [41]. Zhang et al. identified how text mining encompasses text classification, text clustering, the extraction of association rules, and trend analysis [42]. Drury and Roche reviewed the application of text mining for agriculture and concluded that the related applications are mainly those in commodity and food price prediction, pest control, and opinion monitoring [43]. Some scholars also use the text mining approach to dig the existing literature research to sort out the key technologies and research hotspots in the current agricultural field [44]. In this study, text mining was primarily utilized for extracting and analyzing online news data, thereby forming the basis for constructing the initial association matrix database.

(2) Association rule mining

Association rule mining (ARM) is a critical technique aimed at uncovering correlations or causal relationships among factors within unstructured datasets [38]. Let F = {f1, f2, . . ., fn} represent the set of all factors fi(1, 2, . . ., n), and the accident dataset A containing several factors is a subset of F. All such subject datasets together form the subject database B. An association rule is defined as $C \Longrightarrow D$: if C occurs, then D occurs as well, where $C \cap D = \varnothing$ and they form an itemset. C is known as the antecedent of the rule, while D is the consequent.

Key metrics employed to evaluate the strength of the association rules include Support, Confidence, Lift, Leverage, Conviction, and Zhang's Metric [45,46]. The Support and Lift measure the frequency and effectiveness of a rule, respectively. Confidence denotes the conditional probability of the occurrence of D given that C has already occurred. Valid and strong association rules are those with a Lift greater than 1 and the Support and Confidence meeting or exceeding a minimum threshold [46]. Leverage assesses the difference between the observed Support and the expected Support assuming independence of the antecedent and the consequent. A positive value in Leverage indicates a higher frequency of the combined occurrences of C and D than the product of their individual probabilities, suggesting a potential positive correlation or association between them. Conversely, a zero Leverage value implies that the joint frequency of C and D equals the product of their independent frequencies, indicating no significant association and implying independence. Negative Leverage values are indicative of a lesser frequency of C and D appearing together compared with the product of their independent probabilities, potentially signifying a negative correlation between the two variables. Conviction measures the frequency of the occurrence of C in the absence of D compared with the expected frequency if C and D were completely independent. The higher the Conviction value, the higher the efficacy of the rule $C \Longrightarrow D$, implying an increased likelihood of D occurring in the presence of C. A Conviction value significantly higher than 1 indicates that the rule $C \Longrightarrow D$ is highly reliable. Conversely, a Conviction value near 1 suggests that the rule lacks strong predictive power. As the Conviction level increases so does the effectiveness of the rule $C \Longrightarrow D$, implying a higher probability of the concurrent occurrence of C and D. Lastly, Zhang's Metric provides a measure to evaluate the interestingness of a rule by considering both the Confidence and Support. These metrics are integral in identifying the most significant rules that warrant special attention in the analysis. The calculation formulas for metrics such as Support and Confidence are shown in Formulas (1)–(6).

$$\mathrm{Support}(C \Longrightarrow D) = \frac{|\{A : C \cup D \subseteq A, A \subseteq B\}|}{|B|} \tag{1}$$

$$\mathrm{Confidence}(C \Longrightarrow D) = \frac{\mathrm{Support}(C \Longrightarrow D)}{\mathrm{Support}(C)} = \frac{|\{A : C \cup D \subseteq A, A \subseteq B\}|}{|\{A : C \subseteq A, A \subseteq B\}|} \tag{2}$$

$$\mathrm{Lift}(C \Longrightarrow D) = \frac{\mathrm{Support}(C \Longrightarrow D)}{\mathrm{Support}(C) \times \mathrm{Support}(D)} \tag{3}$$

$$\mathrm{Leverage}(C \Longrightarrow D) = \mathrm{Support}\left(C \bigcap D\right) - \mathrm{Support}(C) \times \mathrm{Support}(D) \tag{4}$$

where Support($C \bigcap D$) is the proportional relationship between the concurrent presence of items C and D, Support(C) and Support(D) are the individual occurrences of items C and D.

$$\mathrm{Conviction}(C \Longrightarrow D) = (1 - \mathrm{Support}(D))/(1 - \mathrm{Confidence}(C \Longrightarrow D)) \tag{5}$$

where Support(D) is the degree of Support for D, and Confidence($C \Longrightarrow D$) signifies the probability of the occurrence of itemset D given the presence of itemset C.

$$\mathrm{Zhang}'\mathrm{sMetric}(C \Longrightarrow D) = \frac{\mathrm{Support}(C \bigcap D) - \mathrm{Support}(C) \times \mathrm{Support}(D)}{\max\{\mathrm{Support}(C) \times (1 - \mathrm{Support}(D)), \mathrm{Support}(D) - (1 - \mathrm{Support}(C))\}} \tag{6}$$

where Zhang's Metric has values between -1 and 1. When this value approaches 1, it signifies a strong positive correlation between itemset C and itemset D, indicating that their occurrences are closely linked. Conversely, a value near 0 points to a weaker association, suggesting a less significant relationship. Notably, a negative value in the Zhang metric denotes a negative correlation, implying that the presence of one itemset may inversely affect the probability of the other's occurrence.

Commonly used association rule algorithms include Apriori and FP-Growth. Among these, the Apriori algorithm is the most widely employed due to its simplicity and practicality. It primarily involves two steps as follows: mining all frequent itemsets and generating association rules. The process begins by scanning the original database to identify the first set of candidate items and calculate their Support. Items with a Support that is less than the minimum threshold are discarded, yielding the first frequent itemset. This set is then linked to form the second set of candidate items, which undergoes pruning. The Support for these candidates is computed, and those falling below the threshold are eliminated, resulting in the second frequent itemset. This procedure is repeated until no frequent itemset remain. The Confidence of all the frequent itemsets is calculated, and sets with a Confidence below the minimum threshold are removed, resulting in the formulation of strong association rules. The number of generated rules is closely tied to the parameter thresholds set; too low a threshold leads to an overabundance of rules, making effective filtering challenging, whereas too high a threshold may filter out significant information. Drawing upon the research methodology outlined by Chen et al. [47], this study meticulously analyzes the collected data through statistical methods, determining the quantity of association rules generated under various parameter thresholds, as illustrated in Figure 2. In our rigorous analytical approach, we have established the minimum Support threshold at 0.1 and the minimum Confidence at 0.5. These thresholds significantly exceed those typically set in similar studies of association rules [46], thereby ensuring a heightened level of stringency in the identification of robust association rules.

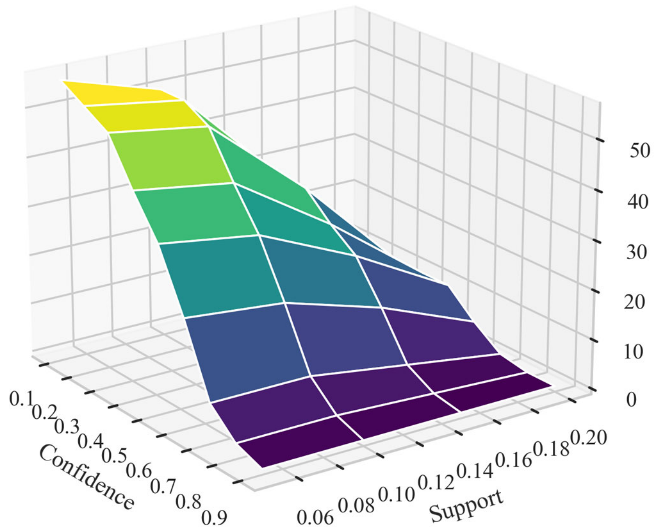

Figure 2. The number of association rules based on different Support and Confidence levels.

(3) Complex Network and Social Network Analysis Methods

In recent decades, complex networks have emerged as a pivotal formalism for representing various scenarios where agent-based models are integral [48]. The formation of these networks is reliant on the dynamic interactions among the diverse components of a system [49]. Four fundamental models characterize complex networks as follows: regular, random, small-world, and scale-free networks, each with unique edge distributions and topological characteristics. For instance, small-world networks are defined by an exponential distribution of nodes, relatively short average path lengths, and high clustering coefficients [50]. Social networks, a specialized form of complex networks, originate from the social sciences and emphasize the social attributes of networks [51]. Social network analysis (SNA) plays a crucial role in mapping diverse networks, elucidating relationships and exchanges between network actors [52]. SNA aims to uncover insights related to the nodes and connections within social networks. Analyzing these networks requires an in-depth examination of their structure [53]. The utilization of visual aids is vital for a comprehensive understanding of social interactions. Scientific visualization tools, such as social network indicators, facilitate the visual analysis of the research object's social network [54].

Social network analysis (SNA) encompasses a variety of indicators crucial for understanding the intricacies of network structures. Key among these are the average degree and various centrality metrics alongside modularity and other parameters. In this study, the numerical aspects of social network analysis (SNA) were conducted using Gephi (version 0.10.2). For the identification of complex network models, Python was employed as the primary computational tool. Additionally, Python programming was utilized to determine the type of network, with specific thresholds set for this classification. In this study, the thresholds for network robustness were determined based on the quantity of nodes and edges within the network. These thresholds were defined as an average clustering coefficient higher than 0.3 and an average shortest path length of less than 5. This methodology allowed for a precise and efficient analysis of network characteristics, aiding in the accurate identification and classification of complex network models.

① The average degree is a pivotal metric in network analysis, representing the mean number of connections per node across the network, as presented in Formula (7) as follows:

$$\text{Average Degree} = \frac{\sum_{i=1}^{n} k_i}{n} \tag{7}$$

where n signifies the total number of nodes in the network, while k_i represents the degree of node i. A higher average degree within the network indicates a more widespread presence of connections, suggesting a faster propagation of information or influence through the network. Conversely, a network with a lower average degree is indicative of a sparser connection state. This distinction in average degree is pivotal as it reflects the network's capacity for efficient information dissemination and the robustness of its interconnectivity.

② The average weighted degree incorporates the average value of edge weights into its calculation. The formula for this is as follows:

$$\text{Average Weighted Degree} = \frac{\sum_{i=1}^{n} w_i \times k_i}{n} \tag{8}$$

where w_i represents the weight of the node I, k_i is the degree of the node i, and n signifies the total number of nodes in the network.

③ The network diameter refers to the maximum value among the lengths of the shortest paths between all the pairs of the nodes in the network. The formula for this is as follows:

$$\text{Network Diameter} = \max(\text{All shortest paths between every pair of nodes}) \tag{9}$$

where the shortest path here refers to the path in the network that has the least number of edges when traveling from one node to another [55].

④ The average path length is the average value of the shortest path lengths between all the possible pairs of the nodes in a network. The formula is as follows:

$$\text{Average Path Length} = \frac{(\text{Sum of the shortest path lengths between all node pairs})}{\left(\frac{n\times(n-1)}{2}\right)} \tag{10}$$

where n is the total number of the node.

⑤ The clustering coefficient is a measure that quantifies the degree to which the neighbors of a given node are interconnected. The formula is as follows:

$$\text{Cluster ingcoefficient} = \frac{2T(i)}{k_i} \tag{11}$$

where T(i) denotes the number of actual edges (triangles) existing among the neighboring nodes of a particular node i. k_i is the degree of node i.

⑥ Centrality analysis is used to measure the importance of the nodes in a network. The main centrality metrics include degree centrality (DC_i), closeness centrality (CC_i), and betweenness centrality (BC_i). In the undirected network, DC_i refers to how many neighbors a node has. The specific formula is as follows:

$$DC_i = \sum_{i=1}^{n} \gamma_{ij} \tag{12}$$

where n is the total number of the nodes; $\gamma_{ij} = 1$ indicates that node i is connected to node j, and $\gamma_{ij} = 0$ indicate that node i is not connected to node j.

The closeness centrality measures the average distance of a node to all the other nodes in the network. The formula is as follows:

$$CC_i = \frac{n-1}{\sum_{j \neq i} d_{ij}} \tag{13}$$

where d_{ij} is the shortest distance between node i and node j. Higher values of CC_i indicate a shorter average distance to the other nodes in the network, allowing for faster communication with other nodes.

The betweenness centrality considers the "bridge" role that a node plays in a network. It is the number of shortest paths in the network that pass through a specific node.

$$DC_i = \sum_{l \neq i \neq m} \frac{\varepsilon_{lm}(i)}{\varepsilon_{lm}} \tag{14}$$

where $\varepsilon_{lm}(i)$ is the number of shortest paths for nodes l to m passing through node i; ε_{lm} is the number of shortest paths for nodes l to m. A node with a high DC_i plays an important role in the flow of information within the network.

⑦ Modularity is used to measure the strength of modules in a network. It indicates how the network is divided into modules.

$$\text{Modularity} = (1/2m) \times \text{sum}\left\{\left[F\{ij\} - \left(\frac{k_i \times k_j}{2m}\right)\right] \times \text{delta}\left(C_i, C_j\right)\right\} \tag{15}$$

where $F\{ij\}$ is an element in the adjacency matrix, indicating whether there is a connection between node i and node j. k_i and k_j are the degrees of node i and node j, m is the total number of edges in the network, and C_i and C_j are community labels between node i and node j, indicating the community to which they belong. Delta is the Kronecker function, which is 1 when $C_i = C_j$, indicating that the two nodes belong to the same community; otherwise, 0 indicates that the two nodes belong to different communities.

⑧ Module tightness is used to measure the degree of close connection between the nodes within each module. The specific calculation formula is as follows:

$$\text{Module tightness} = \frac{L}{M_\theta \times (M_\theta - 1) \div 2} \tag{16}$$

where L represents the number of edges that exist and M is the node within the module θ. The higher the connection density in a module is the closer the connection between nodes in the module is.

4. Results

4.1. Analysis of Correlation Rules among Multiple Entities in Regional Straw Resource Utilization

Based on a comprehensive review of the literature and practical fieldwork, this study reveals that regional straw resource utilization involves a diverse array of stakeholders, including government, companies, farmers, research institutions, brokers, banks, social media organizations, rural cooperatives, community residents, and consumers. Utilizing text mining techniques, this research has compiled a matrix from news articles on China's Agriculture Information Network spanning from January 2016 to September 2023, detailing the involvement of these entities in straw resource utilization, as presented in Table 1.

Table 1. Multi-agent occurrence in the news (part).

Government	Company	Farmer	Research Institution	Broker	Bank	Media	Rural Co-operative	Community Resident	Consumer
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	1	1	0	0	0	0	1	0	0
0	0	1	0	0	0	0	1	0	0

Drawing on the original data from multi-agent news mining and employing Formulas (1)–(3), this study has identified 30 robust multi-agent association rules for regional straw resource utilization. These rules are ranked according to their Lift values, with the top 10 presented in Table 2. Notably, the rule GO, RC $\Longrightarrow$ FA, COM has a Support of 0.1174, a Confidence of 0.5921, and a Lift of 2.0728. This indicates that the joint efforts of the government and rural cooperatives significantly foster enthusiasm among farmers and companies for straw resource utilization. The primary drivers of this trend are the technical challenges and the varied willingness of stakeholders. Currently, the utilization of straw resources is predominantly driven by government initiatives, underscoring the critical role of governmental influence. Meanwhile, as self-organized civil groups, rural cooperatives play a pivotal bridge role in facilitating the scaled utilization of straw resources, mediating between farmers and companies.

Table 2. Top 10 association rules of the regional straw resource utilization multi-agent association Lift.

Antecedents	Consequents	Support	Confidence	Lift
Government, Rural Cooperative	Farmer, Company	0.1174	0.5921	2.0728
Government, Farmer, Company	Rural Cooperative	0.1174	0.6231	1.7836
Farmer, Company	Rural Cooperative	0.1750	0.6128	1.7541
Rural Cooperative	Farmer, Company	0.1750	0.5010	1.7541
Rural Cooperative, Company	Government, Farmer	0.1174	0.5219	1.7527
Government, Farmer, Rural Cooperative	Company	0.1174	0.7347	1.6442
Government, Rural Cooperative	Company	0.1428	0.7198	1.6109
Government, Rural Cooperative, Company	Farmer	0.1174	0.8225	1.6085
Government, Rural Cooperative	Farmer	0.1598	0.8058	1.5759
Government, Farmer	Rural Cooperative	0.1598	0.5367	1.5365

The rule GO, FA, COM $\Longrightarrow$ RC has a Support of 0.1174, a Confidence of 0.6231, and a Lift of 1.7836, This suggests that when governments, companies, and farmers demonstrate a sufficient willingness to utilize straw resources, rural cooperatives are more inclined to engage. Typically, the triangular relationship among governments, companies, and farmers forms a stable supply–demand dynamic for straw resource utilization, making it more attractive to profit-oriented rural cooperatives. This indicates that a stable supply–demand relationship can better attract other market players. However, in the straw resource utilization process, the government's role is mainly that of an external stimulus, with the willingness of companies and farmers being paramount. Therefore, the rule FA, COM $\Longrightarrow$ RC has a Support of 0.1750, a Confidence of 0.6128, and a Lift of 0.7541, highlighting that a complete market structure formed by the supply and demand sides is essential to truly attract other market entities, thereby continually improving and shaping the market.

Utilizing the original data derived from multi-agent news mining and applying Formulas (4)–(6), this study has identified significant Leverage, Conviction, and Zhang's Metric values within the strong association rules of the multi-agent complex network for regional straw resource utilization, as depicted in Figure 3. Among the 30 strong association rules identified, all the Leverage values were positive, with the rule FA $\Longrightarrow$ RC exhibiting the highest Leverage. This indicates that the co-occurrence of FA and RC is more frequent than the product of their independent occurrence probabilities, suggesting a strong positive correlation between them. Similarly, according to the rule RC $\Longrightarrow$ COM, FA showed a high Leverage value, indicating a similar positive correlation. All 30 association rules had Conviction values that were higher than 1, with 13.3% of them exceeding that of 2, thereby affirming their strength. Notably, the rule RC, GO, COM $\Longrightarrow$ FA had a Conviction value of 2.753, underscoring its high effectiveness. This suggests that the occurrence of FA is highly probable when RC, GO, and COM are present, primarily due to government support, corporate utilization, and rural cooperative management of straw resources, which significantly attract farmer participation. The rule RC, GO $\Longrightarrow$ FA had a Conviction value of 2.517, indicating a high probability of FA occurrence in the presence of RC and GO. This suggests that even in the absence of straw resource utilization companies, joint incentives and management by governments and rural cooperatives can enhance farmers' willingness to utilize straw resources. All Zhang's Metric values were higher than 0, indicating a strong correlation between antecedents and consequents in this itemset. The rule RC, COM $\Longrightarrow$ FA had a Zhang's metric value of 0.661, showing a strong positive correlation, thereby implying that transactions including the itemset RC and COM are significantly likely to also include FA. The rule RC, GO $\Longrightarrow$ COM, FA with a Zhang's Metric value of 0.646 demonstrates a strong association between RC, GO, and COM, FA.

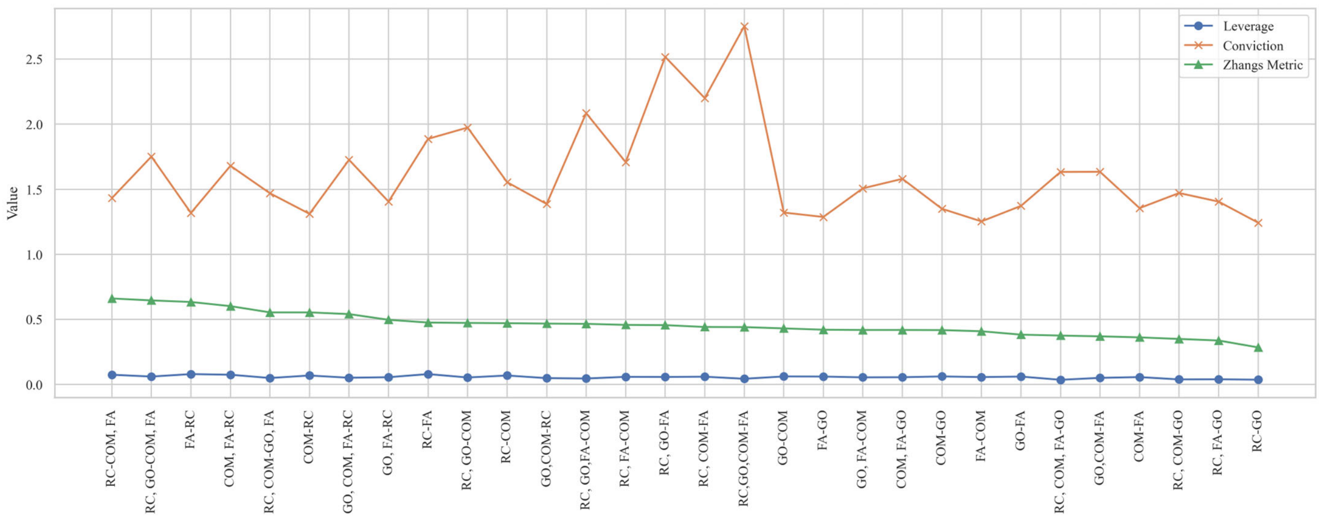

Figure 3. The Leverage, Conviction, and Zhang's Metric values of association rules for regional straw resource utilization in multi-agent complex networks.

4.2. Analysis of Regional Straw Resource Utilization's Multi-Agent Complex Network and Network Characteristics

In this study, focusing on the multi-agent association rules for regional straw resource utilization, we utilized Gephi software to construct an undirected graph network comprising 14 nodes and 24 edges, as illustrated in Figure 4.

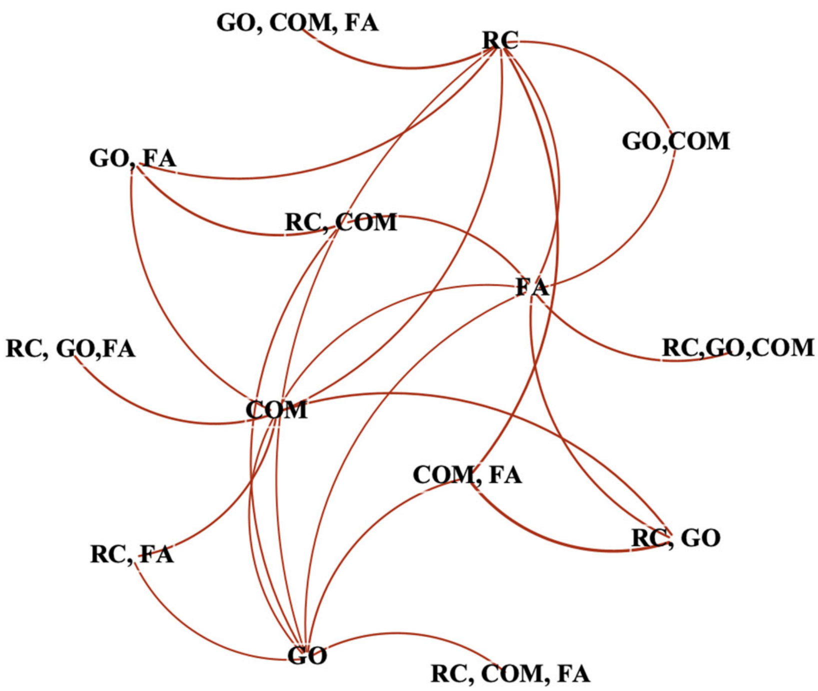

Figure 4. Multi-agent complex network in regional straw resource utilization.

(1) Average degree and average weighted degree

Based on Formulas (7) and (8), our study determined that the average degree of the multi-agent network for regional straw resource utilization is 3.429. This indicates that, within this network, each entity—such as government, farmers, and companies—averages direct connections or interactions with approximately 3.429 other entities. Furthermore, an average weighted degree of 5.169 suggests a robust network not only in terms of the quantity of connections but also in their level of reliance. These findings highlight that the inter-agent relationships within the regional straw resource utilization network are strong both in quantity and quality, thereby underscoring the intricate and interdependent nature of this ecosystem.

(2) Average path length, clustering coefficient, and network model

Utilizing Formulas (9)–(11), our research deduced that the diameter of the multi-agent network in regional straw resource utilization is 3, with an average path length of 1.945. This signifies that, on average, a fluctuation in one node can be triggered in just 1.945 steps, reflecting the close-knit connectivity of the network. The high interconnectivity among various agents, such as government, farmers, and businesses, implies that a change in the state of one node can easily instigate a chain reaction among the others, thereby facilitating the effective allocation and utilization of straw resources. Moreover, the network exhibits a high clustering coefficient of 0.319, indicating a tendency towards tightly knit groupings. Consequently, with its relatively short average path length and high average clustering coefficient, this network aligns with the characteristics of a small-world network. Accordingly, we classify the multi-agent network in regional straw resource utilization as a Newman–Watts small-world network, as evidenced by the uniform degree distribution shown in Figure 5. This classification underscores the network's capability for rapid information and resource dissemination. Even if certain connections or nodes undergo changes, the network retains its core functionality, demonstrating robustness and adaptability to new dynamics. Furthermore, the diverse cooperative models among the different agents contribute to a complex dynamic equilibrium within the network.

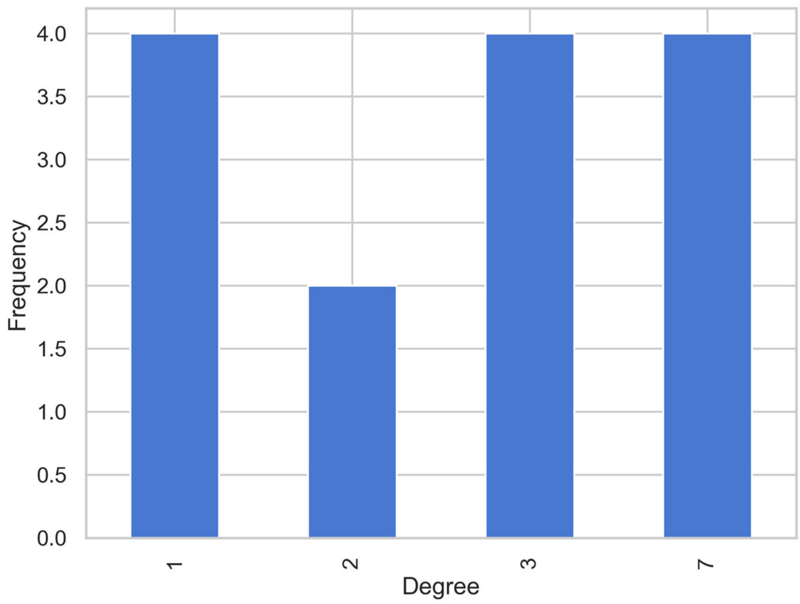

Figure 5. Multi-agent correlation network degree distribution in regional straw resource utilization.

(3) Centrality analysis

Employing Formulas (12)–(14), our study identified the degree centrality, closeness centrality, and betweenness centrality for the 14 nodes within the multi-agent network of regional straw resource utilization, as illustrated in Table 3. Table 3 reveals that individual agents, such as straw resource utilization companies, farmers, governments, and rural cooperatives, play pivotal roles within the entire network of association rules. These entities are also central to the multi-agent network for straw resource utilization. Notably, the betweenness centrality of these four nodes reaches 20.167, underscoring their significant role in the network's information exchange. The centrality indices for the interconnecting nodes between companies and farmers, the government and farmers, rural cooperatives and companies, and rural cooperatives and the government are also elevated, indicating that the supply and demand sides in straw resource utilization consistently occupy crucial positions within the network.

Table 3. Centrality analysis of associated nodes for regional straw resource utilization (part).

Associated Node	Degree Centrality	Closeness Centrality	Betweenness Centrality
Company	7	0.684	20.167
Farmer	7	0.684	20.167
Government	7	0.684	20.167
Rural Cooperative	7	0.684	20.167
Company, Farmer	3	0.52	1.333
Government, Farmer	3	0.52	1.333
Rural Cooperative, Company	3	0.52	1.333
Rural Cooperative, Government	3	0.52	1.333

(4) Modularity

Utilizing the modularity function in Gephi software, the modularity of the multi-agent association rule network for regional straw resource utilization was calculated to be 0.218, with the community network organization and specific divisions being depicted in Figure 6. All four primary agents—government, companies, farmers, and rural cooperatives—are present in each of the four communities. This underscores that these four entities are central among the ten agents identified in our study's regional straw resource utilization network.

The network's overall community structure is distinctly divided into four groups, each with varying degrees of node density and tight internal node connections, highlighting localized network density.

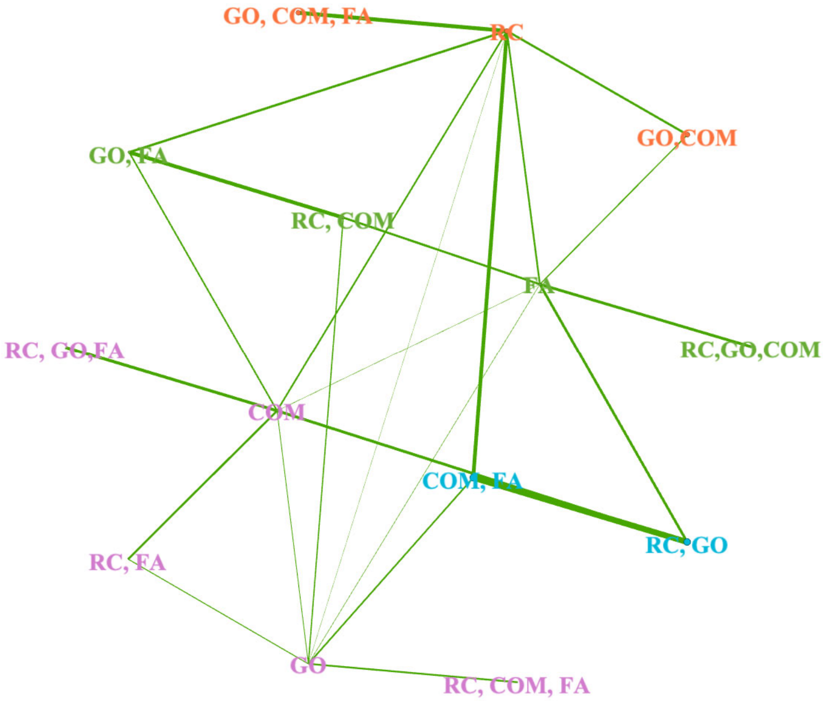

Figure 6. Modularity division diagram of multi-agent association rules for regional straw resource utilization.

According to Formula (16), the module containing the association rules (FA, COM) and (RC, CO) (blue) has a module tightness degree of 1, indicating strong tightness within this module. A likely reason for this is that of the preliminary market relationships established between farmers and resource utilization companies, though these are not yet sufficient. Given the current development stage of straw resource utilization, external stimulation or support are necessary, hence the crucial role of government and rural cooperatives in this association. Another module, comprising (GO, COM), (GO, COM, FA), and (RC) (yellow), has a cohesion degree of 0.667, suggesting tightly knit internal cohesion. This likely results from the involvement of external organizations like rural cooperatives, which are attracted by the initial development scale of the straw resource utilization of government-supported enterprise, further enhancing the regional straw resource utilization market. The module tightness degrees of the other two modules also exceed 0.5, indicating tight interconnections among the various agent networks.

4.3. Robustness Analysis

The robustness analysis of the complex networks, particularly through Monte Carlo simulations, is an essential method for examining network stability and resilience in the face of disruptions such as attacks or failures [56]. This research focuses on the multi-agent networks involved in regional straw resource utilization. Understanding and evaluating the stability of these networks is vital for identifying the central agents and their roles within the overall network structure. Utilizing Python, the study conducts Monte Carlo simulations to implement two strategies as follows: random attacks and targeted attacks based on node significance [57]. This approach facilitates a comprehensive analysis of network robustness, offering critical decision-making support for identifying key agents in straw resource utilization networks.

In this study, we simulated the robustness of network nodes by setting a failure threshold ranging from 1 to 20, with an increment of 1 at each step. Using the Monte

Carlo simulation, we employed two strategies as follows: random attacks and targeted attacks based on node importance. The variations in network robustness following these attacks are recorded in Figure 7. The results show that network robustness gradually decreases with the increase in the number of failed nodes, which occurs irrespective of the attack strategy. However, a comparative analysis reveals that intentional attacks disrupt the network more rapidly than random attacks. This finding suggests that strategically enhancing the willingness of core agents to utilize straw resources is more effective in maintaining network robustness.

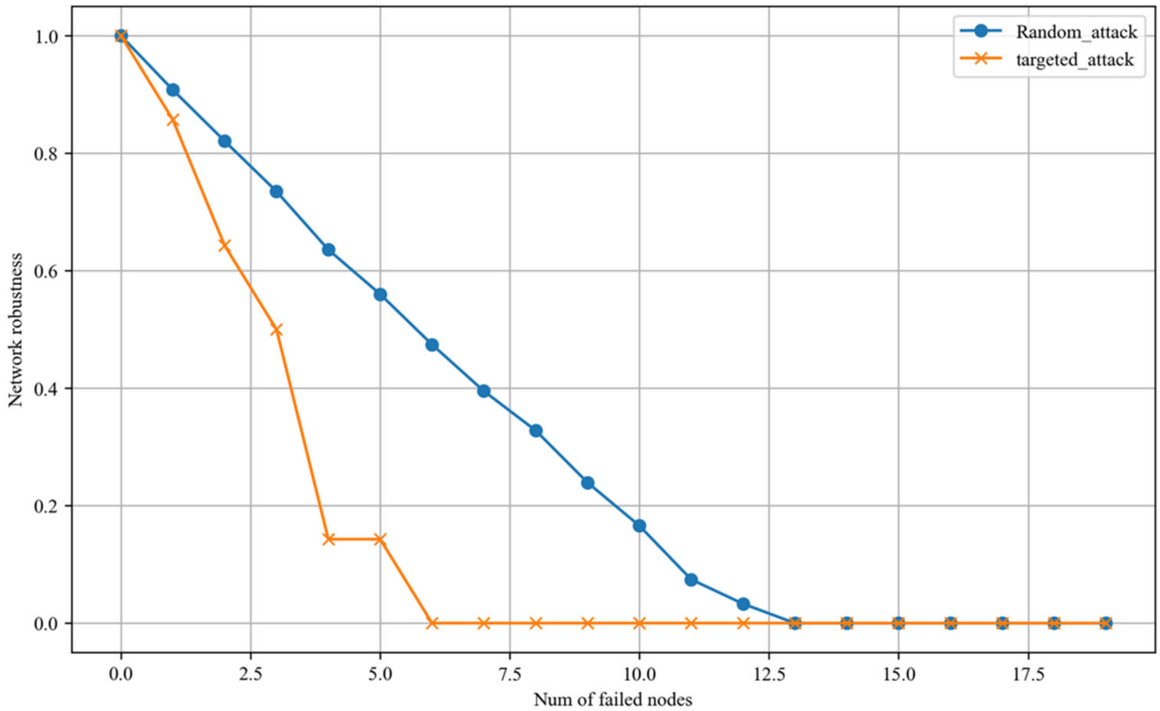

Figure 7. Robustness change diagram of network node failure.

Our study explored the impact of different attack ratios, specifically those of 20%, 40%, and 50%, on the average network reachability following random and targeted attacks, as depicted in Figure 8. After randomly removing 20% of the nodes, the size of the network's largest connected subgraph was on average 82.285% of the original network, thereby indicating that the overall structure and function of the network remain relatively stable when nodes are randomly removed. However, the average network reachability after targeted attacks was 0.6428, signifying that the targeted removal of critical nodes severely impacts the overall connectivity of the network. Similarly, when 40% of the nodes were randomly removed, the average size of the largest connected subgraph reduced to 55.428% of the original network, thereby demonstrating a certain degree of robustness to random attacks but with a significant loss in connectivity. At this point, the average reachability under targeted attacks dropped to 0.1429, indicating that the robustness of the network significantly diminishes under deliberate attacks, with the largest connected subgraph reducing to approximately 14% of the original network. This highlights the severe impact on network connectivity and functionality when critical nodes are targeted. When the attack rate reached 50%, the average network reachability after targeted attacks dropped to 0, signifying the complete collapse of the network.

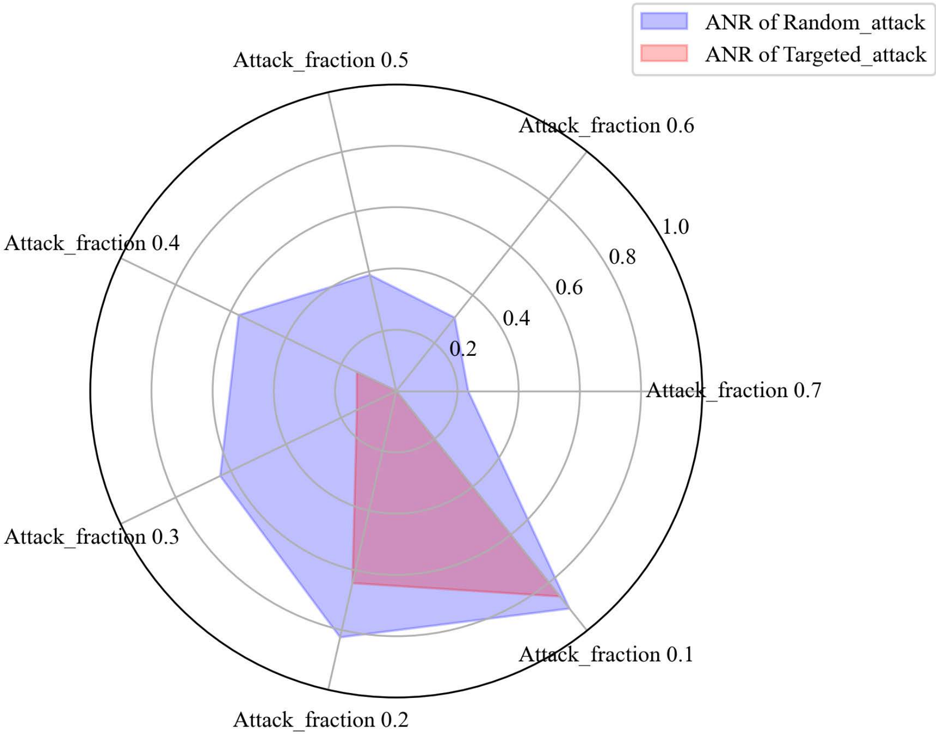

Figure 8. Average network reachability of random attacks and targeted attacks under different attack probabilities.

5. Discussions and Conclusions

5.1. Construct of a Robust Regional Supply and Demand Market for Straw Resource Utilization

In our study of the regional straw resource utilization multi-agent network, we identified 30 closely interconnected associations, each varying in their interrelations. The strongest connections were observed among farmers, businesses, governments, and rural cooperatives. Rural cooperatives, primarily composed of farmers with a high willingness to utilize straw, significantly contribute to the probability of these groups appearing together more frequently than individually. The combination of government and rural cooperatives is tightly linked to the business and farmer duo. The government, as a key external driver in the initial stages of regional straw resource utilization, primarily exerts influence through fiscal measures to guide and stimulate development [58]. Rural cooperatives, as self-organized profit-oriented organizations, are pillars of rural policy, promoting economic cooperation and market integration [59,60]. However, they also exhibit characteristics such as economic fragility and dependency on government support [61]. Therefore, the combination of the external stimulus from the government and cooperatives encourages businesses and farmers to move towards straw utilization. A stable market supply and demand pattern formed by the government, farmers, and companies is crucial in attracting rural cooperatives. Current research focuses on the interrelation of these entities as they are the fundamental market and external environmental entities, thereby forming the base of regional straw resource utilization development [32]. As the straw utilization market evolves, it attracts more market participants, such as rural cooperatives, which also play a role in mitigating the vulnerability of small-scale farmers to poverty [62]. Thus, policymakers should focus on the relationship between market supply and demand, which is formed by farmers and businesses, while continuously improving the utilization market through external forces like those of governments and cooperatives in order to establish a robust utilization framework, as shown as Figure 9.

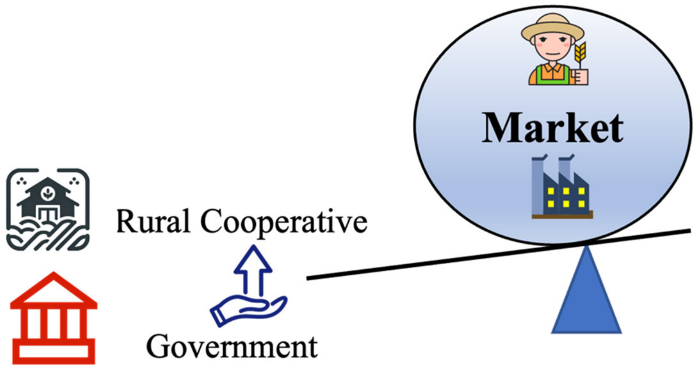

Figure 9. Regional straw resource utilization stabilizes the market and promotes the main subject.

5.2. The Association Network among Agents Is a Small-World Network

Based on indicators like the average weighted degree and network diameter, it is evident that the network of multi-agent associations in regional straw resource utilization is closely-knit, exhibiting the characteristics of the NW small-world network. Small-world networks are known for their high clustering coefficients, short average path lengths, and robustness against random node failures. However, they can be extremely vulnerable to attacks on critical nodes [63,64]. Our study finds that the network of multi-agent associations in straw resource utilization aligns closely with these characteristics.

Current research often focuses on individual entities, such as analyzing farmers' willingness to utilize straw resources from a psychological perspective [13] or the significance of government policies in encouraging such utilization [65]. However, given the small-world network traits of the regional straw resource utilization network, the interconnections and key relationships between different entities should be a focal point. This is especially important when considering the maturation and perfection of the entire network. Particular attention should be paid to the mutual influences among entities during the formation of the basic market as the pursuit of environmental benefits in straw resource utilization is as crucial as its economic benefits are [66]. Thus, in enhancing the level of regional straw resource utilization, it is not only the willingness of individual entities that should be considered but also the interactive influences among them. Recent studies have been focusing on this aspect, employing game theory to analyze the interactive behaviors among multiple entities. This trend is positive, indicating a growing recognition of the importance of inter-entity interactions for the overall utilization level. However, current research has paid less attention to the associations between rural cooperatives and other entities like farmers, businesses, and governments, which are indispensable to the network.

In the NW small-world network of multi-agent associations in regional straw resource utilization, rural cooperatives play a significant role and are closely associated with other entities. Therefore, in efforts to enhance straw resource utilization at the regional level, attention should not only be given to farmers, businesses, and governments but also to external entities like rural cooperatives.

5.3. Diverse Cooperative Models among Multiple Agents in Regional Straw Resource Utilization

In the realm of regional straw resource utilization, multiple agents play a critical role, and their influencing factors are diverse and complex. Consequently, regions develop unique patterns based on their specific characteristics, which are primarily reflected in the varying degrees of interrelations among the involved parties. This study, grounded in original data derived from word frequency analysis in news reports, reveals that the co-occurrence of multiple agents in these reports indicates collaborative links that foster market-oriented development and the effectiveness of external environmental stimuli.

We categorize the existing models of regional straw resource utilization into four types, which are based on the level of market-oriented development and the impact of external stimuli, as illustrated in Figure 10. Module ① represents regions where a stable market for straw resource utilization is emerging, involving companies and farmers with potential for large-scale utilization. Governmental external stimuli are present, but market expansion is limited due to farmers' willingness and corporate costs. In such developmental stages, regions are often advised to use financial incentives and other measures to invigorate the market. Module ② depicts regions with small-scale utilization, lacking the joint drive of government and rural cooperatives. Module ③ includes five interconnected agents with clear external stimuli, such as government incentives for farmers and cooperatives. However, the level of market development and the stability of government incentives are not high, thereby necessitating external stimuli to be more impactful. Module ④ represents an ideal state, forming a tightly knit cooperation model among farmers' cooperatives, companies, and the government.

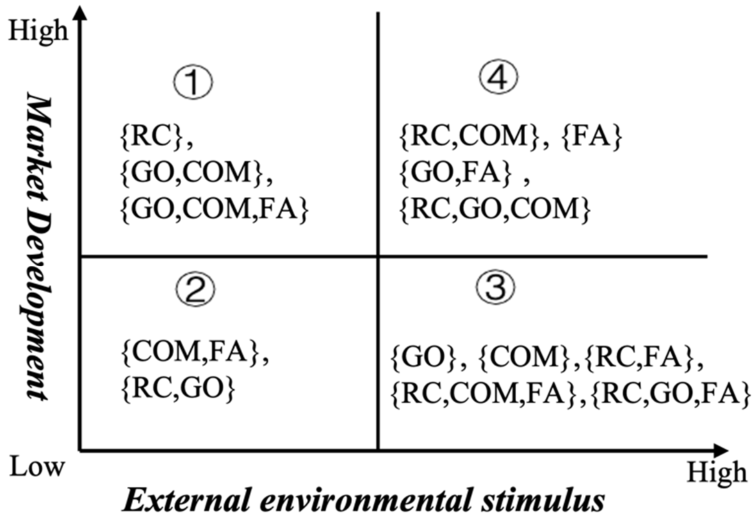

Figure 10. Multi-agent community division matrix of regional straw resource utilization.

Given the distinct characteristics of straw resource utilization in various regions of China, the developmental models differ mainly in the degree and effectiveness of inter-agent relationships. Future development strategies should emphasize the two aspects as follows: firstly, that of market-oriented development, focusing on the utilization intentions of companies and farmers; secondly, that of the support coming from the external environment, such as from governments and cooperatives. However, the roles of other agents should not be overlooked in this dynamic.

In this research, we employed text mining techniques and the Apriori algorithm for association rules to extract a multi-agent relational database from online news sources, thereby analyzing multiple subjects with strong associations. Building upon this, we constructed a regional straw resource utilization multi-agent relational network, examining its network characteristics, model types, and overall stability through robustness testing, with a focus on the influence of core nodes. Key findings include the concentration of regional straw resource utilization among farmers, businesses, governments, and rural cooperatives. Farmers and businesses emerge as market players, while cooperatives and governments act as external facilitators to enhance market development.

Our study reveals that this multi-agent network exhibits the properties of the NW small-world network, characterized by relatively short average path lengths and high average clustering coefficients. We found that targeted attacks on this network result in faster degradation compared with random attacks, with individual agent nodes consistently playing crucial roles. The network is divided into four modules with tight intra-module connections.

Furthermore, the discussion in our study suggests that farmers, businesses, and governments have formed a robust regional straw resource utilization market model. However, considering the small-world network characteristics, market perfection requires the integration of additional external market entities, like rural cooperatives. Current regional straw resource utilization patterns should focus on market-driven development and external environmental stimuli, with targeted policy recommendations to address these aspects.

This study acknowledges certain limitations. For instance, the number of agents identified through the association rule algorithm was limited, excluding roles like brokers. This may be attributed to the underdeveloped logistics supply chain for straw resource utilization in China, which has not significantly contributed to the overall improvement in regional straw resource utilization. However, the involvement of brokers could be beneficial in reducing the costs for businesses to acquire straw and further facilitate the marketization of straw utilization. Additionally, it is important to acknowledge that the data underpinning our study were derived from secondary sources available online rather than being directly sourced from key stakeholders, which might have offered a more nuanced perspective. Moving forward, we aim to integrate these two data modalities more effectively into our future research endeavors.

In subsequent research, the focus will shift towards an in-depth exploration of the evolution and sophistication of the multi-agent network in regional straw resource utilization, with a particular emphasis on the incorporation of key additional agents, notably that of brokers. This is predicated on the understanding that the supply system constitutes one of the fundamental subsystems underpinning the effective utilization of straw resources in the region. Meanwhile, using an approach that is based on the perspective of complex systems theory, our study will scrutinize the subsystems composed of diverse entities and endeavor to synthesize these subsystems into an intricate network. By examining the dynamics and emergent properties of this complex network, we aim to delve into the synergistic effects of multi-agent collaboration in the realm of straw resource utilization. This perspective is crucial for future focus in this field. The approach is designed to foster a more comprehensive grasp of market dynamics and to identify innovative strategies that could significantly augment the efficiency and efficacy of straw resource utilization.

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