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Original scientific paper

A Multi-Dimensional Fusion Method for Identifying Key Nodes in New Energy Vehicle Supply Chains

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Abstract: This paper proposes a multi-dimensional fusion method for identifying key nodes in new energy vehicle supply chains, considering the structural characteristics and risk propagation properties of the network. The method integrates network centrality analysis, the SIR model for risk propagation, and the cascading failure model to comprehensively evaluate the importance of nodes in the supply chain network. The proposed method is applied to the supply chain networks of Tesla and Xpeng brands, constructed from industry data. The results reveal that the key nodes with a strong impact on risk propagation include not only core enterprises such as batteries but also accessory industries with hidden leading positions. The proposed method provides a more comprehensive approach to identifying potential and critical risk control nodes in new energy vehicle supply chains, which has significant practical implications for supply chain risk management.

Keywords: automobile supply chain; cascading failure model; complex network; new energy vehicle; SIR model

1 INTRODUCTION

The automobile supply chain network presents the typical complex network characteristics as it involves many subjects. Using complex automobile supply chain network based knowledge to study the cascading failure mechanism and corresponding management measures in the process of risk factors producing and spreading is of great practical significance to improve the risk resistance and stability of automobile supply chain in our country. Besides, the development of the new-energy-connected-vehicle concept and manufacturing industry has led to the rapid development of new technologies and new business models, which urgently requires the stability of the complex supply chain network in fierce market competition.

Today, the automotive industry is moving towards electrification, networking, intelligence and sharing, which will lead to great changes in the supply chain and supplier structure. Therefore, it is very important to establish a safe, efficient and sustainable supply chain in the development of new energy vehicle industry. Different from the traditional supply chain of automobile industry, the high complexity and high cost of components make the supply chain of new energy vehicle face many risks in the transition and innovation stage. However, relatively few studies have been done on risk management in the supply chain of new energy vehicles (NEV) [1, 2], and most have focused only on single risk factor study. Mihalis and Thanos [3] applied failure mode and effect analysis (FMEA) technique to identify and assess supply chain sustainability-related risks and to test potential correlations between identified risks. Song et al. [4] proposed a rough weighted decision making and trial evaluation laboratory (DEMATEL) to identify key risk factors in sustainable supply chain management. Han et al. [5] derived the optimal centralized decisions of a vertically integrated supply chain and designed a subsidy-sharing-based sales rebate/penalty (SS-SRP) contract which lead to a Pareto-improving win-win situation for both the NEV manufacturer and retailer compared to the non-coordination case. Wu et al. [6] studied new energy vehicle recycling decisions and supply chain contract coordination and found that different manufacturer in the dominant position may cause different influence in supply chain coordination. Shao et al. [7] used the system dynamic model to analyze the coping ability under the demand impact of new energy vehicles and the risk of supply interruption of the lithium supply chain.

Pure electric vehicle (EV) has great potential in reducing environmental pollution and has become an important strategic direction for sustainable development in the future [8]. Wu et al. [9] used a combined hesitant fuzzy linguistic term set with fuzzy synthetic evaluation to conduct the risk assessment on Chinese electric vehicle supply chain and found that the risk related to EV supply chain in China mainly comes from the technical risk and market risk. Li et al. [10] developed a novel two-stage comprehensive mathematical model to select a set of suppliers and assigned an order quantity to each supplier, which help enterprises manage uncertainty in SCRM and new energy vehicles industry. However, supply chain management focused on the buyer and sellers linear relationship [11, 12]. While a linear perspective may help to plan some of the entrenched trading processes between buyers and sellers, it did not reflect the complexity of the strategic behavior of the enterprise [13]. There is a growing discussion about the benefits of adopting a complex network based perspective in supply chain management. At present, dependent networks are mainly divided into physical networks and correlation networks. Brunetti et al. [14] showed that both physical and correlation networks can provide effective market information for enterprises.

Complex networks and network analysis related methods have generated many applications in the supply chain. Liu et al. [15] simulated the evolution process of strategic selection for each supply chain link to set information nodes independently or collectively under the unconstrained government rewards conditions and punishments. Zhao et al. [16] proposed a node removal model to realize the lean of supply chain network. Mishra et al. [17] used the Nash security point to obtain the bargaining solution describing the optimal links in a complex supply chain network. Wang et al. [18] conducted an intelligent analysis of the information flow in the enterprise logistics management based on the supply chain management, and obtained the increasing efficiency by the artificial intelligence algorithm. Wang et al. [19] proposed a framework for identifying vulnerable agents in supply chain network, consisting of three main components: supply chain dynamic network, risk transmission model, and identifying vulnerable nodes.

The existing methods for identifying key nodes in supply chain networks have several limitations. One significant limitation is the trade-off between time efficiency and accuracy; many methods cannot optimize both simultaneously [20]. Another issue is the neglect of local clustering coefficients, which are critical for evaluating a node's importance within its immediate network [21]. Additionally, while some methods consider degree and neighborhood information, they often lack a tunable parameter to adjust the influence of neighbor information, which is essential for adapting the importance of nodes to specific network characteristics [22]. These limitations highlight the need for more advanced methods that can provide a nuanced measure of node centrality.

Risk propagation in supply chain has been the subject in many studies. If one enterprise supplying failure is causing its partners producing failure, the risk will spread to other enterprises in the network one after another. Therefore, it is necessary to study the network robustness under cascading failures [23-25]. Zeng. et al. [26] established a cluster supply chain network cascade model and introduced the concept of network load entropy to analyze and predict the dynamic behaviors of the vulnerability during the process of failure spreading. Tang et al. [27] studied the robustness of an assembly supply chain network under numerical simulation by constructing a cascading failure model of risk propagation. Buldyrev et al. [28] developed a framework for understanding the robustness of interacting networks subject affected by cascading failure and proposed exact analytical solution for the critical fraction of nodes. Zhu et al. [29] established two multi-objective optimization models considering the operational cost of the edges and the robustness of the networks to improve the robustness of the network. Tan et al. [30] proposed a model of modified betweenness based on defined controllable coefficient of initial load and took simulation experiments to obtain a better coefficient for network viability and survivability.

For automotive supply chains, there is also some outstanding research work, Pasha J. et al. [31] studied on the selection of vehicles for factory-in-a-box manufacturing and decisions regarding the optimal routes within the supply chain, and a customized multi-objective hybrid metaheuristic solution algorithm is designed to minimize the total cost associated with traversing the edges of the network and the total cost associated with visiting the nodes of the network. Fathollahi-Fard et al. [32] for the first time proposed a dual-channel, multi-product, multi-period, multi-echelon closed-loop supply chain network design under uncertainty for the tire industry, and two new hybrid meta-heuristic algorithms with new procedures is applied. Due to the growing interest in sustainability and green economy, many scholars have considered circular economy and green development in automotive supply chain management [33-37]. In addition, since the automotive supply chain industry contains a large amount of data and involves many enterprises, some recent studies have incorporated the most advanced blockchain technology into the automotive supply chain management to ensure the nontampering and traceability of data at different stages of the automotive supply chain [38-41].

In the NEV industry, supply chain risk management is confronted with a series of unique challenges. The complexity of the supply chain in this sector is exceptionally high, encompassing multiple stages from raw material procurement to final product delivery [42]. Rapid technological changes necessitate that supply chains swiftly adapt to new manufacturing processes and product designs [43]. Additionally, policy uncertainty, such as changes in subsidies for electric vehicles and environmental regulations, adds further complexity to supply chain management [44]. These characteristics demand that researchers and practitioners develop new methods for risk management. Moreover, the complex automobile supply chain network has the characteristics of long supply chain, many participators and complex relationships. Therefore, when a single node or a group of nodes fails, the network is prone to cascading failure, which leads to the efficiency reduction and function failure of automobile supply chain.

This article firstly constructs the TESLA motors supply chain network and the XPENG motors supply chain network, and analyzes the centrality characteristics of two networks. At the same time, considering the systemic characteristics of automobile supply chain, the risk immune propagation model is introduced to analyze the network and discover the key nodes. Finally, the two networks are analyzed by cascading failure model for the key nodes from another perspective. Through the integration of the aforementioned models, our objective is to develop a comprehensive evaluation framework aimed at identifying pivotal nodes of risk propagation within the automotive supply chain network from a multidimensional standpoint. This approach seeks to tackle the challenge of pinpointing critical nodes within the actual automotive supply chain, especially when only supplier relationships are accessible. By adopting this strategy, we can discern crucial enterprises beyond conventional core entities like battery manufacturers, thereby offering a more thorough methodology for assessing risks within the new energy vehicle supply chain.

This work has significant implications for supply chain risk management in the new energy vehicle industry and beyond. Firstly, it offers a fresh perspective on identifying and assessing risk propagation paths and key nodes within supply chains, crucial for optimizing structures and bolstering resilience. Secondly, our multidimensional analysis uncovers overlooked key enterprises, aiding managers in devising better risk mitigation strategies. Lastly, our methodologies and findings can be applied to risk management in other industries, providing valuable assessment tools and decision support. These contributions enhance reliability and offer innovative risk management solutions for the new energy vehicle sector and beyond.

2 METHODS AND MATERIALS

2.1 Datasets

We obtained information from public data and websites about the companies that TESLA and

XPENGMotors have business relationships in the Chinese region. The data source of this article is published in the China Federation of Logistics and Purchasing website by China New Energy Vehicle Supply Chain Industry Overview 2022 (http://www.chinawuliu.com.cn/xsyj /202301/13/597476.shtml). The report integrates the relevant statistical data of Zhongshang Industry Research Institute, Apsoto Automobile Research Institute and Founder Securities. We use real data where there are transactions between each other, anecdotal data or data where it is not possible to verify that a real purchase has taken place has been cleaned and filtered. And then we constructed an adjacency matrix with each company as a node, and built a supply chain network for XPENG Motors and TESLA Motors. In our previous work [45], the data was organized and correlation networks were constructed by the adjacency matrix.

2.2 Structural Features in Network

Degree centrality is the most direct metric to portray node centrality in network analysis. Degree centrality of a node is calculated as $DC_i = \frac{k_i}{N-1}$, and k_i denotes the number of existing edges connected to node i, $N - 1$ denotes the number of edges of node i that are connected to all other nodes.

The eigenvector centrality assumes that the influence of a node is determined by both the number of neighbors and the impact of these neighbors. It can be expressed as $EC_i = \sum_j A_{ij} C_E(j)$, where A_{ij} = 1 if i connects to j otherwise 0.

The betweenness centrality BC_i measures the importance of node i along the shortest path between other nodes which is defined as $BC_i = \sum_{s<t} \frac{n_{st}^i}{g_{st}}$, where g_{st} is the number of shortest paths between node s and t, n_{st}^i is the number of shortest path passing through node i.

Define d_{ij} as the length of shortest path between nodes i and j, then the average length of the shortest path between node i and other nodes is denoted as $l_i = \frac{1}{n}\sum_j d_{ij}$. The closeness centrality of node i as $C_c(I) = \frac{1}{L_I}\frac{N}{\sum_j d_{ij}}$

The relevant model parameters are the best results obtained through testing and suggestions from the relevant literature. Limitations: the existing method can only judge whether it is in the center of the structural features, and cannot measure all structural features, relatively single and not comprehensive. Possible impact on the results: the more indicators are selected, the more accurate the results of the ranking of indicators will be, the current consideration is not comprehensive enough resulting in limited accuracy.

2.3 Cascading Failure Model

Tan et al [30] used the model of modified betweenness to deal with the propagation effect of node failure in real time networks and avoid the occurrence of network collapse. They established a scale-free network to conduct simulation experiments and determined the appropriate model parameters. In this part, we use above model, build a load distribution model of node failure, which can attack each node by traversing. The goal of network load rebalance is achieved by distributing the load of the failed node to adjacent nodes with larger load capacity. By comparing the proportion of effective nodes that still exist in the network after attacking, we can evaluate the influence of every enterprise on Cascade Failure.

The initial load [30] on the node is:

$$L_n(0) = (1+q)B_n^\alpha \tag{1}$$

where q and α are parameters used to control the initial load distribution, B_n^α is the betweenness of node n. In the case of α = 0.6, the nodes with larger or smaller betweenness have the least influence on the network when they are attacked, and the network is more robust [28]. So we take q = 0.5, α = 0.6 to choose the nodes that still have a greater impact on the network.

The capacity of the node is defined by its initial load as:

$$C_n(0) = (1+\beta)L_n(0) \tag{2}$$

where $\beta > 0$ denotes the tolerance coefficient of the node. The bigger β of the node, the more additional capacity it has, and the better invulnerability at cascading failure, but the higher of its network cost. So we strike an average of β = 0.5 after several experiments. The load distribution strategy of the node is as follows: when node n fails, its load is distributed to the node with large capacity in the adjacent node.

Thus, the percentage of allocated load per node at this point is:

$$\prod_e = \frac{C_e}{\sum_{i\in F_n} C_i} \tag{3}$$

where C_e is the load of node e evolved from the initial node load in Eq. (2). The allocated load of failed nodes adjacent node e is:

$$\Delta L_{en} = \prod_e L_n \tag{4}$$

If the adjacent node e receives the allocated load and the accumulated load exceeds its capacity, as

$$L_e(t) = L_e(t-1) + \Delta L_{en} \ge C_e \tag{5}$$

It will cause the failure of the adjacent node. So the ratio S of the effective nodes before (N) and after (N') the node failure is used to measure the invulnerability of the network.

$$S = \frac{N'}{N} \tag{6}$$

The smaller the value of S is, the more influence it has on the network when it fails, and the more important it is. The relevant model settings are the best results obtained through suggestions from the relevant literature. The model settings were selected as the optimal values based on the findings of the relevant studies, which did not have a significant impact on the results.

2.4 Sensitivity Analysis

First, the calculation of centrality has no error and can be accurate to any bit. However, the result of centrality calculation is retained from the fourth bit, and only the change in the third bit will affect the result. Artificial perturbation affects the ranking only when the value of centrality changes by more than 0.01, which means the sensitivity of the parameter is weak.

Second, since the final ranking takes the top ten or twenty, we consider these nodes to be important. There is an effect on the SIR model and the cascade failure model, but it is not significant, especially since the cascade failure model is the optimal value selected based on relevant studies.

2.5 Expert Interview

We conduct interviews with industry experts to validate the practicality and usefulness of the proposed method in real-world supply chain risk management. This will provide valuable feedback on the strengths and limitations of the method and guide future research directions.

3 RESULTS

3.1 Construction of Supply Chain Network

In this section, we construct TESLA and XPENG automobile supply chain network and analyze the centrality characteristic of the network, as the first part of our comprehensive evaluation model. At present, the new energy vehicle supply chain has a high degree of similarity, this paper selects Xiaopeng and Tesla as typical domestic and foreign enterprise representatives for analysis. In addition, at present, Xiaopeng and Tesla are the two new energy vehicle enterprises that have the better disclosure of information in the public channel and more complete information of the upstream and downstream supply chain. Based on our previous work [45], we constructed the TESLA and XPENG supply chain networks by the adjacency matrix. The nodes of the two supply chain networks are suppliers in the relevant automotive supply chain. The connecting edges between the nodes indicate that there is a verifiable cooperative relationship between the two nodes (suppliers).

3.1.1 Supply Chain Network and Characteristics of TESLA

There are 127 nodes and 154 edges in TESLA supply chain network (T) (as shown in Fig. 1). The average degree of the network is 2.425, the average path length is 2.671, and the average clustering coefficient is 0.0833.

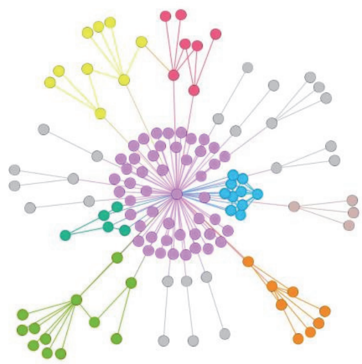


Figure 1 TESLA supply chain network

Table 1 TESLA supply chain network analysis of node characteristic

Num	Degree		Eigenvector		Intermediate		Proximity Degree	
	Name	Value	Name	Value	Name	Value	Name	Value
1	Tesla	0.6349	Tesla	0.6852	Tesla	0.9727	Tesla	0.7325
2	Token Sciences	0.0793	DMEGC	0.1603	Token Sciences	0.1158	Token Sciences	0.4500
3	DMEGC	0.0714	Zhejiang Wanma	0.1004	Wus Printed Circuit	0.0779	Wus Printed Circuit	0.4421
4	TDG	0.0634	Guodian Nanjing Automation	0.1004	Hitachi Chemical	0.0623	Sumitomo Chemical	0.4390
5	Wus Printed Circuit	0.0555	EAST	0.1004	Sumitomo Chemical	0.0546	Hitachi Chemical	0.4390
6	Sumitomo Chemical	0.0476	TGOOD	0.1004	TPK	0.0472	JDI	0.4375
7	Hitachi Chemical	0.0476	Shenzhen Clou Electronics*	0.1004	Magna	0.0472	DMEGC	0.4375
8	Panasonic	0.0317	Kstar*	0.1004	Panasonic	0.0390	Panasonic	0.4329
9	Nbtm	0.0317	ZHONHEN*	0.1004	MITSUBISHI	0.0316	Nbtm	0.4329
10	TPK	0.0317	SAEPP*	0.1004	BGRT	0.0316	TPK	0.4329
11	Magna	0.0317	Token Sciences	0.0923	Nbtm	0.0308	Magna	0.4329

For the Tesla Supply Chain Network, the degree centrality, the eigenvector centrality, the intermediate centrality and the proximity degree centrality are calculated respectively, the top 11(due to juxtaposition) nodes are shown in Tab. 1 (There are Some abbreviations in Tab. 1: SAEPP means Shenzhen Auto Electric Power Plant; Nbtm means Nbtm New Materials Group; BGRT means Bengbu Gaohua Resolution Technology; MITSUBISHI means MITSUBISHI Chemical holdings).

In a supply chain network, nodes with high value of degree centrality usually have more business relationship with other nodes. Enterprises in line "Degree" of Tab. 1 have large scale and powerful antirisk ability. But if they have problems and cannot cooperate with the connected nodes, the risk will spread rapidly. So improving the risk resistance of these enterprises or supporting them when exposed to risk shocks can effectively reduce the speed of risk diffusion and impact scale, which can control the risk effect at a lower cost. The eigenvector centrality of a node indicates the importance of its adjacent nodes, which emphasizes the cooperative environment that the more important the connected enterprises are, the more important the enterprise is. In a complex automobile supply chain network, except the degree centrality, the nodes with high value of eigenvector centrality should be evaluated as key nodes because of their important cooperative relationship. What's more, enterprises marked with "*" in line "Eigenvector" of Tab. 1 do not appear in line "Degree".

After our analysis, these enterprises have fewer business ties with other enterprises, but their partners in automotive supply chain network play the central part and leading action, therefore, the influence of their commodity flow and capital flow on supply chain network cannot be ignored. The intermediate centrality reflects the shortest path between nodes, which means node with higher value has stronger control over the information transmission. In the supply chain network, this information usually represents the flow of funds. So enterprise as hub node with higher value should pay more attention to its financial status and avoid the financial risk which may cause the connected enterprises to difficult position of the fund flow disruption. The proximity degree centrality measures the average length of the shortest path from each node to the other nodes. It always appears at the same time with the intermediate centrality.

3.1.2 Supply Chain Network and Characteristics of XPENG Motors

There are 72 nodes and 73 edges in XPENG supply chain network (XP) (as shown in Fig. 2). The average degree of the network is 2.028, the average path length is 2.234, and the average clustering coefficient is 0.0556.

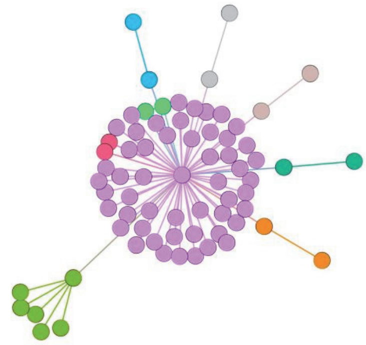


Figure 2 XPENG supply chain network

For the XPENG Supply Chain Network, the degree centrality, the eigenvector centrality, the intermediate centrality and the proximity degree centrality are calculated respectively, the top 11 (due to juxtaposition) nodes are shown in Tab. 2.

Table 2 XPENG supply chain network analysis of node characteristic

Num	Degree		Eigenvector		Intermediate		Proximity Degree	
	Name	Value	Name	Value	Name	Value	Name	Value
1	XPeng Motors	0.8591	XPeng Motors	0.7041	XPeng Motors	0.9911	XPeng Motors	0.8765
2	CAT	0.0845	HUAWEI	0.1026	CAT	0.1368	CAT	0.5035
3	HUAWEI	0.0281	Infypower	0.1026	Shenzhen Clou Electronics	0.0281	Shenzhen Clou Electronics	0.4765
4	Shenzhen Clou Electronics	0.0281	Desay SV	0.1026	CYGSUNRI	0.0281	CYGSUNRI	0.4765
5	Infypower	0.0281	NVIDIA	0.1026	WuHanMingjie	0.0281	WuHanMingjie	0.4765
6	CYGSUNRI	0.0281	CAT	0.0975	CFAA	0.0281	CFAA	0.4765
7	Desay SV	0.0281	Shenzhen Clou Electronics	0.0910	Yanfeng	0.0281	Yanfeng	0.4765
8	NVIDIA	0.0281	CYGSUNRI	0.0910	SunKyung	0	HUAWEI	0.4733
9	WuHanMingjie	0.0281	WuHanMingjie	0.0910	NRNET	0	Infypower	0.4733
10	CFAA	0.0281	CFAA	0.0910	Xiamen Tungsten	0	Desay SV	0.4733
11	Yanfeng	0.0281	Yanfeng	0.0910	Ganfeng Lithium	0	NVIDIA	0.4733

The characteristic analysis of the degree centrality, the eigenvector centrality, the intermediate centrality and the proximity degree centrality are normally the same with last chapter. It is worth noting that in the XPENG supply chain network, the value of the intermediate centrality is 0 starting from Num. 8 SunKyung because of the structure of the supply chain network. The enterprises with low value or 0 value mostly play the roles of supplier and seller in the network, while the enterprises with high value are the manufacturers, as the hub node controls the capital flow between upstream and downstream enterprises. This also explains that the key enterprises in the supply chain network are mostly manufacturers.

3.1.3 Comparison Analysis

As can be seen from the generated network (Fig. 1 and Fig. 2), the two networks are formed with TESLA and XPENG motors as the key node respectively. The degree of TESLA and XPENG is large, while most of other nodes are small. TESLA and XPENG motors play an absolutely dominant role in supply chain networks, and both networks have scale-free characteristic. Due to their business scale and operation capacity, these two enterprises have strong ability of risk resistance and internal digestion, which can avoid risk spreading on the network. But once the risk level exceeds their sustainability and causes the failure of the enterprise, due to the scale-free characteristic, it may directly lead to the collapse of the entire network.

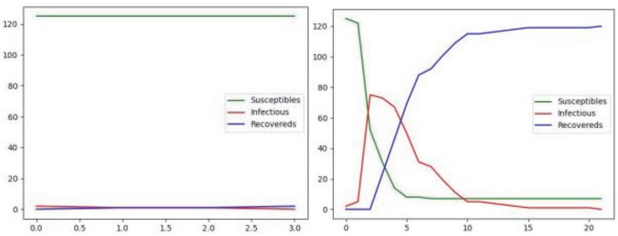
Compared with Tab. 1 and Tab. 2, the top 11 enterprises in TESLA and XPENG supply chain network do not appear repeatedly. Therefore, the core enterprises in the two supply chain networks are different and independent.

3.2 Construction of Supply Chain Network

In this section, we use the risk immune propagation model to analyze the TELSA and XPENG networks and discover the key nodes with high transmission influence, considering the systemic characteristics of automobile supply chain. When some agents in the supply chain are failure, the whole supply chain may be influenced [19]. And the risk propagation process in the supply chain network has strong similarity with virus diffusion in terms of diffusion environment, diffusion process, diffusion object and diffusion direction. The above explanation provides an idea for the application of the SIR model to the immune propagation of risk in automotive supply chain networks.

3.2.1 SIR Model Analysis of TESLA Supply Chain Network

The SIR Model for Tesla Motors Supply Chain Networks is constructed with related methods [46], and the infection rate and recovery rate of the SIR model are set at 0.3 and 0.1 respectively. The infection rate and recovery rate are obtained by traversing all parameters of [0.1] at intervals of 0.1. By randomly selecting an initial node as the susceptible node, it is found that due to the structural characteristics of the network the risk propagation in most cases is as shown in Fig. 3a. The SIR risk propagation diagram after many times simulations is shown in Fig. 3b.



(a) (b)

Figure 3 TESLA supply chain network risk transmission

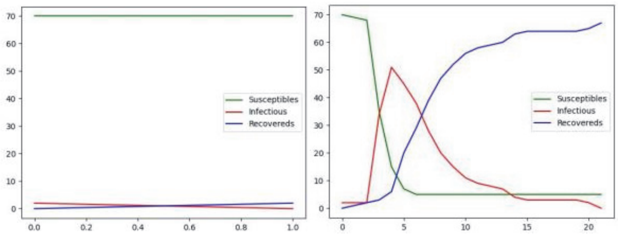
In order to explore the influence of initial risk points on network risk propagation, each node in the network is analyzed as an initial infection node. Use "(number of infected nodes + number of recovered nodes)/total nodes" as an evaluation index to measure the transmission influence caused by each node. According to Fig. 3b, we set the infection rate as 0.3, the recovery rate as 0.1, and the experimental steps as 10 steps. After 100 times of experiments, the average value is taken as the final evaluation index, and the top 20 nodes among 127 nodes are finally selected. The results are shown in Tab. 3 (Some abbreviations: HAT means Hongteo Accurate Technology; SAEPP means Shenzhen Auto Electric Power Plant; ATT means Anhui Tatfook Technology; GNA means Guodian Nanjing Automation; FGIG means Fuyao Glass Industry Group; NYSM means Nanjing Yunhai Special Metal.).

Table 3 TESLA supply chain network analysis of SIR model

	Name	Value		Name	Value
1	FUTURIS	0.7877	11	Michelyne	0.7758
2	Ningbo Tuopu Group	0.7866	12	ATT	0.7742
3	DMEGC	0.7861	13	GNA	0.7704
4	Tesla	0.7858	14	TDG	0.7700
5	ShenzhenClou Electronics	0.7834	15	FGIG	0.7676
6	BizLink	0.7812	16	Eande Technology	0.7633
7	Kstar	0.7806	17	Asahi Glass	0.7633
8	NVIDIA	0.7786	18	XJ ELECTRIC	0.7621
9	HAT	0.7774	19	HVCC	0.7620
10	SAEPP	0.7763	20	NYSM	0.7604

3.2.2 SIR Model Analysis of XPENG Supply Chain Network

The SIR Model for XPENG Motors Supply Chain Networks is constructed, and the infection rate and recovery rate of the SIR model are set at 0.3 and 0.1 respectively. By randomly selecting an initial node as the susceptible node, it is found that due to the structural characteristics of the network the risk propagation in most cases is as shown in Fig. 4a.The SIR risk propagation diagram after many times simulations is shown in Fig. 4b.



(a) (b)

Figure 4 XPENG supply chain network risk transmission

In order to explore the influence of initial risk points on network risk propagation, each node in the network is analyzed as an initial infection node. We set the infection rate as 0.3, the recovery rate as 0.1, and the experimental steps as 10 steps. After 100 times of experiments, the average value is taken as the final evaluation index, and the top 10 nodes among 72 nodes are finally selected. The results are shown in Tab. 4.

Table 4 XPENG supply chain network analysis of SIR model

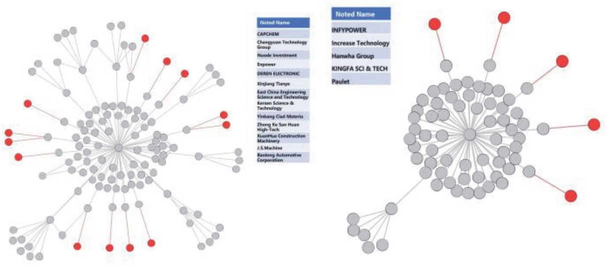
Num	Name	Value
1	XPeng Motors	0.7272
2	TGOOD	0.7141
3	Kstar	0.6638
4	HUAWEI	0.6631
5	HUIZHONG	0.6544
6	NVIDIA	0.6501
7	LG	0.6493
8	Topology	0.6455
9	iFLYTEK	0.6452
10	Michelyne	0.6423

Compared with Tab. 1 and Tab. 3, Tab. 2 and Tab. 4, it can be seen that most of the nodes selected by centrality index also exist in the nodes selected by SIR Model, which can verify the accuracy of the method for key node selection on the one hand.

3.3 Cascading Failure Analysis of Two Networks

In this section, we use the cascading failure model to analyze the TESLA and XPENG networks and to find the key nodes of risk transmission, as the last part of our comprehensive evaluation model. $q = 0.5$ and $\alpha = 0.6$ are taken to choose the nodes that still have a greater impact on the network. And the whole cascading failure model is shown in Method part.

We attack every node in the supply chain network of TESLA and XPENG and compare their S value. The selected nodes ranked by S value in each networks are shown in Fig. 5a and Fig. 5b. In TESLA supply chain network, the enterprise ranked by the lowest S value is: CAPCHEM, Changyuan Technology Group, Nuode Investment, Enpower, DEREN ELECTRONIC, Xinjiang Tianye, East China Engineering Science and Technology, Kersen Science & Technology, Yinbang, Clad Materia, Zhong Ke San Huan HighTech, XuanHua Construction Machinery, J.S.Machine, Baolong Automotive Corporation. And in XPENG supply chain network, the enterprise ranked by the lowest S value is: INFYPOWER, Increase Technology, Hanwha Group, KINGFA SCI & TECH, Paulet.



(a) (b)

Figure 5 Selected nodes in each network

It is generally believed that the enterprises in NEV supply chain networks producing core components such as charging posts, batteries, motors and electronic control are the most important ones. In TESLA supply chain network, Nuode Investment shares more than 35% in the domestic power battery market, which is No. 1 in China. As a secondary supplier to TESLA, CAPCHEM provides electrolyte for Panasonics lithium batteries, which is one of the leading suppliers in electrolyte area with a market share of about 17%. Enpower mainly produces the New Energy Vehicle Power Assembly, Power Assembly, drive motor and other core parts in the new energy vehicle power field with the market share of about 27.5%. And in XPENG supply chain network, INFYPOWER specializes in power supply and system solutions for the new energy industry and plays an important role in the automotive supply chain system, whose degree centrality, eigenvector centrality and proximity degree centrality are also in the front rank. Although Increase Technology is not the core of the network, as a secondary supplier, its main business is to produce the core components of charging post, which indirectly has an important impact on the network risk propagation.

The cascading failure model shows that these enterprises are the core component suppliers of new energy vehicles, their market scale is large, which has an important impact on the supply chain network risk propagation.

3.4 Discussion

After analyzing the rest of enterprises ranked by the cascading failure model, we found that although these enterprises are structurally less important than enterprises that directly supply the core components of new energy vehicles, such as charging posts and batteries, most of them are leaders in their industries, taking a large share of the market.

In TESLA supply chain network, Zhong Ke San Huan HighTech has over 30% market share of neodymium-iron-boron magnet for automobile. Their products are widely used in various fields such as transportation, energy, communication, home appliances, machinery, and medical care. These magnets are key components of electric motors in new energy vehicles, crucial for enhancing motor efficiency and performance. J.S.Machine manufactures control arms for TESLA Systems, and its foundry subsidiary is the exclusive supplier of some parts of TESLA's models. DEREN ELECTRONIC, which is responsible for automotive connectors and wiring harnesses in the automobile supply chain, is the leading manufacturer of connectors and the largest and most powerful professional electrical connector manufacturer in China. East China Engineering Science and Technology, as a producer of ethylene glycol which is the main component of new energy vehicle antifreeze, takes the market share as high as 60%.

And in XPENG supply chain network, Hanwha Group, KINGFA SCI & TECH and Paulet are all producers of engineering plastics. For the sake of lightweight in new energy vehicles, vehicle modified plastics are widely used in automotive interior and exterior decoration such as dashboard assembly, door panels, bumpers, lights, wheel cover and other parts. So once these enterprises fail, many automobile parts involved cannot be produced, which has a negative impact on the normal operation of related enterprises and leads to cascading failure of the network. Especially KINGFA SCI & TECH, which is the domestic and Asia-Pacific regions largest modified plastics producer in the modified plastics industry, has market share of 10%. Since its role in supplying the modified plastic to XPENG is irreplaceable, the network is more vulnerable if it fails.

The enterprises mentioned wield significant influence on supply chain risk management for Tesla and XPeng. For instance, Zhong Ke San Huan HighTech's dominance in supplying neodymium-iron-boron magnets for Tesla's electric motors underscores the need for diversification of magnet suppliers or investment in alternative motor technologies. Similarly, collaborative efforts between Tesla and DEREN ELECTRONIC could enhance supply chain visibility to mitigate risks associated with disruptions in connector or wiring harness supply. XPeng, on the other hand, may explore strategies like inventory optimization and dual sourcing to address potential disruptions stemming from key suppliers like Hanwha Group and KINGFA SCI & TECH. Proactive measures such as these are essential to bolster supply chain resilience and mitigate the impact of disruptions within these automotive supply chains.

After analyzing the results, we conducted interviews with industry experts of China Automotive Logistics Association of China Federation of Logistics and Purchasing. The experts believe that the proposed methodology is meaningful for the current new energy vehicle supply chain and is also important for the development of related companies. Therefore, the identification of key nodes in the supply chain network by our model holds significant implications for risk management practices in the NEV industry. The products of these companies directly affect the performance and safety of new energy vehicles, hence their position in the supply chain directly relates to the industry's risk level. For instance, the quality and supply stability of magnetic materials can impact the reliability of motors, while the use of high-performance materials is closely related to the durability and safety of vehicles. In conclusion, although unimportant in the network structure analysis of centrality index, nodes selected by cascading failure model need to be concerned because of their high market share in each industry. When their failure interrupts the supply, fewer enterprises in the network can share its load leading to risk propagation.

4 CONCLUSION

Through the above multi-perspective analysis, we suggest that in the automotive supply chain network, we should not only pay attention to the influence of core enterprises on risk propagation, but also avoid ignoring the influence of the accessory industries with hidden leading position. Under the comprehensive and multi-dimensional fusion of key nodes identification in risk propagation, the potential key nodes for risk control in the new energy vehicle supply chain network can be well found. The results obtained in this paper enrich the previous understanding of the important nodes of risk propagation in the new energy vehicle supply chain networks, and are of great significance to the risk prevention of the network.

This paper proposes a multi-dimensional fusion method for identifying key nodes in new energy vehicle supply chains, which integrates network centrality analysis, the SIR model for risk propagation, and the cascading failure model. The method is applied to the supply chain networks of Tesla and Xpeng brands, revealing that the key nodes with a strong impact on risk propagation include not only core enterprises such as batteries but also accessory industries with hidden leading positions, such as Zhong Ke San Huan HighTech and KINGFA SCI & TECH. The proposed method provides a more comprehensive approach to identifying potential and critical risk control nodes in new energy vehicle supply chains, compared to existing single-factor studies or network structure-based methods. The findings have significant practical implications for supply chain risk management in the new energy vehicle industry, such as informing targeted mitigation strategies and resilience measures. However, the current study is limited by the scope of the supply chain networks analyzed and the potential biases in the data sources. Future research could explore the generalizability of the proposed method to other industries, incorporate dynamic risk propagation models, and investigate the impact of supply chain network structure on risk resilience. Overall, the multi-dimensional fusion method proposed in this paper contributes to the advancement of supply chain risk management research and practice, particularly in the context of the rapidly evolving new energy vehicle industry.

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