Hindawi
International Journal of Intelligent Systems
Volume 2023, Article ID 3338184, 10 pages
https://doi.org/10.1155/2023/3338184

Research Article

Industrial Chain Disruption Events Monitoring with Deep Learning Methods: A Practical Application in China

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Received 2 March 2023; Revised 26 July 2023; Accepted 10 August 2023; Published 11 September 2023

Academic Editor: B. B. Gupta

Globalization has made the industrial chain longer and more complex, resulting in greater vulnerability to emergencies, such as the COVID-19 pandemic, earthquakes, and wars. Emergencies will lead to plant shutdowns, supply shortages, market blockades, and other risk events, leading to large-scale supply chain disruption, also known as industrial chain disruption. The safety and stability of the industrial chain are the foundation of national economic stability. All countries attach great importance to risk monitoring leading to the interruption of the industrial chain. However, at present, the risk monitoring method of the industrial chain is mainly to screen out the risk events that may cause the industrial chain disruption from news by manually monitoring the news media. It is of great significance to establish an efficient automatic monitoring system for industrial chain disruption events (ICDE). In this paper, an ICDE monitoring model is proposed to identify ICDE automatically using deep learning technology. The ICDE monitoring model consists of an ICDE identification model and an ICDE correlation model. The former identifies risk events from online news through the Ernie model, while the latter matches risk events with industrial chain nodes through similar nodes and virtual nodes. Similar nodes refer to synonyms in industrial chain nodes. Virtual nodes refer to the words that appear in a large number in the news and do not exist in the industrial chain, but they form an inclusive relationship with the nodes of the industrial chain. Finally, the model is applied to the new energy vehicle industry chain as an example. The application results show that the model can monitor ICDE on each node of the industry chain in real time, and the identification accuracy of ICDE is 92%. Through the ICDE monitoring model, the national or local government can formulate measures to reduce industrial losses in time and track the risk status of the industrial chain in real time.

1. Introduction

Globalization has created a longer and more complex supply chain. Supply chain disruption refers to the interruption of the flow of certain goods or services in the supply chain of an enterprise [1, 2]. Any disruption in the supply chain may lead to the failure of the entire supply chain [3]. It has a serious negative impact on the company's customers and suppliers and will affect the company's performance [4–6]. Recently, COVID-19 has had an unprecedented impact on normal supply and demand patterns, leading to the disruption of logistics and supply chain systems [7, 8]. This kind of supply chain disruption is no longer only for a single enterprise but for all enterprises in the industry. This large-scale supply chain disruption of the industry is called industrial chain disruption, and it causes a great impact.

Hou and Zhao [9] developed a methodology for identifying, prioritizing, and managing the potential supply chain risks based on hierarchical holographic modeling. The model filters risk sources according to the interests and responsibilities of supply chain managers. In supply chain networks, many companies rely on specific suppliers. Zare-Garizy and others [10] combined multiparty computational cryptography methods with risk identification algorithms in social network analysis to identify risks in supply chain networks. From the 1980s to the 2010s, the technology for identifying supply chain risks significantly shifted from reactive methods to proactive methods [11]. Deiva Ganesh and Kalpana [12] used text mining methods to understand potential supply chain risk factors in real time. Aboutorab and others [13] used reinforcement learning to proactively identify operational risk events in the supply chain. The current research still focuses on the supply chain risk, mainly for the monitoring and identification of the supply chain risk faced by a company. It can be seen that some scholars turn to artificial intelligence technology to actively identify supply chain risks and improve the efficiency of risk identification.

In terms of industrial chain risk monitoring and identification, Okabe and Ohtani [14] constructed a risk model for evaluating the risks involved in industrial safety. Levner and Ptuskin [15] proposed an entropy-based optimization model to evaluate the economic loss caused by environmental risks in the supply chain. Wu and others [16] used the Interval Type-2 Fuzzy Prospect Theory and TOPSIS method to evaluate the resilience level of the coal industrial chain. A subjective scoring method is used to score the coal industry chain in Shaanxi Province. Li and others [17] established an evaluation index system to evaluate the trade risks of industrial chain nodes for different countries. The HS code is used to associate the nodes of the industrial chain to obtain the international trade data of each node. At present, there is little research on the risk of industrial chain, mainly using the evaluation method to evaluate and analyse the overall risk of industrial chain. Although some studies have analysed the risk of industrial chain nodes, it is still a static risk and cannot actively identify the risk of industrial chain.

The industrial chain disruption will affect all enterprises in the industrial chain, and active risk management is very important for the industrial chain. The traditional way of industrial chain risk monitoring is to send researchers to pay attention to news on major media websites, extract news events that affect the industrial chain, and then judge the affected nodes and the degree of risk. With the increasing number of industrial chains that need to be monitored, the manual monitoring method has problems such as being time-consuming and labor-intensive, limited news sources for monitoring, and large time delay from monitoring to output results. Automated and intelligent processing of news can greatly improve the efficiency of industrial chain disruption events (ICDE) monitoring. In terms of news recognition, public opinion monitoring has been widely used in various fields. Under the big data environment, the university network public opinion dynamic monitoring system model was built, which has the characteristics of short monitoring time and high monitoring accuracy [18]. The Internet of Things was explored for campus public opinion monitoring [19]. An online public opinion monitoring system for agricultural products was established to help the agricultural sector shift from passive public opinion to active public opinion [20]. A GloVe-LSTM model was established to monitor COVID-19 related tweets [21]. A multichannel deep learning model was proposed to detect fake news, with an accuracy of 95% [22]. The current deep learning technology can effectively understand text semantics and perform text classification, so the current deep learning technology can be used to achieve intelligent monitoring.

Deep learning approaches have been utilized to process tasks such as images, videos, and text [23–25]. Among them, BERT (Bidirectional Encoder Representations from Transformers) [26] has been successfully applied in many NLP tasks [27–29]. The ERNIR pretraining model includes entity-level masking and phrase-level masking, which has achieved better results on Chinese natural language processing tasks [30]. This paper aims to establish an ICDE monitoring model based on deep learning methods to automatically identify the risk events on the nodes of the industrial chain. Timely discovery and prompt of possible risks of the industrial chain nodes will help the national or local governments locate the risk nodes of the industrial chain faster, formulate measures to stabilize the industrial chain as soon as possible, and reduce the impact of industrial chain interruption.

The main contributions of this paper include the following aspects:

First, massive news events are used for industrial chain risk monitoring. It has changed the previous qualitative analysis mode of the industrial chain risk and improved the industrial chain risk monitoring system.

Second, the ICDE identification model is established with deep learning methods, which can monitor and identify the risk events in the industrial chain with high frequency and automatically.

Third, the ICDE correlation model is established to match and correlate ICDE with industrial chain nodes. The model improves the matching hit rate by building an industrial chain node database based on virtual nodes and similar nodes.

The rest of this paper is organized as follows: Section 2 introduces the ICDE identification model; Section 3 describes the ICDE correlation model and gives the example results of matching and correlation; Section 4 shows the application results; Section 5 presents the conclusion.

2. ICDE Identification Model

2.1. Dataset. The model uses news titles as input to identify whether news is an ICDE. A total of more than 20000 news titles were collected, and the risk was marked through manual review. Finally, a set of industrial chain event data set containing more than 600 risk events was formed. Some examples of data are shown in Table 1.

According to the number of risk events, 150 (25%) risk events were randomly selected and the same number of risk-free events was randomly selected. A total of 300 news data constitute a test set, and the rest are used as a training set.

2.2. Modeling. The ERNIE model is a pretrained model trained from massive unlabeled data, which can be used in specific fields using fine-tuning. The ICDE identification model is based on the ERNIR pretraining model, and a classifier layer is added at the top of the model. A total of more than 20000 news titles were collected to form a training set by manually marking risk events in the industrial chain

Table 1: Sample data.

News title	Risk label
AFS: 34000 vehicles were lost worldwide due to lack of core last week, and the loss of production fell for the third consecutive week	Risk
Greenland revoked the local iron ore mining license of Chinese companies	Risk
EU ambassador extends sanctions on China and the EU-China investment agreement gets into trouble	Risk
Mobile phone manufacturers are also doomed, and the global chip shortage has begun to sweep across the smartphone industry	Risk
Indonesia announced a one-month ban on coal exports, accounting for 75% of China's coal imports	Risk
Can hair coloring cause cancer? More and more studies have found that these cancer risks will increase	Risk-free
UK LGIM continues to hold Chinese stocks, although Chinese companies are subject to regulatory pressure and believe that the risk of European and American stock markets is greater	Risk-free
Analysts look down on precious metals, and the price of gold may plummet to $1600 in the next year	Risk-free
India's largest steel company cut production by 10% due to an oxygen shortage	Risk-free
Tesla CEO Musk exercised options and sold some shares to pay taxes	Risk-free

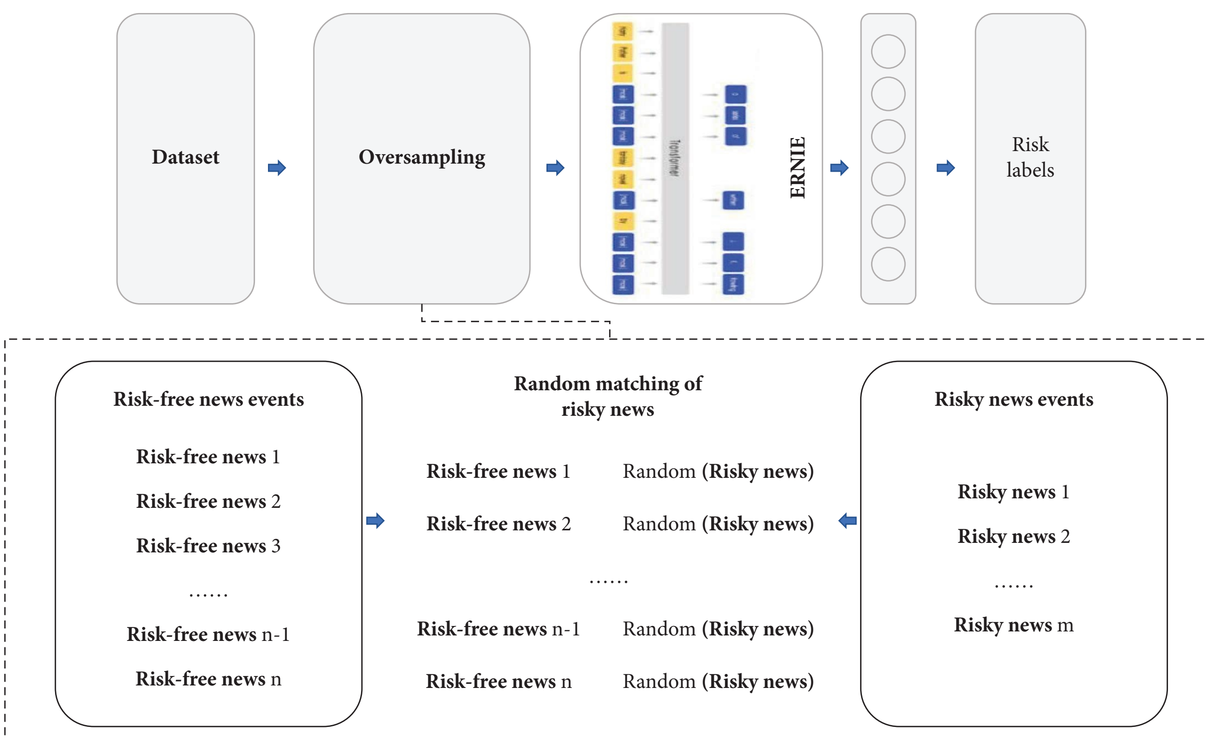

Figure 1: Model framework.

(see Section 2.1 for details). The obtained training set was used to fine-tune the model. Since the training set is a data set with unbalanced samples, the oversampling method was used to balance the data. Each risk-free event was randomly matched to a risk event, which balanced the proportion of risk-free events and risk events in the training set. The framework of the ICDE identification model is shown in Figure 1.

An Nvidia T4 was used to fine-tune the model. After one epoch of training, the model has been well fitted. The fitting process is shown in Figure 2, and the prediction accuracy in the test set is 91%. As a comparison, a sentiment classification model is used to identify the risk events of the test set. Treat positive sentiment events as risk-free events and negative sentiment events as risk events. The test results show that the accuracy rate of the sentiment classification model is only 31%. Because the number of risk events used for training and testing is too small, the ICDE identification model may have overfitting problems. Therefore, the ICDE identification model was iterated several times to improve the generalization ability and accuracy of the model. The iterative process is shown in Figure 3. The model

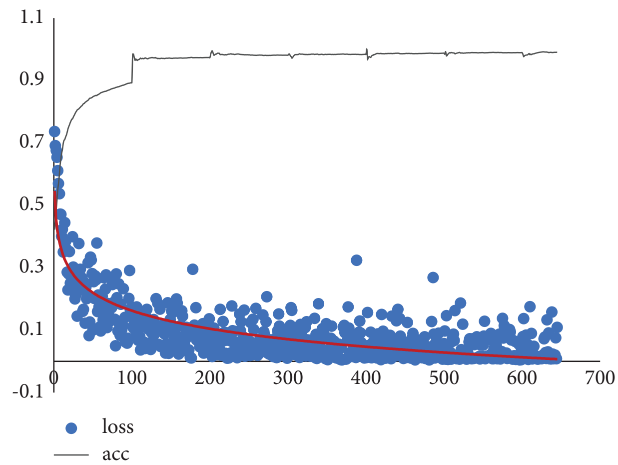

Figure 2: The fitting loss of model fine-tuning.

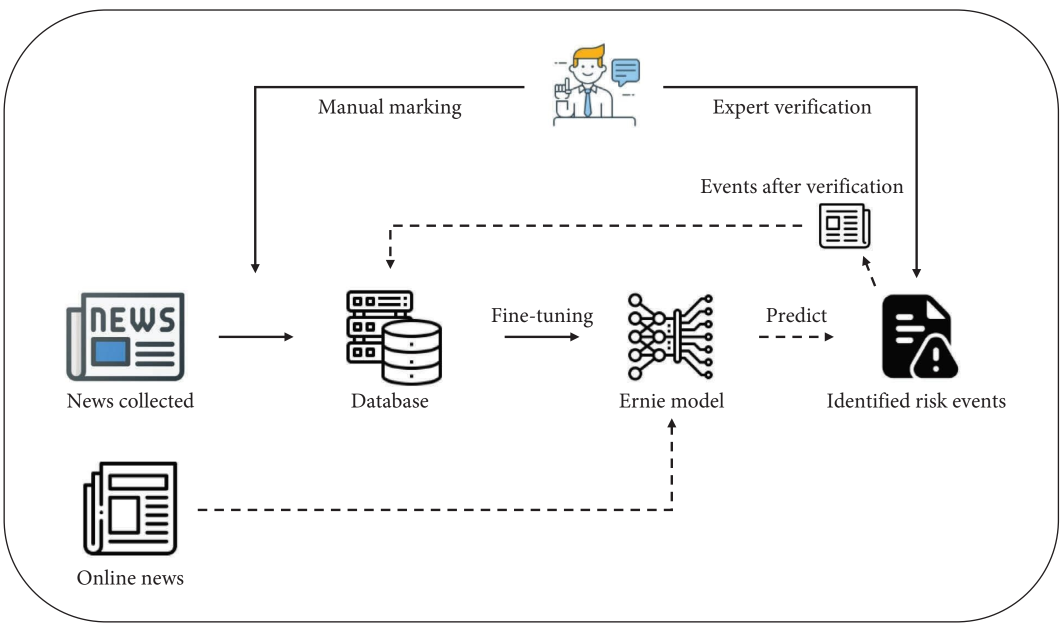

Figure 3: Model iterative optimization process.

continuously predicts the online news, and the predicted ICDE are added to the database after being verified by experts. The model is trained again with the supplemented data, and the accuracy and generalization ability of the model are continuously improved through multiple iterations.

The ICDE identification model V1.0 identified 7846 risk events in 400000 news data, but the actual number of risk events after a manual review was only 578, accounting for less than one-tenth. After two iterations, the model V3.0 identifies about 1000 risk events per month, which can accurately identify ICDE from massive news events. The processing speed of the model is 500 news per second, which can efficiently process daily news.

3. ICDE Correlation Model

3.1. Industrial Chain Structure. Industrial chain disruption refers to the impact of a risk event on a node in the industrial chain that affects the entire industrial chain. Therefore, it is necessary to determine which node in the industrial chain is affected by the ICDE. However, the industrial chain is not standardized but customized. Different enterprises and institutions draw different industrial chains. For example, in the new energy vehicle industry chain, some people write the names of vehicle nodes as new energy vehicles, while others write them as electric vehicles. Some people do not write power batteries but lithium iron phosphate battery and ternary lithium batteries. Due to the diversity of node names

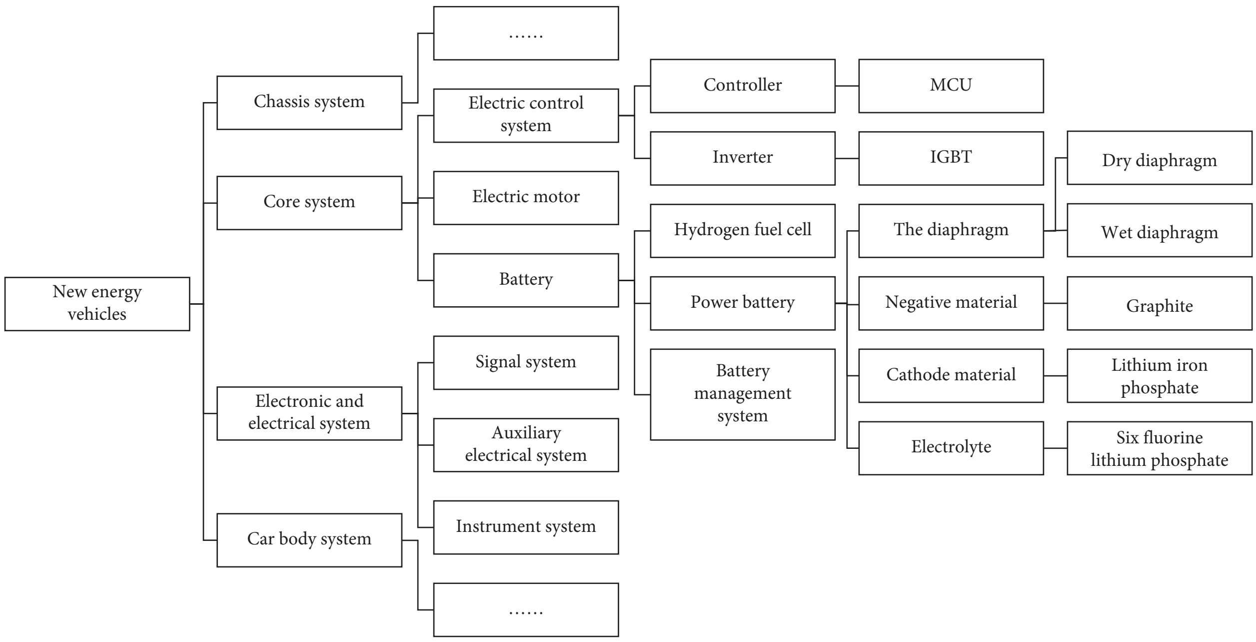

Figure 4: The new energy vehicle industry chain.

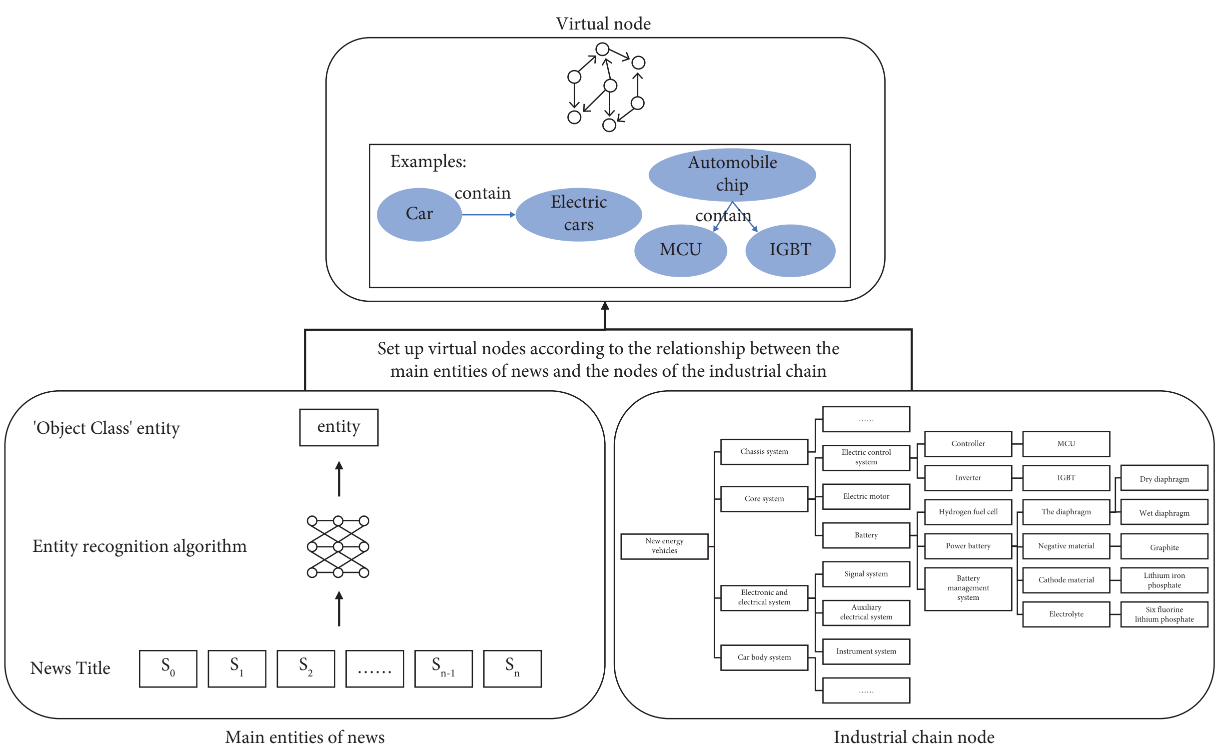

Figure 5: Establishment process of virtual nodes.

in the industrial chain, simply correlating risk events based on whether node names appear in risk events can result in a large number of omissions. Therefore, a model needs to be established to match and correlate ICDE with industrial chain nodes.

Take the new energy vehicle industry chain as an example. As can be seen in Figure 4, the upstream of new energy vehicles includes the chassis system, core system, body system, etc. The core system includes an electric motor, electric control system, and battery. The upstream

Table 2: Example of similarity matching results of industrial chain nodes.

Industrial chain node	Similar word 1	Similar word 2	Similar word 3	Similar word 4
Battery	Lithium battery	LFP battery	The cell phone battery	Soft package battery
Solid electrolyte membrane	Li-ion battery diaphragm	Oxygen ion conductor	Lithium-ion battery diaphragm	Focusing on the antibody
Membrane electrode component	Electronic components	Efficient components	Lithium battery electrode	Solar energy components
Power battery	LFP power battery	Electric vehicle battery	High power battery	A fuel cell
Six fluorine lithium phosphate	Lithium iron phosphate batteries			
The diaphragm	Thin film	Wet diaphragm	Battery diaphragm	Thin film platinum
Dry diaphragm	Wet diaphragm	Li-ion battery diaphragm	Battery diaphragm	The diaphragm
MCU chip	8 nm chips	3 nm chips	14 nm chips	6 nm chips
Inverter	Main inverter	Photovoltaic inverter	Microinverter	Controller

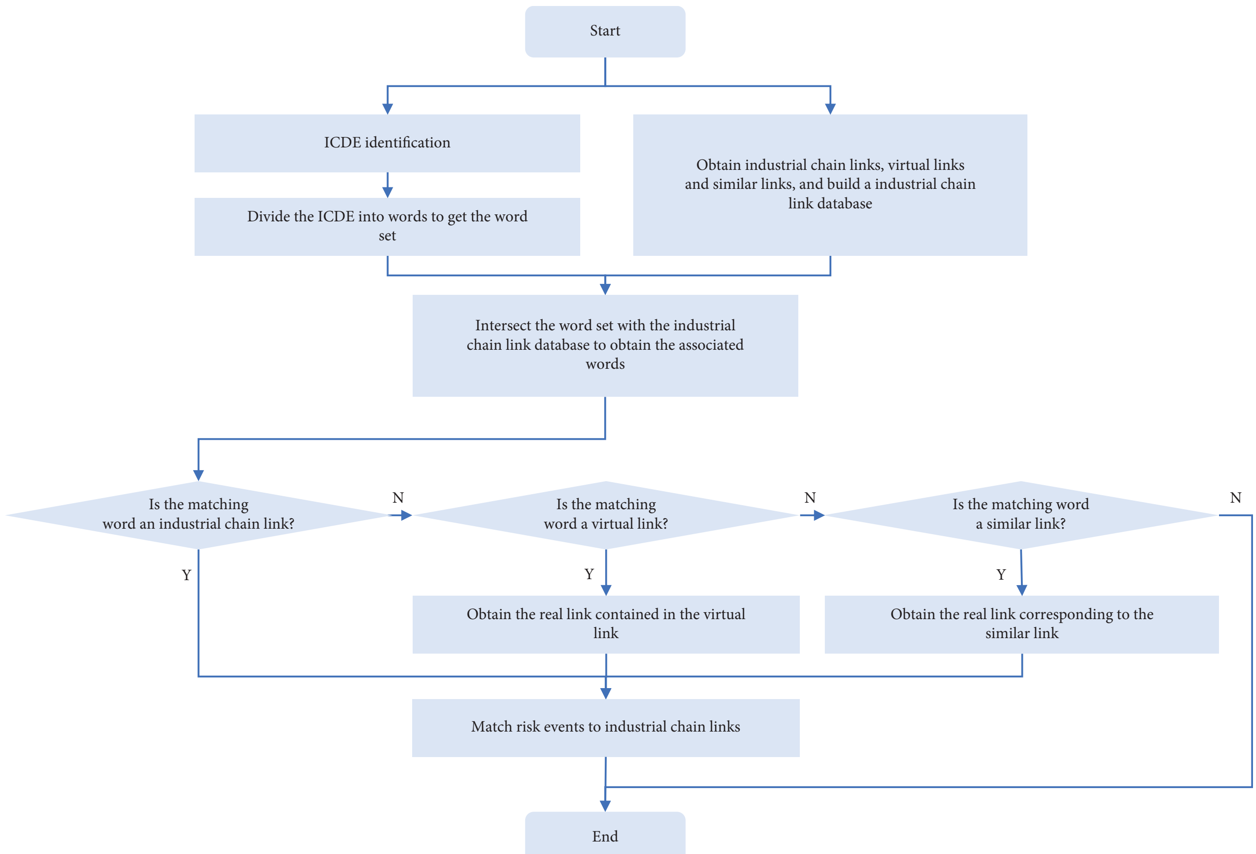

Figure 6: Matching and correlation process of the ICDE correlation model.

Table 3: Examples of matching and correlation results.

Industrial chain node	ICDE
Battery	Sichuan's industrial production power consumption is limited. Will battery prices continue to rise?
Power battery	Disable ternary lithium battery! the "delisting" list of medium and large electrochemical energy storage power stations was announced
Power battery	One of the main lithium battery production bases in China: Ningde shidai sichuan battery factory was shut down due to power restriction
MCU chip	Electronic industry weekly: The delivery time of NZP products continues to lengthen, and the supply of automobile chips remains in short supply
Lithium hexafluorophosphate	Polyfluoropoly: In the short term, lithium hexafluorophosphate and other materials still maintain a tight supply pattern
Silicon wafer	TECHCET: The global silicon wafer shortage is difficult to alleviate before 2024
Power battery	Rivian CEO: The battery shortage of electric vehicles may be more serious than the chip shortage
Negative material	The supply gap of negative electrode material head enterprises may be around 300000 tons this year

of the power battery includes a diaphragm, positive material, and negative material. The upstream of the controller is MCU, and the upstream of the inverter is IGBT. Although different institutions may use different node names to describe the same thing when drawing industry chains. These node names are either similar words, or there is an inclusion relationship between the names. Therefore, this section built an industrial chain node database based on virtual nodes and similar nodes and then matched and correlated ICDE with specific industrial chain nodes based on the industry chain node database.

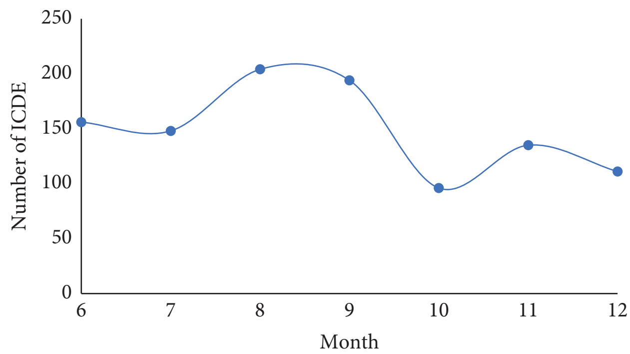

FIGURE 7: Number of ICDE in the new energy vehicle industry chain.

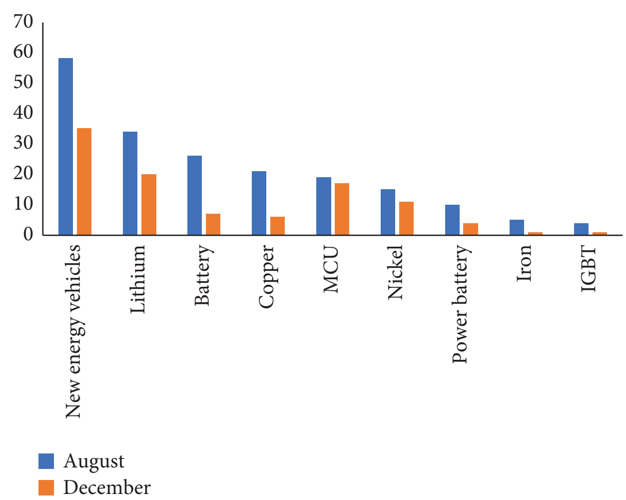

FIGURE 8: Comparison of the number of risk events at each industry chain node.

3.2. Virtual Nodes. The virtual nodes form an inclusion relationship with the real industrial chain nodes. Assuming ICDE as "shortage of automobile chips," there is no "automobile chip" node in the defined industry chain. There are only two nodes in the industry chain, "MCU chip," and "IGBT chip." If the correlation is only based on whether the node name appears in the ICDE, this ICDE cannot be matched to the corresponding industry chain nodes, leading to risk omission. In fact, MCU chips and IGBT chips are both automobile chips, and they have an inclusion relationship. Therefore, if a virtual node called "automobile chip" is established and its inclusion relationship with the "MCU Chip" and "IGBT Chip" nodes is established, ICDE can be correlated with the corresponding real nodes through the virtual node.

The entity recognition algorithm was used to identify entities of news events and extract key entities related to nodes. For example, for the event "Volkswagen: The global chip shortcut will continue until 2022 The next challenge is battery supply" can take "object class" as "chip." The entity names of the "object class" of all news were extracted, and virtual nodes with high-frequency entity names were established. The establishment process of virtual nodes is shown in Figure 5.

3.3. Similar Nodes. Due to the diversity of node names, the subjects in ICDE may not be consistent with the names of industry chain nodes. But in reality, they represent the same thing. The purpose of building similar nodes is to expand the industrial chain nodes and improve the hit rate of ICDE. The ICDE model V3.0 was used to extract the word vector of all words, and the similarity between the real industrial chain node and all words was calculated. Words were arranged in the descending order of similarity with the real industrial chain nodes, and the similar nodes were established in the way of manual review.

Taking some nodes of the new energy automobile industry chain as an example, words similar to each node are shown in Table 2. A similar node construction method based on word similarity can improve construction efficiency compared with manual enumeration.

Based on the virtual nodes and similar nodes, the industrial chain node database was formed and the ICDE was matched and correlated with the industrial chain nodes through the industrial chain node database. The specific correlation process is shown in Figure 6.

4. Application Results

News from June 2022 to December 2022 was continuously collected and monitored. Through the proposed ICDE monitoring model, ICDE can be identified and matched to specific industrial chain nodes. The matching and correlation results are shown in Table 3.

Figure 7 shows the changing trend of the number of risk events in the new energy vehicle industry chain. It can be seen that in the second half of 2022, the risk of the new energy vehicle industry chain reached its peak in August 2022 and then decreased. By the end of 2022, there were still certain risks in the new energy vehicle industry chain. The comparison of the number of risk events at different industrial chain nodes in August and December is shown in Figure 8. The risk of battery was significantly reduced, but the problem of lack of chips continued.

5. Conclusions

This paper has provided a dynamic and high-frequency monitoring method of the industrial chain risk based on news, which can timely capture events that cause risk impact on the industrial chain. News data from China have been used to apply the proposed model.

The ICDE identification model has been established to identify the risk events that may have an impact on the industry chain from the mass news. This model is based on the pretraining deep learning model ERNIE. After several iterations, the identification accuracy in the test set is 92%. The ICDE correlation model has been established to match and correlate the ICDE with the nodes of the industrial chain so as to more accurately know which node of the industrial chain may have risks. In the ICDE correlation model, virtual nodes and similar nodes have been proposed to improve the matching hit rate of ICDE and industrial chain nodes. The paper takes the new energy vehicle industry chain as an example to demonstrate the effectiveness of ICDE monitoring for this industry chain. The proposed model has good scalability. After defining the industry chain node database based on the ICDE correlation model, dynamic monitoring can be carried out on any industry chain.

The model established in this paper can effectively and accurately monitor the ICDE, and it can help national or local government personnel automatically monitor the ICDE. Compared with the current manual monitoring, the model can efficiently identify the ICDE from massive news and automatically classify them to the corresponding industrial chain nodes so as to reduce a large number of labor costs and time costs. Through the ICDE monitoring model, the national or local government can formulate measures to reduce industrial losses in time. For example, if the monitoring model discovers a shortage of a certain component, the government can issue an early warning to remind downstream enterprises to increase their component reserves, manufacturing enterprises to expand production capacity in a timely manner, and establish supply and demand coordination meetings to maximize the supply of components. Although Chinese data were used for the actual use of the model in this paper, the architecture of the model can be used in any country's language. Policy makers and relevant researchers can combine the monitoring results of events with the characteristics of the industrial chain itself to establish an industrial chain risk warning system. In the future, with the deepening understanding of ICDE, they can be classified into different types of risks. In addition, due to false and exaggerated news, the risk of being monitored will be overestimated. Therefore, a model is also needed to filter out false and exaggerated news, which is also where we will consider optimization in the next step.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the Youth Project of the China Academy of Information and Communications Technology.

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