Fuzzy cognitive map based vulnerability analysis of agricultural products cold chain logistics: a perspective of carbon footprint

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Abstract. As an important part of the development of a low-carbon economy, developing low-carbon logistics is an important measure to implement transform the economic development mode and cope with global warming. In order to effectively realize the low-carbon operation of agricultural cold chain logistics, a fuzzy cognitive map is employed to analyze the vulnerability of agricultural cold chain logistics on the perspective of carbon footprint. With the analysis above, the influencing factors of carbon emissions in cold chain logistics operations can be identified. Therefore, the carbon reduction strategy of the cold chain logistics of agricultural products can be obtained. Our findings can be as decision-making reference for relevant departments and enterprises to better formulate cold chain low carbon emission strategies and promote green logistics to achieve high-quality development.

1. Introduction
In recent years, global warming has constituted a research threat to the sustainable development of natural ecosystems and human society, and in this context, low-carbon economy has emerged. The Chinese government has also actively responded to international carbon reduction needs, and has adopted legal, administrative, economic and other government measures to ensure the implementation of energy conservation and emission reduction tasks for enterprises in various industries. Low-carbon logistics is an important part of the low-carbon economy, and should actively promote the low-carbon green development of the logistics industry.

With the rapid development of China's economy and the improvement of people's living standards, consumers' demand for fresh agricultural products continues to grow, and the quality requirements are increasing, which in turn drives the development of cold chain logistics. As a large agricultural country, China has about 400 million tons of fresh agricultural products entering the circulation field every year. Cold-chain logistics is required to escort agricultural products from procurement, processing, transportation, storage, to distribution. As a result, more fossil fuels are consumed, resulting in an increase in carbon emissions. The cold chain is the business that consumes the most energy and carbon emissions in the logistics industry. How to introduce the concept of emission reduction into the entire logistics management strategy, how to make the cold chain comply with the low carbon requirements of economic development, and adapt to the policy orientation of the country's cold chain logistics to help the poor get rid of poverty, which is a subject worthy of serious exploration.

2. Materials and methods

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At present, cold chain logistics has developed relatively mature abroad, but it is still in its infancy in China. From the perspective of literature search, the research fields at home and abroad mainly focus on the following aspects:

1. The development status, existing problems and countermeasures of agricultural cold chain logistics, Such as Neil V Ass. M. D [1] (2006), Kun Liang (2015) [2], etc.

2. Agricultural product cold chain logistics operation management. Specifically, it includes the control of agricultural product cold chain logistics quality, cost control, optimization of cold chain logistics system, cold chain distribution location and route optimization, and so on. For instance, A. Osvald, Stirn [3], H. Nazif, L. S. Lee (2010) [4], Ran Ban (2018) [5], Yaming Zhang and Yanming Li(2012) [6].

3. Measurement of carbon emissions from cold chain logistics of agricultural products and low carbon development strategies, such as Tristram O West and Gregg Marland [7], Kai-Kang, Jie-Han (2019)[8], Xing-Xu, Renwang Li(2018) [9], etc.

In summary, domestic and foreign experts and scholars have used different methods to study the cold chain logistics of agricultural products based on different perspectives, and accumulated rich results. However, there are not many studies on the low carbon development of cold chain logistics, and the only research is too general and abstract, and the reference is not very strong. Taking the vulnerability of cold chain logistics as the entry point and based on the carbon footprint perspective, combining low-carbon environmental protection with cold chain logistics, and discussing the results of cold chain low-carbon operation is almost blank. Especially in the new situation of China's active development of low-carbon economy and the help of cold-chain logistics to help the poor, there is an urgent need for practical research in this area. In view of this, this paper takes the carbon footprint as the research perspective, aims at reducing the carbon emissions of cold chain logistics of agricultural products, and carries out the analysis of the fragility of cold chain logistics of agricultural products, and then discusses the carbon reduction strategy of the cold chain logistics operation of agricultural products. It has theoretical and practical significance.

3. Research method

3.1. Introduction to fuzzy cognitive map

Fuzzy Cognitive Map (FCM) was proposed by Kosko and other scholars in 1986, which fused Axelord cognitive graph theory and Zadeh's fuzzy set theory. Cognitive Map (CM) is a graph model used to express and cause causal relationships between concepts. Since the cognitive graph model cannot quantify the degree of causality between conceptual nodes, in order to overcome the defects of cognitive graphs, fuzzy numbers are included, and fuzzy cognitive maps are generated.

The fuzzy cognitive graph is an extension of the cognitive graph. It quantifies the degree of causality between concepts by introducing fuzzy measures into the traditional cognitive graph model. Therefore, fuzzy cognitive graph is a soft computing method, which is the product of the combination of fuzzy logic and network. Because of its dual advantages of fuzzy logic and neural network, and strong mathematical reasoning ability, good interpret ability and intuitive knowledge representation, FCM has attracted extensive attention and research from scholars and has been applied in multiple Different fields, including teaching research [10], engineering control [11], business modeling and decision support [12], risk assessment [13], medical diagnosis [14-15].

3.2. Construction of fuzzy cognitive map

A fuzzy cognitive map is a graphical representation of knowledge, a fuzzy, signed, and feedback graph. Its graphical architecture consists of nodes, symbols, directions, and weighted arcs. Nodes represent events, and directed arcs between nodes represent causal relationships between events. The weight of each directed arc varies, representing the extent to which the previous node affects the next node. The basic structure of the fuzzy cognitive map is shown in Figure 1.
3.2.1. Determination of concept nodes
A node in a fuzzy cognitive graph is called a concept or concept node, and is used to represent the actions, causes, results, and trends of the system, which denoted by \( C \). In the fuzzy cognition, there is a set of finite concept nodes, that is \( C = \{C_1, C_2, \ldots, C_n\} \), if the state of node \( C_i \) changes, then \( C_j \) is the reason node of \( C_i \), \( C_j \) is the result node of \( C_i \).

3.2.2. Determination of weight
The degree of influence relationship between the conceptual nodes is represented by the connection weights marked \( W_{ij} = \{i, j = 1, 2, \ldots, n\} \) on the directed edges, and \( W_{ij} \in [-1, 1] \). Among them, \( W_{ij} \in (0, 1] \) indicates that there is a positive causality between \( C_i \) and \( C_j \), \( W_{ij} \in [-1, 0) \) indicates that there is a negative causality between \( C_i \) and \( C_j \), and \( W_{ij} = 0 \) indicates that there is no causality between the two. The fuzzy causal relationship between conceptual nodes in FCM is represented by a weighted adjacency matrix.

\[
E = \begin{bmatrix}
W_{11} & \cdots & W_{1n} \\
\vdots & \ddots & \vdots \\
W_{n1} & \cdots & W_{nn}
\end{bmatrix}
\]  \hspace{1cm} (1)

3.2.3. Weighted aggregation
A represents the factor weight matrix given by the kth expert, integrates the opinions of multiple experts and finds the arithmetic average, and obtains the associated weight matrix \( Ec \) of the whole system FCM.

\[
E_C = \frac{1}{m} \sum_{k=1}^{m} E_k
\]  \hspace{1cm} (2)

3.2.4. Inference of concept change
(1) Select the threshold function
The function of the threshold function is to prevent the variable value \( C_i \) on the node from exceeding the domain during the operation, and its shape represents the operation mode of the entire system association mode. There are three types of threshold functions, including Bivalent, Trivalent and Logistic Signal. The threshold functions of the first two forms are relatively easy to obtain stable or oscillating results. The more commonly used threshold function B is the Bivalent form, which has the following form:
The operation, the weight threshold extends the divergence. The operation, the weight threshold extends the divergence.

\[ B: C_i(t + 1) = \begin{cases} 
1, & \text{if } C_i(t) \times E_{C_i} > 0 \\
0, & \text{if } C_i(t) \times E_{C_i} \leq 0 
\end{cases} \tag{3} \]

Figure 2. Threshold function of FCM bivalent morphological

In the above formula, \( C_i(t + 1) \) represents the matrix of the variable state values of the node at the \((t+1)\) th operation, \( C_i(t) \) represents the matrix of the variable state values of the node at the \(t\) th operation, \( E_{C_i} \) represents the factor weight matrix of the node. Here, the threshold function is set to zero. The significance of the threshold function is that after calculating the matrix result, the state values of all variables greater than 1 are adjusted to 1, and the state values of all variables less than 0 are adjusted to 0, as shown in Figure 2.

(2) Establish learning rules

The learning rule is used to judge whether the causal weight value between concepts in the operation process needs to be changed, so as to promptly correct the causal relationship of the node due to time change. In a simple fuzzy cognitive graph, the weight value of the causal edge can be set to a fixed value, and the variation rule of the concept node can utilize the basic concept of matrix operation, that is, multiply the initial value matrix by the factor weight matrix and then pass the threshold function. To filter out the obvious factors, and finally make the relationship between the concepts in the system clear and clear. Its calculation formula is:

\[ C_i(t + 1) = B(C_i(t) \times E_{C_i}) \tag{4} \]

(3) Setting the initial value

In order to facilitate the calculation and analysis in the operation process, generally only one target variable is selected, and its initial value is set to 1, and the operation of the change inference is started until convergence. The nodes of the fuzzy cognitive graph may produce three kinds of results after the change inference: stability, oscillation or divergence. The oscillation state is a finite cycle, and the node value will oscillate and change with the cycle of the number of operations.

4. Empirical research

4.1. Case background introduction

F Agricultural Products Group Co., Ltd. (hereinafter referred to as F Group) is a group trading company in the southeastern region of China. It takes the development, construction, management and wholesale market as its core business, then extends its business by base planting and breeding, logistics and distribution, and fresh terminal operation. Now it has 8 holding companies including food processing, fresh food distribution, grain trade and cold storage business, and has opened a number of professional agricultural and sideline products wholesale markets. The group has won many honorary titles such as the National “Cooking Basket” reassuring engineering excellent enterprise, the national 100 large agricultural product circulation enterprises, and the national food safety demonstration unit.
4.2. **Correlation analysis between cold chain logistics and carbon footprint**

From the production field to the consumption field, agricultural products need to be harvested, pre-cooled, processed and packaged, warehousing, transportation, wholesale and retail, and so on. It is necessary to provide full-length cold chain monitoring and management. As shown in Figure 3, the upper part represents the entire supply chain process of agricultural products, the lower part represents the cold chain logistics operation process of agricultural products, the solid arrow indicates the operation flow, and the hollow arrow indicates the carbon footprint correlation. In order to help the whole process of cold chain energy conservation and emission reduction, reduce consumption and increase efficiency, it is necessary to integrate the carbon footprint theory into the logistics operation process of F Group, combined with the measurement method of carbon footprint, to measure the carbon footprint in all links of cold chain operation, and realize the cold chain. The statistics of carbon emissions throughout the operation provide reference for enterprises to formulate energy-saving and emission reduction strategies.

**Figure 3.** Association model of cold chain logistics operation process and carbon footprint

4.3. **Determination of concept nodes**

Determining the concept node is critical, which is directly related to the construction of the fuzzy cognitive graph model. Combining the characteristics and structure of chain logistics operation and carbon emission problems, the relevant factors are initially screened out as the conceptual nodes needed to construct the FCM model. In order to ensure the accuracy and effectiveness of the concept nodes, the author invited a number of industry experts and scholars and industry insiders to form a group of experts to discuss, and finally the ten concept nodes for constructing the FCM model are determined: carbon emissions, service levels, clean fuel usage, transportation batches, transportation road conditions, refrigerated truck types, storage temperature control, handling, transportation and packaging (as shown in Table 1).

| Concept node | Description |
|--------------|-------------|
| A.carbon emission | Average greenhouse gas emissions from the production, transportation, use and recycling of agricultural products. |
| B.Service Level | The customer has a psychological expectation and expectation of the logistics service elements obtained and the formation of such elements. |
| C.Clean fuel usage | The ratio of the amount of clean energy consumed in the transportation and... |
4.4. Weight determination of concept nodes

4.4.1. Weight training

In order to determine the connection relationship between the concept nodes, the author obtains the influence degree \( W_{ij} = (i, j = 1, 2, \ldots, n) \) between each node by issuing a questionnaire to the expert group. The description of the form is as follows: if the two concepts are positively correlated, the value entered is between 0 and 1, that is \( W_{ij} \in (0, 1] \); if the two concepts are negatively correlated, the value filled in is between Negative 1 and 0, that is \( W_{ij} \in [-1, 0) \); if the two concepts have no influence, they are directly filled with 0. The initial weight of the model is given by the experts according to the specific situation of F Group cold chain logistics operation.

4.4.2. Obfuscation of raw data

The data collected by the questionnaire is simply processed using the formulas (1) and (2) to obtain the associated weight matrix of the FCM system, and specific steps are as follows:

1. For the numerical vector of each concept node \( V_{ij} = (i, j = 1, 2, \ldots, n) \), the numerical vector is the pointer to the i-th concept node, the i-th expert scores, finds the maximum value in the vector element, that is, the highest score of the expert for all concept nodes, defined as \( \text{MAX}(v) \), assigning a value to 1, that is, \( \text{MAX}(v)V_{ij} = 1 \).

2. For the value vector of each concept node \( V_{ij} = (i, j = 1, 2, \ldots, n) \), look for the minimum value in the vector element, that is, the lowest score that the expert hits all concept nodes, defined as \( \text{MIN}(v) \), assigning a value to 0, that is, \( \text{MIN}(v)V_{ij} = 0 \).

3. For each data of the concept node, the lowest score and the highest score are substituted into the fuzzy formula (5) perform the fuzzification on [0, 1], and the fuzzy result of all the data can be obtained.

\[
XV(v) = \frac{V_{ij} - \text{MIN}(v)}{\text{MAX}(v) - \text{MIN}(v)} \quad (5)
\]

4. In the statistical questionnaire, the expert gives the score value of each concept node and finds the simple arithmetic average, which is used as the initial value of the fuzzy cognitive graph model. That is, the state evaluation value. The processed data is summarized in Table 2.

| Table 2. Weight values between conceptual nodes |
| --- |
| A | 0.00 | 0.18 | 0.44 | 0.60 | 0.45 | 0.56 | 0.40 | 0.20 | 0.30 | 0.32 |
|   | B   | C   | D   | E   | F   | G   | H   | I   | J   | Rating |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|
|   | 0.12| 0.48| 0.64| 0.56| 0.70| 0.52| 0.22| 0.26| 0.25| 0.82   |
|   | 0.00| 0.18| 0.12| 0.26| 0.41| 0.54| 0.42| 0.42| 0.40| 0.36   |
|   | 0.36| 0.01| 0.16| 0.20| 0.34| 0.19| 0.08| 0.10| 0.12| 0.40   |
|   | 0.32| 0.13| 0.00| 0.56| 0.46| -0.04| 0.54| 0.10| 0.25| 0.40   |
|   | 0.29| 0.23| 0.00| 0.00| 0.46| 0.14| 0.12| 0.38| 0.12| 0.54   |
|   | 0.44| 0.36| 0.46| 0.14| 0.44| 0.44| 0.20| 0.46| 0.36| 0.46   |
|   | 0.38| 0.16| 0.04| 0.00| 0.64| 0.00| 0.36| 0.52| 0.36| 0.46   |
|   | 0.40| 0.08| 0.32| 0.30| 0.34| 0.08| 0.00| 0.58| 0.48| 0.48   |
|   | 0.36| 0.10| 0.00| 0.52| 0.48| 0.12| 0.38| 0.50| 0.48| 0.48   |
|   | 0.44| 0.36| 0.46| 0.48| 0.58| 0.00| 0.48| 0.40| 0.48| 0.00   |

4.5. The establishment of fuzzy cognitive maps
Bringing the relationship strength between the concepts after fuzzification into the basic structure of the fuzzy cognitive map, we can construct a fuzzy cognitive map of the cold chain logistics operation vulnerability analysis based on the carbon footprint perspective for the case, as shown in Figure 4.

![Figure 4. Fuzzy cognitive map of the case company](image)

4.6. Causal Analysis of Fuzzy Cognitive Map
In order to further identify the vulnerability of agricultural product cold chain logistics from the perspective of carbon footprint, it is necessary to expound the causal relationship between the conceptual nodes and carbon emissions in the fuzzy cognitive map:

As shown in Figure 4, there is a positive causal relationship between the nine concept nodes and the carbon emissions of agricultural cold chain logistics. Among them, D (transportation batch), F (refrigerated vehicle type) and carbon emissions have a strong causal relationship, and the agricultural product transportation volume and The type of refrigerated truck directly affects the amount of carbon emissions; E (transportation road conditions), C (clean fuel usage rate), G (storage temperature control), I (transport), J (packaging), etc. Moderate causality, rational planning of transportation routes, improvement of traffic conditions, improvement of clean fuel utilization rate, and reasonable regulation of storage temperature have a strong incentive to reduce carbon emissions; B (service level), H (loading and handling) and Carbon emissions show a weak causal relationship, indicating a lower impact on carbon emissions.

In summary, the refrigerated transport links have the most carbon emissions. The carbon emissions caused by refrigerated transport during transportation are also related to the transportation distance and transportation quality. The reduction of carbon emissions can be started from the formulation of...
transportation routes and the optimization of technology in the manufacturing process; the staged pre-cooling and processing and packaging links in the cold chain logistics correspond to the “transport, assembly and packaging in the production process”, in this regard, optimized balance between machines can effectively reduce carbon emissions; warehousing, transportation and wholesale and retail links of cold chain logistics correspond to the “use” in the production process of the product, proper planning of the space and time of cold chain storage and the establishment of a recycling system are one of the effective ways to reduce carbon emissions.

5. Conclusions
Based on the analysis of the correlation model between agricultural product cold chain logistics operation process and carbon footprint, this paper constructs a fuzzy cognitive map of agricultural product cold chain logistics operation vulnerability based on carbon footprint perspective with FCM theory and expert questionnaire method. The FCM architecture is based on carbon emissions and service levels in agricultural cold chain logistics operations, focusing on the relationship between key concept nodes and carbon emissions and the associated weights to properly handle the impact of agricultural cold chain logistics operations. The causal relationship between the various influencing factors of carbon emissions, which makes the construction process and results more in line with the actual situation, and provides effective decision-making reference for relevant departments and enterprises to develop low-carbon operation policies or measures for cold chain logistics. In the process of constructing FCM, the threshold impact analysis is used to understand the impact of threshold on FCM formation, so as to construct the required impact weight more objectively.

From the results of the case analysis, it is suggested that the operation of the low-carbon chain of cold chain can consider efforts to improve energy efficiency, optimize transportation routes, strengthen cold chain logistics technology innovation, and build a complete cold chain logistics transportation system.

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