Bayesian Network Modelling for “Direct Farm” Mode based Agricultural Supply Chain Risk

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Abstract. "Direct Farm" is a special supply chain mode which can effectively improve the circulation efficiency of agricultural products in China. However, the development of "Direct Farm" is limited due to its potential risks. Based on this, we use Bayesian network to model the risks of agricultural supply chain under the "Direct Farm" mode, then the forward reasoning and reverse reasoning of the model can help managers to predict and analyse the risks of supply chain, and take timely risk response measures to ensure the stable operation of agricultural supply chain.

1. Introduction
"Direct Farm" mode is one of the important ways to improve the circulation efficiency of agricultural products, it can effectively reduce the circulation link and the circulation risk of agricultural supply chain, but it also causes other potential risks, which seriously affects the stable operation of agricultural supply chain and hinders the promotion of "Direct Farm" in China [1]. Therefore, it is of great significance to the development of "Direct Farm" and the improvement of the circulation level of agricultural products to effectively warn the risks of the "Direct Farm" mode based agricultural supply chain and to assist managers to take timely risk response measures to ensure the stable operation of agricultural supply chain. Many scholars are interested in the risk of agricultural supply chain. Tah [2] pointed out that the main shortcomings of risk management in agricultural supply chain are technical means, management process and management tools. Larson [3] showed that the supply chain of agricultural products is itself high-risk, and the quality and safety risk of agricultural products runs through the whole process of the supply chain. Yan Bo [4] shows that it is necessary to quantitatively evaluate the risk regularly and adjust the management strategy in time to ensure the stable operation of the supply chain because risks always exist in the supply chain of agricultural products. The research on risk modelling of agricultural supply chain has been paid more and more attention by scholars, and many valuable research results have been obtained. But the existing research on the dynamic and conductive mechanism of agricultural supply chain is insufficient, and there is little research on the risk of the agricultural supply chain that based on the "Direct Farm" mode.

Risk analysis and modelling generally use qualitative and quantitative methods, such as Fuzzy Risk Analysis, Analytic Hierarchy Process (AHP), ISM, Artificial Neural Network, Genetic Algorithms, etc. But these methods have some limitations, they cannot reflect the probability interdependence between risks, and cannot be disseminated and updated after receiving new information. So, we decided to choose a more dominant method to study the risk of "Direct Farm" based agricultural supply chain. Bayesian network is one of the most effective models for uncertain knowledge representation and analysis, which is superior for risk research of complex systems. Supply chain is a dynamic complex system, and the uncertainty in agricultural supply chain is also high, so it is meaningful to use Bayesian network to model the risks of "Direct Farm" based agricultural supply chain.
system, but only a few scholars have applied Bayesian network to supply chain research. Ritesh et al. [5] provides a holistic measurement approach based on Bayesian network for predicting the complex behaviour of risk propagation for improved supply chain risk management. Zheng Xiaojing [6] analysed the probability of various risks and the possibility of co-occurrence of risk events by establishing a Bayesian network model of supply chain risk.

In this paper, we use Bayesian network method to study the risk of agricultural supply chain. By quantifying various risks, we develop a risk early warning model of "Direct Farm" agricultural supply chain based on Bayesian network. Through the forward reasoning and reverse reasoning functions of the model by Netica(a software for Bayesian network reasoning), the risk can be warned and the decision-making basis for managers can be provided.

2. Methodology

2.1. Bayesian Network

A Bayesian network (BN) is a directed acyclic graph where the nodes represent variables and the directed arcs define statistical relationships. If there is a directed arc from a variable $X_1$ to a variable $X_2$, the arc indicates that a value taken by $X_2$ depends on the value taken by $X_1$ or $X_1$ "influences" $X_2$. $X_1$ is called the parent of $X_2$ and $X_2$ the child of $X_1$. Conditional independence relationships are implicit in the directed acyclic graph: all nodes are conditionally independent of their ancestors, given their parents. Consider a BN has $n$ nodes, which are $X_1$-$X_n$. The chain rule of probability theory allows factoring joint probabilities, as given in the following formula. By this formula, the answer that the system will give under some certain probability states can be calculated.

$$P(X_1,\ldots,X_n) = \prod_{i=1}^{n} P(X_i|\pi(X_i))$$  \hspace{1cm} (1)

In (1), $\pi(X_i)$ denotes the parent node of $X_i$. Through forward reasoning, the probability that the state of the node $X_i$ is $a_k$ is obtained as follows:

$$P(X_i = a_k) = \sum_{X_j} P(X_1,\ldots,X_n)$$  \hspace{1cm} (2)

Reverse reasoning, the state of a node is known, and the posterior probability distribution of its parent node is obtained according to the conditional probability formula. If a state of $X_i$ is known to occur, the posterior probability of a state of node $X_j$ ($X_j$ is a parent of $X_i$) is:

$$P(X_j|X_i) = \frac{P(X_j|X_i)P(X_i)}{P(X_i)}$$  \hspace{1cm} (3)

2.2. Process of Risk Early Warning Model Development

We divide the construction of "Direct Farm" agricultural supply chain risk early warning model into two stages: qualitative stage and quantitative stage. The detailed process is shown in Figure 1.

3. Model Development

3.1. Risk Identification and BN Construction

At present, there are various patterns of "Direct Farm" in China, such as "supermarket-wholesale market-cooperatives-farmer" mode, "supermarket-cooperative-farmer" mode, "joint direct purchase" mode, "supermarket direct sale" mode and so on [7]. In this paper, as shown in Figure 2, we take "farmers-cooperatives-supermarkets" mode based agricultural supply chain as the research object, because of its widespread implementation. According to relevant literature and combined with the characteristics of "Direct Farm". In this paper, the "Direct Farm" based agricultural supply chain risk is divided into three main risk items: supply risk (SR), technology and management risk (TR), docking risk (DR). The external risk (ER) has an impact on all aspects of the supply chain risk, and then affects the overall risk level, as shown in Figure 3.
Through field research, questionnaires and interviews with relevant experts, the main risk factors are shown in Table 1. After several modifications according to the expert opinions, the final BN structure is shown in Figure 4.

Figure 1. Process of risk early warning model development.

Figure 2. "farmers + cooperatives + supermarkets" mode.

Figure 3. The relationship between risks.
Table 1. Major risk factors.

| Node | Factor                     | Node | Factor                     |
|------|---------------------------|------|---------------------------|
| S1   | Stale products            | T6   | Improper corporate strategy|
| S2   | Quality and safety issues | D1   | Unreasonable agreement    |
| S3   | Unapproved GM crops       | D2   | Low organizational efficiency|
| S4   | Demand exceeds supply     | D3   | Insufficient cooperation  |
| S5   | Supply exceeds demand     | D4   | Lack of cooperation intention|
| S6   | Low yield                 | D5   | Insufficient capacity of famer |
| S7   | Cargo loss                | D6   | short duration of famer Cooperative |
| S8   | Delivery delay            | E1   | Natural disaster          |
| S9   | Traffic accident          | E2   | severe weather            |
| T1   | Lack of infrastructure    | E3   | Inadequate government subsidies |
| T2   | Employee operational accidents |     | E4   | Consumer preferences      |
| T3   | Cryogenic technical fault | E5   | Public opinion direction  |
| T4   | Insufficient grasp of the market | E6   | Price fluctuation         |
| T5   |                             | E7   | Economic crisis           |

3.2. Bayesian Network node Setting and Value Assignment

The next step is to assign values to each node, that is, to obtain the prior probability values of each node and assign corresponding probability values to the each state of them. Different state levels are set according to the characteristics of different nodes. For example, the status of SCR node at the top level is divided into five levels: very high (VH), high (H), medium (M), low (L) and very low (VL). The status of the DR node is divided into three levels: high (H), medium (M) and low (L). And there are two levels of S1: occurrence (Y) and nonoccurrence (N). The assignment results are obtained through statistical data and survey data, as well as consulting with experts in the field and relevant industry personnel. All nodes are assigned and checked in this paper (no complete assignment table is provided in this paper due to space limitation). The complete prior probability chart of "Direct Farm" mode based agricultural product supply chain is shown in Figure.5.

3.3. The Risk Detection Model

As the output part of risk early warning model, the risk detection model shows the risk level of risk nodes. In this model, we only care about the risk state of five-state node and three-state node because two-state node corresponds to risk factors rather than risk items.

- Let RV (N) = the risk value of node N.
- RL (N) = the risk level of node N.
- p (N_i) = the probability of i state of node N.
We assign appropriate weights (the weights reference Li Min’s research as in [8]) to different states of risk to get risk value of each risk items. For five-state node,

\[
RV(N) = \frac{7p(N_{10})}{20} + \frac{3p(N_{15})}{10} + \frac{p(N_{25})}{5} + \frac{p(N_{35})}{10} + \frac{p(N_{40})}{20}
\]

then the output of RL(N) is shown in Figure 6(a). And for three-state node,

\[
RV(N) = \frac{p(N_{20})}{2} + \frac{3p(N_{30})}{10} + \frac{p(N_{40})}{5}
\]

then the output of RL(N) is shown in Figure 6(b).

4. Reasoning

The model is used for forward reasoning and reverse reasoning of risk. Forward reasoning is to modify the value of the corresponding risk nodes in BN according to the received risk-related information, and then observe the changes of each node and analyse the influence of the changing node on other risk items. Reverse reasoning is to find out the key influencing factors by adjusting the assignment of a certain risk item and observing the changes of relevant nodes.
4.1. Forward Reasoning

After receiving the new information, managers can modify the assignment of some nodes, observe the mutual influence of other risk factors, and then analyse the risk level of the "Direct Farm" mode based agricultural supply chain and give early warning of the risk. Give an example as follows:

The impact of government subsidies: Assuming that the local government modifies the subsidy policy, which will lead to the reduction of subsidies for "Direct Farm ". It is assumed that the probability of insufficient government subsidy (E3) will change from 2\% to 80\% (In practice, the probability here should be adjusted in a reasonable way). The state of relevant nodes before and after the modification of E3 node is shown in Figure 7(a) and Figure 7(b). The RV and RL of the related risk items are obtained from the lamp model as shown in Table 2. The risk level of DR changed from risk-free to medium risk, and the risk level of SCR changed from low risk to medium risk. It can be considered that insufficient government subsidies will cause greater risks. By observing the changes of relevant nodes in BN, we find that insufficient government subsidies will greatly reduce the cooperation intention of members, resulting in insufficient cooperation, which will lead to inefficiency of organizations, and have a negative impact on the duration of farmer cooperatives, thus have a serious negative impact on the operation of the supply chain model. Accordingly, the local government should actively play its role of guidance and incentive, formulate a series of reasonable subsidy policy of "Direct farm" to improve the enthusiasm of the members to participate in "Direct farm" and ensure a stable docking state so as to promote the development of "Direct farm" in the region, enhance the circulation level of agricultural products.

![Figure 7(a). The state of the relevant nodes before E3 node changed.](image)

![Figure 7(b). The state of the relevant nodes after E3 node changed.](image)

Table 2. Changes in RV and RL of related risk items of E3.

| Risk Item | RV | RL |
|-----------|----|----|
| DR        | Change before 23.9 | Change after 30.1 | Change before Risk-free | Change after Medium risk |
| SCR       | Change before 13.9 | Change after 17.4 | Change before Low risk | Change after Medium risk |

4.2. Reverse Reasoning

Reverse reasoning is used to analyse the impact of various influencing factors on risk items, so as to assist managers in rational allocation of resources and minimize the risk level of supply chain. Take SR, DR and TR as examples. The probability of VH, H, M, L and VL in the five states of SCR was set from 6.84\%, 10.9\%, 21.9\%, 45.6\% and 14.7\% to 40\%, 30\%, 10\% and 10\% respectively. It was observed that the states of TR, SR and DR also changed correspondingly with the change of SCR, as shown in Figure 8(a) and Figure 8(b). Then the RV and RL of the related risk items are obtained from the lamp model as shown in Table 3. The risk level of DR changed from risk-free to medium risk, while the risk level of SR and TR remained risk-free. It can be concluded that docking risk is the key risk item of "Direct Farm" mode based agricultural supply chain, and when considering the optimal allocation of resources, managers should give priority to the management of docking risk to ensure the stable operation of the supply chain.
Figure 8(a). The state of the relevant nodes before SCR node changed. 

Figure 8(b). The state of the relevant nodes after SCR node changed.

Table 3. Changes in RV and RL of related risk items of SCR.

| Risk Item | RV    | Change before | Change after | RL    | Change before | Change after |
|-----------|-------|---------------|--------------|-------|---------------|--------------|
| DR        | 23.9  | 30.3          | Risk-free    | Medium risk |
| SR        | 22.8  | 26            | Risk-free    | Risk-free  |
| TR        | 21.7  | 23            | Risk-free    | Risk-free  |

5. Conclusion and Future Research

This paper analyses the risk of agricultural product supply chain under the "Direct Farm" mode, quantifies the transmission relationships between various risk factors and risk factors and embodies them in a BN structure, and sets up a risk detection model. Therefore, a complete "Direct Farm" based mode agricultural supply chain risk warning model is established to help the relevant managers of the supply chain to take timely measures to reduce losses and ensure the stable operation of the supply chain. However, the risk early warning model constructed in this paper has certain limitations. This is because the risk factors faced by the "Direct Farm" supply chain in different regions are different. This article only selectively targets some regions, and the risk factors and states have certain limitations. Therefore, the model structure or assignment should be modified according to the actual situation in different regions. The next focus of research should be to address the universality of the model.

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7. References

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