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# INTEGRATED INVENTORY OPTIMIZATION OF FRESH AGRICULTURAL PRODUCT SUPPLY CHAIN BASED ON NEURAL NETWORK

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Abstract. *In order to improve the effectiveness of comprehensive inventory optimization in the supply chain of Fresh Agricultural Products (FAPs), this paper analyzes the optimization of comprehensive inventory in the supply chain of fresh agricultural products using neural networks. In response to the characteristic of uncertainty and uncertainty often mixed together and difficult to exist independently in the system, a set pair attribute soft computing method was introduced into inventory information entropy to construct a connection entropy in a complete inventory information system. In addition, this article also constructs an FAP supply chain integrated inventory optimization model based on BP neural network. A Particle Swarm Optimization (PSO) algorithm is proposed to optimize the Back Propagation (BP) neural network in response to its slow convergence speed, tendency to fall into local optima, and complex structural parameters. The results showed that the PSO-BP neural network completed convergence at the 10th iteration, while the BP neural network only completed convergence at the 50th iteration. Simulation experiments have verified that the optimization effect of FAP supply chain integrated inventory based on BP neural network is significant.*
**Keywords:** BP neural network, FAPs, Supply chain, Integration, Inventory optimization

1. **Introduction.** Fruits, vegetables and other products, as well as many dairy products, such as milk, and cottage cheese, are sold without packaging and have a random lifespan, which will be affected by the sales situation [1]. Chen and Zhao [2] study the perishables inventory model under the integration. In the future research on fresh product inventory and pricing, it will become more and more specific.

As the necessities closest to national life, FAPs have attracted great attention from consumers [3]. Therefore, consumers judge the overall quality and price of FAPs according to their own demand utility to decide whether to buy FAPs [4]. If the products are still sold at the same price as fresh products, then the decline in freshness will lead to a decline in sales [5]. Discounts are usually offered in order to boost sales when freshness decays to a certain level. If an appropriate discount strategy is chosen, it can effectively increase sales revenue [6].

Kupriyanovsky et al. [7] divide the change of demand into variable with price, random change, fixed and exponentially increasing with time; the rate of deterioration is divided into linear function of time, linearly increasing function of time, fixed and subject to three-parameter Weibull distribution. In these cases, establish inventory models to study

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FAPs, in order to find the lowest inventory cost and reduce unnecessary losses [8]. On this basis, Sun et al. [9] include passenger flow analysis as an influencing factor of the inventory model. [10] does not think that the transportation of FAPs is in place immediately, and incorporates the order lead time into the consideration of the inventory model, and uses digital simulation to analyze the relationship between various influencing factors. In the analysis of the inventory model of FAPs, the influencing factor of shelf life is added, and it is believed that the shelf life is a manifestation of the deterioration of FAPs, and the deterioration rate of products can be determined by the shelf life, and solve the profit maximization value by simulating the relationship between shelf life and spoilage rate [11]. Coatney and Poliak [12] propose to use sensory evaluation, logistics evaluation, chemical evaluation and microbiological evaluation as the evaluation indicators of freshness, and use the freshness function to describe the deterioration of fresh products. From the perspective of supply chain, the principle of maximizing the interests of suppliers and retailers is considered, and the single-level and multi-level inventory models are considered. Hawkins [13] considers the impact of quantity discounts and price discounts provided by suppliers on the order quantity of fresh products, proposes that the loss rate is affected by the efforts of operators to protect commodities, compares the length of the life cycle with the order cycle, and analyzes its impact on the order quantity. The impact of ordering strategy; considers the impact of value loss and physical loss on the inventory model in the circulation process of fresh products [14]. Alsayaydeh et al. [15] consider that there is a value-added period when fresh products enter the stable growth stage, when they can be harvested but not fully mature, and the value of FAPs in the value-added period will increase. By assuming the inventory models of replenishment and non-replenishment respectively, a better inventory strategy is obtained when the product is out of stock and not replenished during the product growth and value-added period.

For specific problems, logistics simulation can realize the following applications: analysis and optimization of production rhythm and production; analysis of production site layout; bottleneck analysis; analysis of the impact of equipment failures on production; rational allocation of human resources [16]; understanding of equipment operating status changes: identify appropriate strategies; evaluate different options. According to the different system state changes, the system simulation model can be divided into continuous system simulation model and discrete system simulation model [17]. The continuous system refers to the state of the system that changes continuously with time. The fields that belong to the continuous system include aerospace, aviation, automatic control systems, and power systems. Discrete system means that the state of the system does not change continuously with time, but changes at discrete time points. Generally, transportation systems, supply chain multi-level inventory systems, and production logistics systems are all discrete systems. Therefore, the simulation optimization for the multi-level inventory of FAPs is also based on the discrete system theory [18,19].

In summary, FAP price, transportation time, shelf life, freshness, and discount strength are all factors that need to be considered in the optimization of FAP comprehensive supply chain. FAP comprehensive supply chain is also a common discrete system. In order to improve the effectiveness of comprehensive inventory optimization in FAP supply chain, this paper analyzes the optimization of FAP supply chain comprehensive inventory using neural networks and establishes an intelligent model to promote the effective operation of FAP. Research innovatively combines the PSO algorithm with the BP neural network to improve the BP neural network, and uses the improved algorithm to establish an FAP integrated supply chain discrete system simulation model.

## 2. Set Pair Inventory Information Entropy in Inventory Information System.

Aiming at the fact that the certainty and uncertainty in the system are often mixed together and difficult to exist independently, a set pair attribute soft calculation method is introduced into the inventory information entropy. Moreover, this paper constructs a link entropy in the complete inventory information system, and proposes the set pair inventory information entropy in the inventory information system, which realizes the unified measurement of the uncertainty in the inventory information system.

### 2.1. Set pair correlation function.

The set pair connection degree $m$ is essentially a composite function $m = f(H, W, T)$ of the set pair $H$, the specific problem background $W$ and the research process $T$. Therefore, in the sense of inventory information system, based on the concepts of knowledge base and approximate set in rough set theory, attribute correlation function and set pair correlation function are established, a soft calculation method of set pair attribute in inventory information system is proposed, and its basic properties are discussed.

**Definition 2.1.** *The equivalent division on the universe $U$ is $U/P$. The upper and lower approximation sets of the rough set $X$ with respect to $P$ are called $\left(\overline{P}(X), \underline{P}(X)\right)$, and we call*

$$\mu_P(X) = a_P + b_P i + c_P j \tag{1}$$

*$\mu_P(X)$ is the attribute association function of $X$ with respect to the attribute set $P$, where*

$$a_P = |\underline{P}(X)|/|U|,\ c_P = \left|U - \overline{P}(X)\right| / |U|,\ b_P = \left|\overline{P}(X) - \underline{P}(X)\right| / |U| \tag{2}$$

*$a_P$, $c_P$, $b_P$ are the degree of identity, degree of oppositeness and degree of difference, $a_P + b_P + c_P = 1$ satisfies the normalization condition, and $i \in [-1, 1]$, $j = -1$ have the dual meaning of value and symbol.*

We give $K = (U, A)$ and $P, Q \subseteq A$, set $U = \left\{x_1, x_2, \dots, x_{|U|}\right\}$, $\sigma = \left\{\{x_1\}, \{x_2\}, \dots, \left\{x_{|U|}\right\}\right\}$, and the attribute correlation function $\mu_P(X)$ of rough set $X \subseteq U$ based on $P$ has the following properties.

**Property 2.1.** *Attribute association function $\mu_P(X) = i \Leftrightarrow U/P = U$.*

Certification:

$$a_P = 0,\ b_P = 1,\ c_P = 0 \tag{3}$$

We get $\mu_P(X) = i$.

Necessity: When $\mu_P(X) = i$,

$$\overline{P}(X) = U,\ \underline{P}(X) = \phi \tag{4}$$

We get $U/P = U$.

**Property 2.2.** *Attribute association function $\mu_P(X) = a_P + c_P j \Leftrightarrow U/P = \sigma$.*

Certification:

Adequacy: When $U/P = \sigma$, then

$$b_P = \left|\overline{P}(X) - \underline{P}(X)\right| / |U| = 0 \tag{5}$$

We get $\mu_P(X) = a_P + c_P j$

Necessity: When $\mu_P(X) = a_P + c_P j$, $b_P = 0$, then

$$\overline{P}(X) = \underline{P}(X) = X \tag{6}$$

We get $U/P = \sigma$.

We set $R = P \bigcup Q$, and the attribute association function $\mu_R(X) = a_R + b_R i + c_R j$ has $a_R \geq a_P$, $a_R \geq a_Q$, $c_R \geq c_P$, $c_R \geq c_Q$, $b_R \leq b_P$, $b_R \leq b_Q$.

Rough approximation is shown in Figure 1. We arbitrarily take two sets $X$, $Y$ in the universe $U$ to form a set pair $H(X,Y)$. A set pair correlation function is constructed to make the relationship between the certainty and uncertainty expressed by the set pair connection degree more objective and effective.

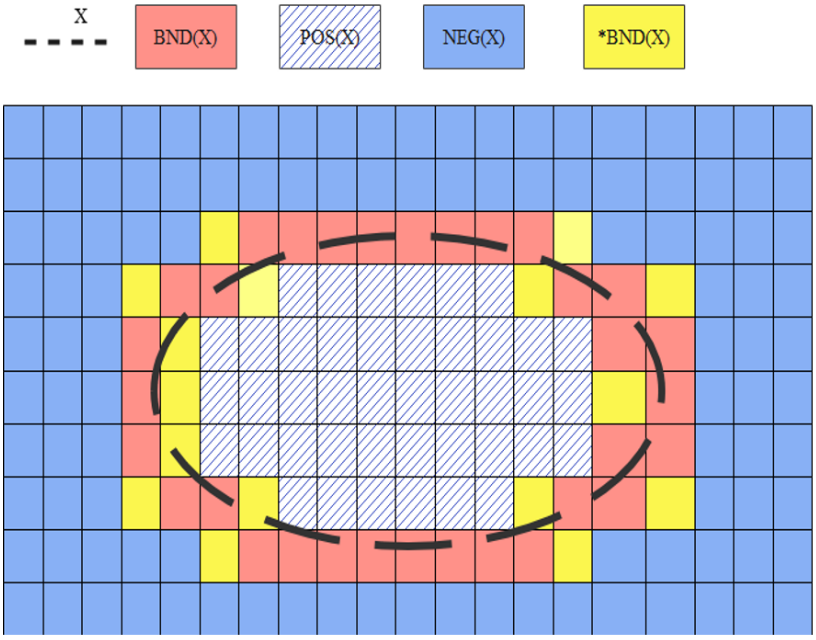


FIGURE 1. (color online) Rough approximation

**Definition 2.2.** *We give the inventory information system* $K = (U, A)$ *and the attribute set, and choose any two sets* $X$, $Y$ *in* $U$ *to form a set pair* $H(X,Y)$. *Set pair rough approximation is shown in Figure 2.*

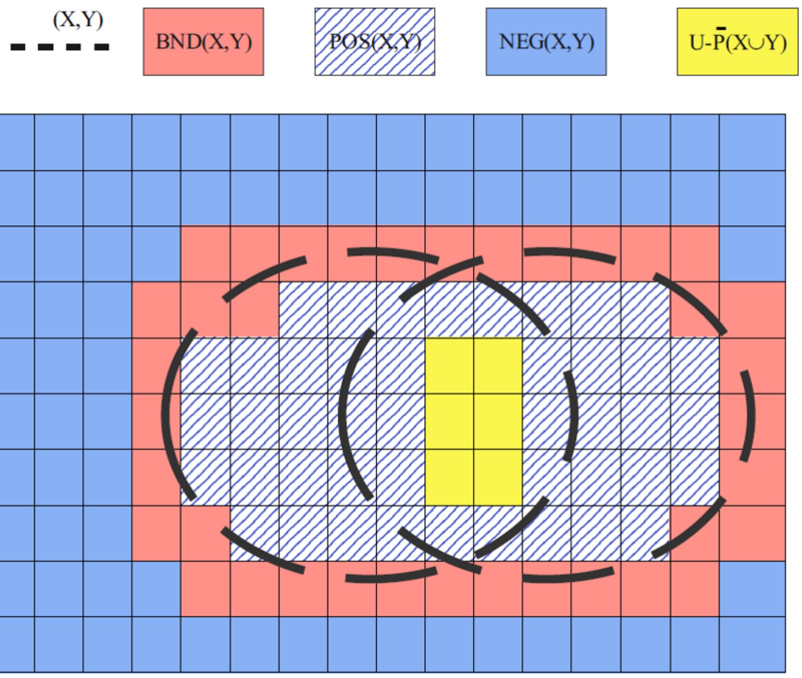


FIGURE 2. (color online) Set pair rough approximation

**Definition 2.3.** *We call*

$$\mu_P(X,Y) = a_P^H + b_P^H i + c_P^H j \tag{7}$$

*$\mu_P(X,Y)$ is the set pair association function of set pair $H(X,Y)$ on the attribute set $P$, are the degree of identity, degree of oppositeness and degree of difference of $H(X,Y)$ with respect to $P$, respectively, $i \in [-1,1]$, $j = -1$ have the dual meaning of value and mark symbol, and $a_P^H + b_P^H + c_P^H = 1$ still satisfies the normalization condition.*

The set pair correlation function of set pair $H(X,Y)$ has the following properties.

**Property 2.3.** *Set pair correlation function $\mu_P(X,Y) = i \Leftrightarrow U/P = U$.*

We get $\mu_P(X,Y) = i$.
Necessity: that is, $a_P^H = 0$, $b_P^H = 1$, $c_P^H = 0$, and

$$\overline{P}(X,Y) = \overline{P}(X \cup Y),\ \underline{P}(X,Y) = \phi \tag{8}$$

We get $U/P = U$.

**Property 2.4.** *Set pair correlation function $\mu_P(X,Y) = a_P^H + c_P^H j \Leftrightarrow U/P = \sigma$.*

Certification:
Adequacy: when $U/P = \sigma$, then

$$b_P^H = \left|\overline{P}(X,Y) - \underline{P}(X,Y)\right| / \left|\overline{P}(X \cup Y)\right| = 0 \tag{9}$$

We get $\mu_P(X,Y) = a_P^H + c_P^H j$.
Necessity: when $\mu_P(X,Y) = a_P^H + c_P^H j$, $b_P^H = 0$, then

$$\overline{P}(X,Y) = \underline{P}(X,Y) = X \bigcap Y \tag{10}$$

**Property 2.5.** *$R = P \cup Q$ and the set pair correlation functions of $H(X,Y)$ on $\mu_R(X,Y)$ are $a_P^H \le a_R^H$, $a_Q^H \le a_R^H$, $b_P^H \ge b_R^H$, $b_Q^H \ge b_R^H$, $c_P^H \le c_R^H$, $c_Q^H \le c_R^H$.*

Through the above discussion, it can be seen that the sets $X$, $Y$, and the set pair correlation function $\mu_P(X,Y)$ characterize the similarity, difference and inverse relationship between sets $X$ and $Y$, which is closely related to the equivalent division $U/P$ of the universe of discourse by the attribute set $P$. When the sets $X$, $Y$ change, $\mu_P(X,Y)$ will change accordingly.

**Theorem 2.1.** *When the set $Y = U$, $\mu_P(X,Y) = \mu_P(X)$.*

This theorem shows that the set pair correlation function is an extension of the attribute correlation function. When any set that constitutes a set pair is expanded into the entire universe, the set pair correlation function degenerates into an attribute correlation function.

The set pair association function contains two dynamic factors: attribute set and set pair. Different attribute sets represent different perceptions of uncertainty about things, and set pairs represent the set of things discussed. The increase or decrease of attribute sets and set pairs can be expressed by the intersection and union of sets. Therefore, this paper proposes two synthetic operations of set pair association function based on attribute set and element set.

The set pair correlation functions of set pair $H(X,Y)$ about $P$, $Q$ are as follows.

**Definition 2.4.** *($U^*$ compositing operation): For set pair correlation functions $\mu_P(X,Y)$ and $\mu_Q(X,Y)$, we set the attribute set $R = P \cup Q$, "$U^{\Re}$" is the union symbol of set pair associative function based on $R = P \cup Q$.*

The equivalence class of $U/R$ can be obtained by dividing and refining the equivalence class of $U/P$ and $U/Q$ through the intersection operation. At this time, some of the equivalence classes belonging to the boundary domain will be transformed into the lower approximation set due to the segmentation, and some will be transformed outside the upper approximation set, and the boundary domain will be reduced, as shown in Figure 3.

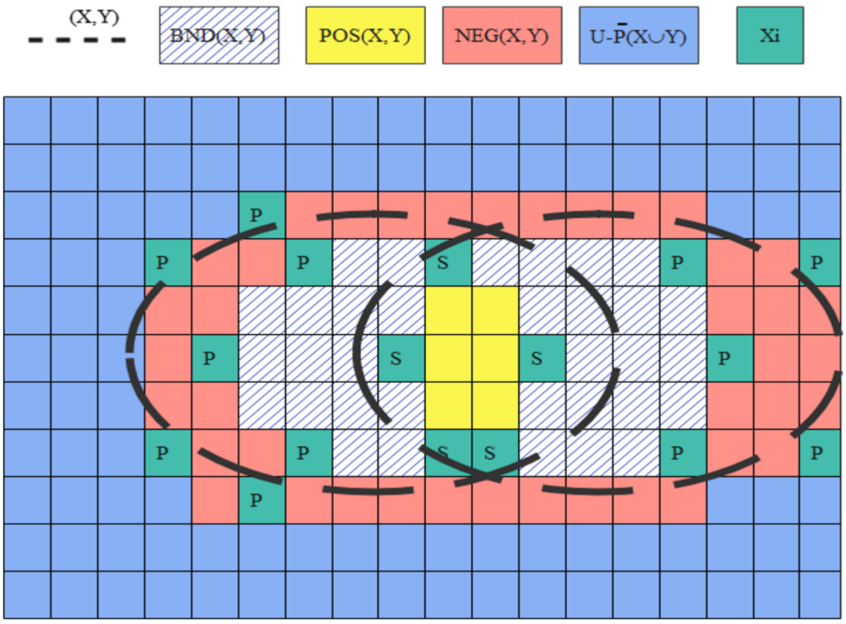


FIGURE 3. (color online) Boundary simplification

Therefore, the composite operation of the set pair correlation function $\mu_P(X,Y)$ and $\mu_Q(X,Y)$ on the attribute set $R = P \cup Q$ is to find the equivalence class that changes on the basis of $U/P$ and $U/Q$ to calculate $\left(\overline{R}(X,Y), \underline{R}(X,Y)\right)$.

2.2. **Set pair inventory information entropy in inventory information system.** The defined inventory information entropy $H(P)$ can not only measure the importance of attribute set $P$, but also measure the uncertainty of inventory information system. The greater the inventory information entropy, the stronger the ability of the attribute to distinguish the element set in the universe, the more important the attribute, and the greater the disorder degree of the system. The set pair attribute soft calculation method is an effective tool to study the uncertainty in the inventory information system. This method is introduced into the inventory information entropy, and positive is entropy, negative anti-entropy and difference entropy are defined on the set pair positive domain, negative domain and boundary domain, respectively. The inventory information is measured in the positive, negative and boundary fields of the set pair, and the inventory information entropy of the set pair is uniformly represented, so that the certainty and uncertainty in the knowledge system can be uniformly measured.

**Definition 2.5.** *We give the inventory information system $K = (U, A)$ and the attribute set $P$, and choose any two sets $X$, $Y$ in $U$ to form set pair $H(X,Y)$. The equivalent divisions of $POS(X,Y)$, $NEG(X,Y)$ and $BND(X,Y)$ on $P$ are*

$$POS(X,Y)/P = \left\{X_1^P, X_2^P, \ldots, X_m^P\right\}$$
$$NEG(X,Y)/P = \left\{X_1^N, X_2^N, \ldots, X_l^N\right\}$$

$$BND(X,Y)/P = \left\{X_1^B, X_2^B, \ldots, X_t^B\right\} \tag{11}$$

**Definition 2.6.** *The probability distributions on $POS(X,Y)$, $NEG(X,Y)$ and $BND(X,Y)$ of set pair $H(X,Y)$, $H(X,Y)$ composed of sets $X$, $Y$ are respectively*

$$\begin{aligned}
&\sum_{i=1}^{m} p_i^P + \sum_{i=1}^{l} p_i^N + \sum_{i=1}^{t} p_i^B = 1\\
&H_P^P(X,Y) = -\sum_{i=1}^{m} p_i^P \log p_i^P\\
&H_P^N(X,Y) = -\sum_{i=1}^{l} p_i^N \log p_i^N\\
&H_P^B(X,Y) = -\sum_{i=1}^{t} p_i^B \log p_i^B
\end{aligned} \tag{12}$$

Among them, the meanings of $i$ and $j$ are consistent with the connection degree of set pair, which has the dual meaning of value and mark symbol.

The set pair inventory information entropy $SH\{P\}(X,Y)$ has the following properties.

**Property 2.6.** *Since the values of $i$ and $j$ are $-1 \le i \le 1$, $j = -1$ respectively, the set pair inventory information entropy $SH_P(X,Y)$ does not satisfy non-negativity. If and only if $p_i^P = p_i^B = 0$, $p_i^N = 1$, $p_i^P = p_i^N = 0$, $p_i^B = 1$, $p_i^B = p_i^N = 0$, $p_i^P = 1$.*

Certification:

Since the probability distribution $p_i^P$, $p_i^B$, $p_i^N$ satisfies $0 \le p_i^P, p_i^B, p_i^N \le 1$, where

$$-p_i^P \log p_i^P \ge 0,\ -p_i^B \log p_i^B \ge 0,\ -p_i^N \log p_i^N \ge 0$$

then

$$\begin{aligned}
H_P^P(X,Y) &= -\sum_{i=1}^{m} p_i^P \log p_i^P \ge 0\\
H_P^N(X,Y) &= -\sum_{i=1}^{l} p_i^N \log p_i^N \ge 0\\
H_P^B(X,Y) &= -\sum_{i=1}^{t} p_i^B \log p_i^B \ge 0
\end{aligned} \tag{13}$$

It can be seen from the above discussion that the set pair inventory information entropy can not only describe the statistical characteristics of the overall probability distribution of the inventory information system, but also establishes the similarities, differences and opposites between attribute features, which is an extension to describe the support and dependency between attribute sets, and is closely related to the equivalence division $U/P$.

1) After adding a new attribute, the granularity of the equivalence class obtained by the equivalence division of the attribute set pair universe becomes smaller, and the corresponding probability distribution will change, which will cause the change of the set pair inventory information entropy.

We give $K = (U, A)$ and $P$. The $P$-based set pair inventory information entropy of set pair $H(X,Y)$ is $SH_P(X,Y)$. If attributes $a \in A$ are added to attribute set $P$, $Q = P \bigcup \{a\}$, $P \subseteq Q \subseteq A$ and the following two relationships exist between attribute sets $P$ and $Q$:

(a) If the object $P$ can distinguish, and the newly added attribute $a$ can also distinguish. If the object $P$ cannot distinguish, and the newly added $a$ is also indistinguishable, then there is an equivalence relationship $P \approx Q$ between $P$ and $Q$;

(b) If the object $P$ cannot distinguish, and the newly added attribute $a$ can distinguish, then there is a partial order relationship $P \prec Q$ between $P$ and $Q$.

For the case (a), the new attribute $a$ will not affect the original equivalence class, that is, there is an equivalence relationship $P \approx Q$ between the attribute sets $P$ and $Q$, the corresponding probability distribution is the same, and the set pair inventory information entropy is ${}^2H_P(X,Y) = SH_Q(X,Y)$. For case (b), the new $a$ subdivides the original equivalence class, and the corresponding probability distribution changes. It makes the internal (positive isoentropy, negative antientropy and difference entropy) structure of the set pair inventory information entropy change.

**Theorem 2.2.** *We give $K = (U, A)$ and $P$, add a new attribute $a$, and for the set pair inventory information entropy $SH_P(X,Y)$, $Q = P \cup \{a\}$.*

The new attribute $a$ divides the equivalence class $X_i$ into $t$ equivalence classes. Then, there is a permutation $Y'_1, Y'_2, \ldots, Y'_m$, $m = n+t-1$ in $U/Q$ such that $X_1 = Y'_1$, $X_2 = Y'_2$, $\ldots$, and $X_i = Y'_i \cup Y_{i+1} \cup \cdots \cup Y'_{i+1}$, $X_{i+1} = Y_{i+t+1}, \ldots, X_n = Y_{n+t-1}$.

The probability distribution is

$$p(X_k) = p\left(Y'_k\right),\ k \in (0,i) \cup [i+t+1, n++-1]$$
$$p(X_i) = p\left(Y'_i\right) + p\left(Y'_{i+1}\right) + \cdots + p(Y_{i+1}) \tag{14}$$

$$-p(X_i)\log p(X_i) \le -\sum_{j=0}^{t} p(Y_{i+j})\log p(Y_{i+j}) \tag{15}$$

We get

$$H_P^P(X,Y) \le H_\varrho^P(X,Y),\ H_P^N(X,Y) \le H_\varrho^N(X,Y) \tag{16}$$

The certificate is complete.

The theorem states that in the inventory information system, if there is a partial order relationship $P \le Q$ between attribute sets $P$ and $Q$, the set pair inventory information entropy $SH_Q(X,Y)$ is more refined than $SH_P(X,Y)$.

2) After adding a new research object, one (some) of the equivalence classes formed based on the equivalence division of attribute sets in the universe of discourse will change accordingly, and the corresponding probability distribution will also change. This may also cause changes in set pair inventory information entropy.

**Definition 2.7.** *After the new object $u$ is added to the inventory information system, it is said that the attribute set $P$ can distinguish the new object $X_i$; otherwise, $u$ must be added to an equivalence class $r$, that is, $\forall x \in X_i$, $\forall a \in P$, $f(x,a) \ne f(u,a)$.*

We give $K = (U, A)$ and $P \subseteq A$, the equivalent partition $U/P = \{X_1, X_2, \ldots, X_n\}$, and for the set pair $H(X,Y)$ composed of the set $X, Y \subseteq U$ in the universe, the $P$-based set pair inventory information entropy is $SH_P(X,Y)$. If a new object $u$ is added to the universe of discourse $U$, the impact on $SH_P(X,Y)$ can be divided into the following two situations. It may be set that after the new object is added, the set pair inventory information entropy is $SH'_P(X,Y)$:

(a) If $P$ can distinguish the newly added $u$, it is advisable to set the equivalent division to be $U \bigcup \{u\}/P = \{X_1, X_2, \ldots, X_n, \{u\}\}$, then $u \in U \bigcup \{u\} - \overline{P}(X \cup Y)$ and $H_P(X,Y)$ have not changed, that is, $SH'_P(X,Y) = SH_P(X,Y)$;

(b) After adding the object $u$, if $\forall x \in X_k$, $\forall a \in P$, $f(x,a) \ne f(u,a)$, the equivalent division is $U \cup \{u\}/P = \{X_1, X_2, \ldots, X_k \cup \{u\}, X_{k+1}, \ldots, X_n\}$, then $u \in \overline{P}(X \cup Y)$.

The above analysis gives the update situation of the set pair inventory information entropy $SH_P(X,Y)$ after adding an object $u$, and makes a preliminary discussion for the research on the update method of the set pair inventory information entropy.

2.3. **Set pair inventory information entropy and correlation function, inventory information entropy, joint entropy and negative entropy.** In the sense of inventory information system, in the set pair correlation function $\mu_P(X,Y) = a_P^H + b_P^H i + c_P^H j$ based on equivalence division. $a_P^H$ represents the part with the same meaning between sets under a certain classification standard. $b_P^H$ represents that the relationship between sets is in a vague and uncertain state, $c_P^H$ represents the parts with opposite meanings, and the three parts jointly describe the state of the same, different, and opposite connection between sets.

The set pair inventory information entropy provides an inventory information explanation for the identity, difference and negativity of the set pair, and provides a deeper characterization of the similarities, differences and negativity between sets.

The inventory information system is $K = (U,A) : U = \{x_1, x_2, \ldots, x_8\}$, and the set pair correlation function of $H(X,Y)$ based on $R$ is $\mu_R(X,Y) = \frac{1}{8} + \frac{7}{8}i$.

Among them, the degree of difference $b_R^H = \left|\overline{R}(X,Y) - \underline{R}(X,Y)\right| / \left|\overline{R}(X \cup Y)\right| = 7/8$ does not reflect the granularity characteristics within the difference, namely $\left|\overline{R}(X,Y) - \underline{R}(X,Y)\right| = \{\{x_1, x_3, x_4\}, \{x_5, x_7\}, \{x_6, x_8\}\}$.

The set pair inventory information entropy based on attribute set $R$ of set pair $H(X,Y)$ is

$$SH_R(X,Y) = -\frac{1}{8}\log\frac{1}{8} - i\left(\frac{3}{8}\log\frac{3}{8} + \frac{2}{8}\log\frac{2}{8} + \frac{2}{8}\log\frac{2}{8}\right) \tag{17}$$

It can not only describe the relationship between the sets $X$ and $Y$, but also reflect the internal granular structure of the difference $b_P^H$ in more detail.

It can be seen that the set pair correlation function is the basis of the set pair inventory information entropy, and the set pair inventory information entropy is the inventory information measure of the identity, difference and opposition in the set pair correlation function.

The theorem states that if the set $X, Y$ is expanded to the entire discussion area, the set pair inventory information entropy $SH_P(X,Y)$ degenerates into the inventory information quotient $H(P)$.

We give $K = (U,A)$ and $P, Q \subseteq A$, and by the definition of joint entropy

$$H(P,Q) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p(X_i, Y_j)\log p(X_i, Y_j) \tag{18}$$

It can be seen that the joint entropy represents the average uncertainty of the same degree of knowledge $P$ and $Q$ on the division of the universe of discourse $U$. In fact, the probability distribution $p(X_i, Y_j) = |X_i \cap Y_j| / |U|$ does not necessarily indicate that knowledge $P$ and $Q$ divide the universe of discourse $U$ to the same degree. For example, in the inventory information system $K = (U,A) : U = \{u_1, u_2, u_3, u_4, u_5\}$. $M_1, M_2 \subseteq A$, the equivalent division is $U/M_1 = U/M_2 = \{\{u_1, u_3, u_4\}, \{u_2\}, \{u_5\}\}$, and then the joint entropy is

$$H(M_1, M_2) = -\left(\frac{3}{5}\log\frac{3}{5} + \frac{2}{5}\log\frac{1}{5}\right) \tag{19}$$

It can be seen that the positive same entropy part in the set pair inventory information entropy has the same meaning as the joint entropy, and can be used to measure the positive correlation between two events. In addition, the difference entropy and negative anti-entropy in the set pair inventory information entropy also measure the relative uncertainty and negative correlation between things.

3. **Integrated Inventory Optimization of FAP Supply Chain Based on Neural Network.** BP neural network is currently one of the most widely used and researched neural networks. It has the following advantages: self-learning ability wall; having good generalization ability; high fault tolerance for data; it can be processed in parallel and distributed manner. Similarly, it also has the following obvious drawbacks: easy to fall into local optima; slow convergence speed; parameter adjustment is cumbersome; difficulty in selecting structure. However, PSO has fast convergence and strong global optimization ability, which can make up for the shortcomings of BP's slow convergence speed and local extremum. Therefore, this paper establishes the PSO-BP neural network prediction model to carry out nonlinear prediction of the cold chain logistics demand of FAPs, and its modeling realization is shown in Figure 4.

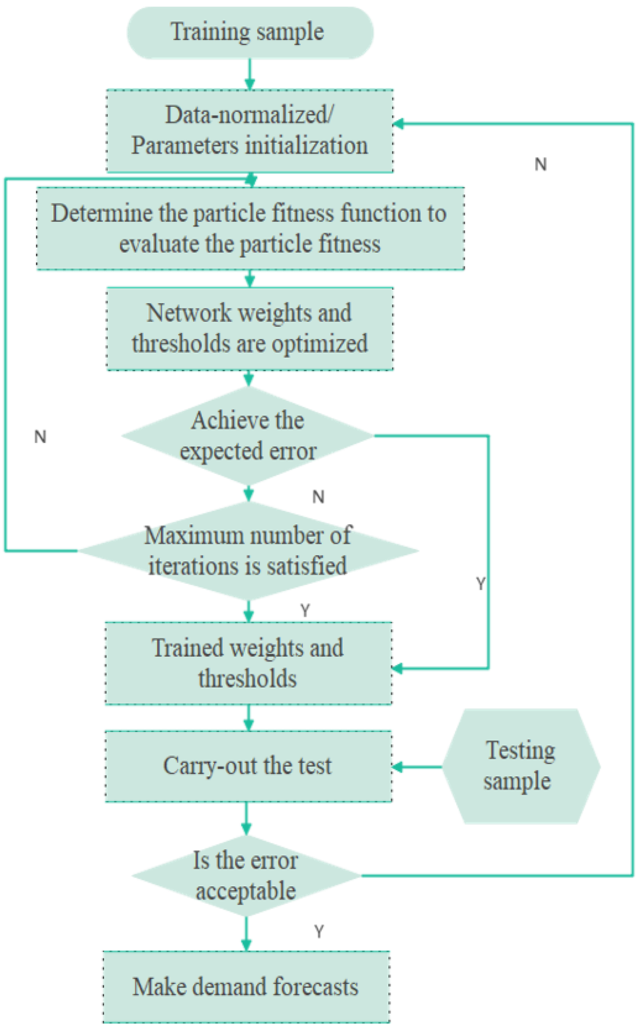


Figure 4. The modeling process of the PSO-BP neural network prediction model

After the supplier receives the demand information, it will be packaged according to the requirements of each booth, and the purchasing staff will check the relevant agricultural products. If the quality is qualified, they will be uniformly distributed to the farmers market. After receiving the relevant products, each booth will hand over the payment

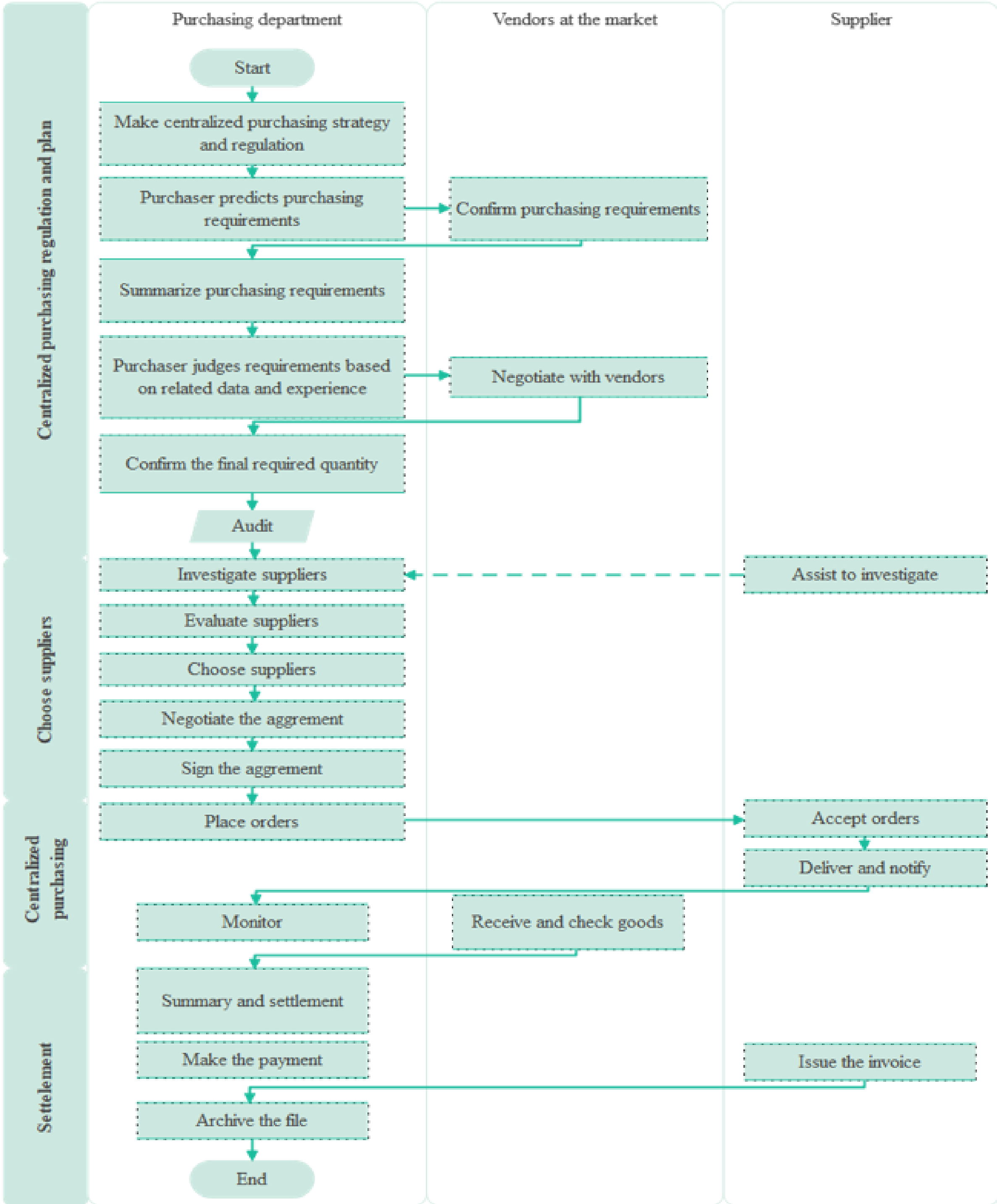


FIGURE 5. Centralized procurement process of FAPs

for the goods to the purchasing department, and the purchasing department will pay the supplier uniformly. Its related process is shown in Figure 5.

According to the idea of TCO (Total Cost of Ownership) analysis method, the purchase cost composition of FAPs is analyzed. The total cost of ownership method is a long-term analysis method. When purchasing related agricultural products in the farmers market, it is required to analyze the cost structure of each link, not only to consider the purchase price, but also to pay attention to other expenses when purchasing agricultural products, as shown in Figure 6.

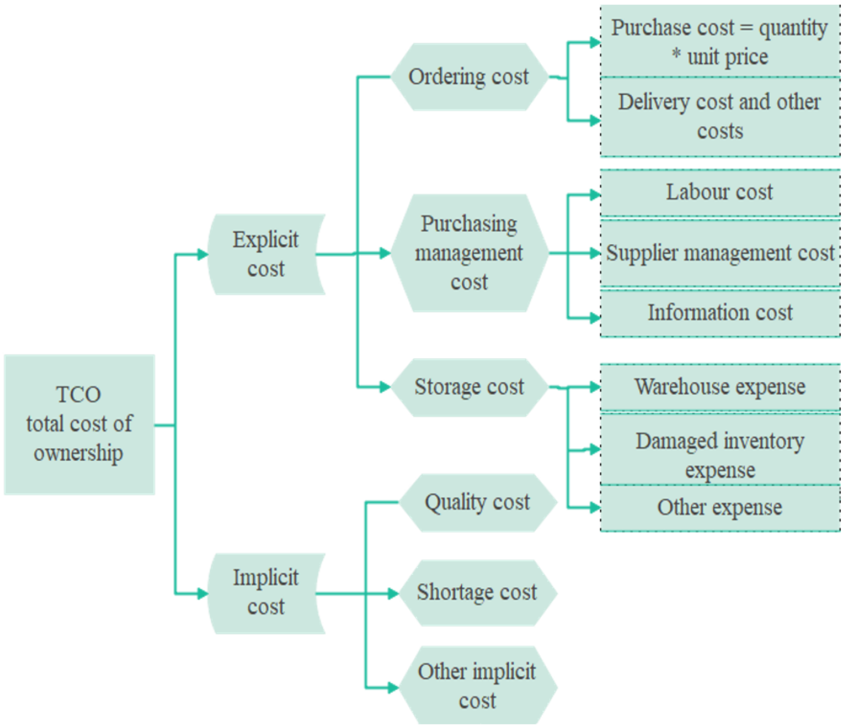


FIGURE 6. Structure diagram of procurement Total Cost of Ownership (TCO)

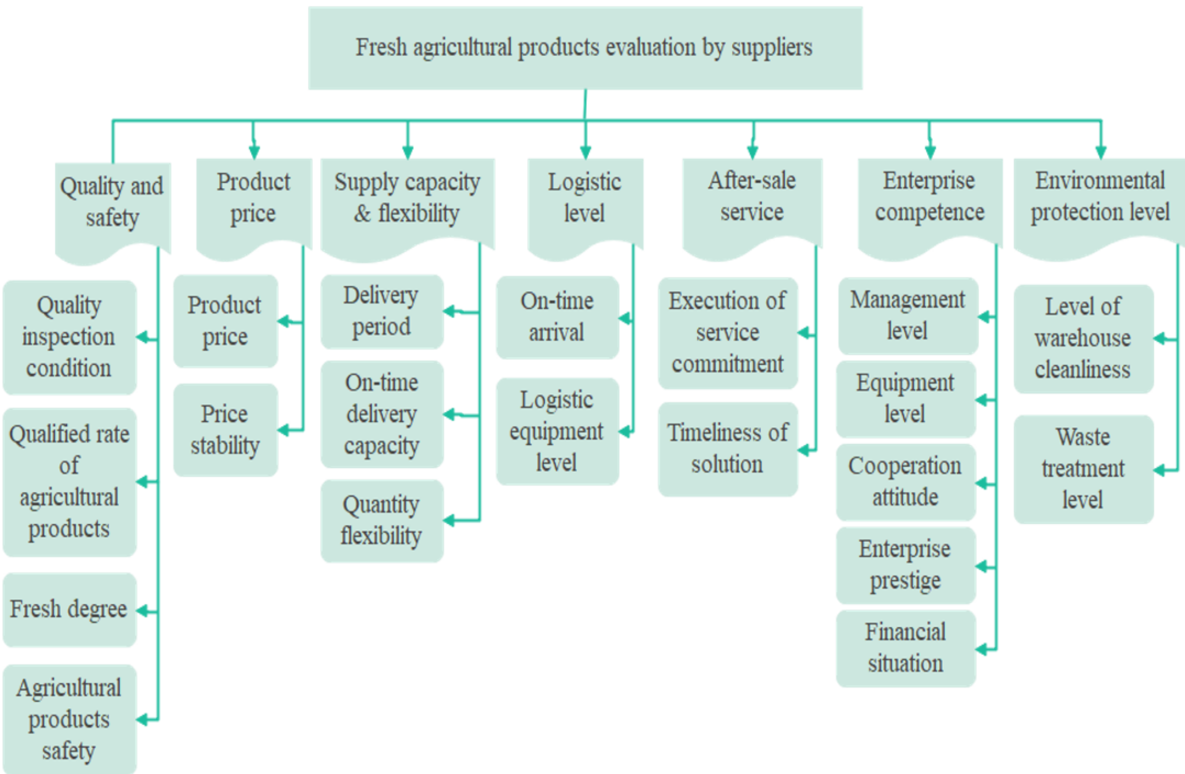


FIGURE 7. The evaluation hierarchy of FAPs suppliers

AHP decomposes the multi-objective decision-making problem into several levels of multiple indicators, calculates the weights of each level through the fuzzy quantification method of qualitative indicators, and finally performs a total ranking according to the impact on the target value. According to different attributes, the various factors related to supplier evaluation are decomposed into several levels, the same level factors have an impact on the upper level factors, and at the same time have an effect on the lower level factors, as shown in Figure 7.

System dynamics flow diagrams are used to describe the cumulative effects that affect the dynamic performance of a feedback system, further representing the distinction between variables of different properties. When we perform refinement in terms of system causality, a system flow graph can be depicted, as shown in Figure 8.

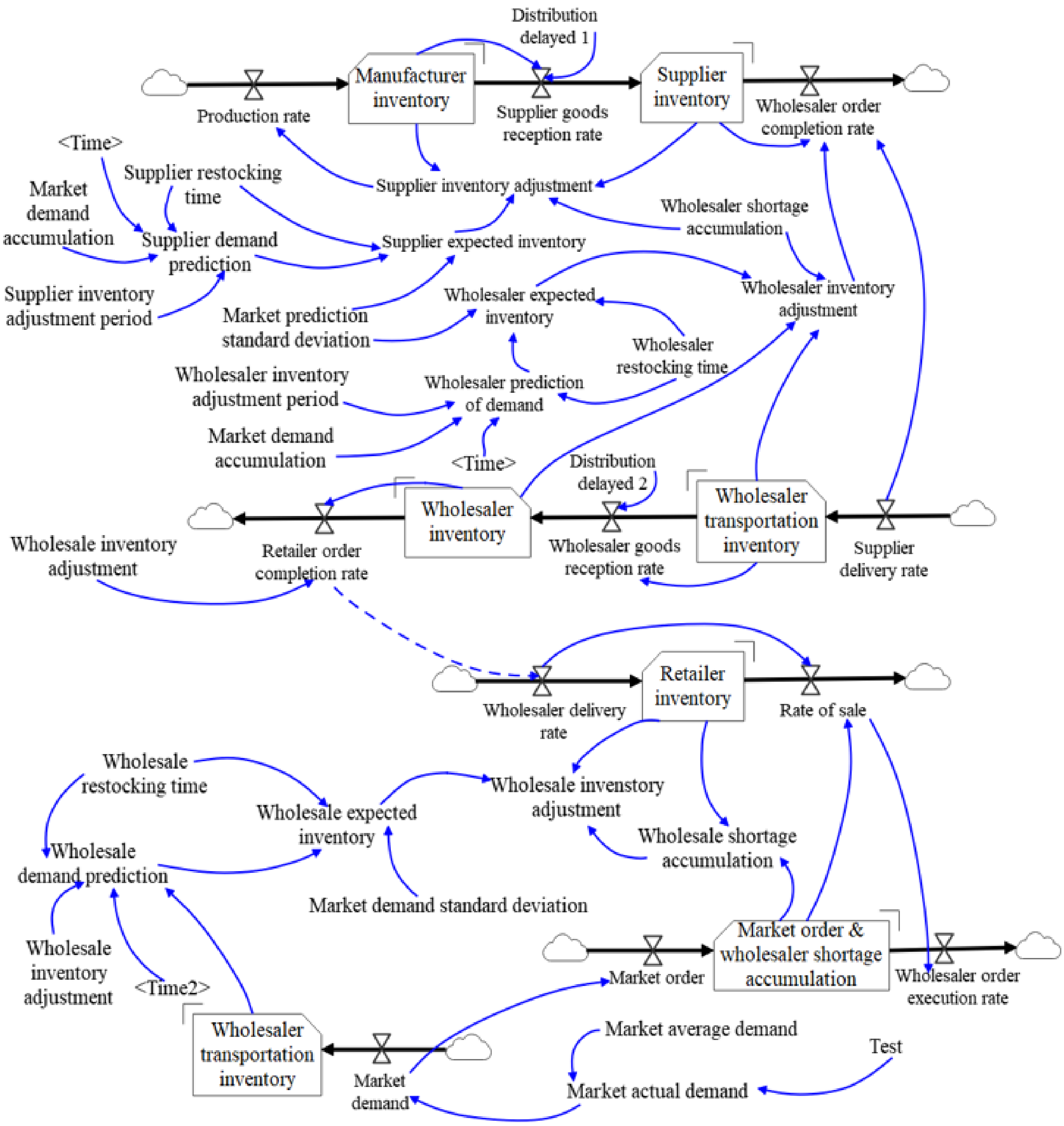


FIGURE 8. Flow diagram of FAP supply chain inventory system

In order to verify the effectiveness of the improvements made to the BP neural network in this article, a system model was run on the VensimPLE platform to compare the convergence speed of the BP neural network and the PSO-BP neural network. The results are shown in Figure 9.

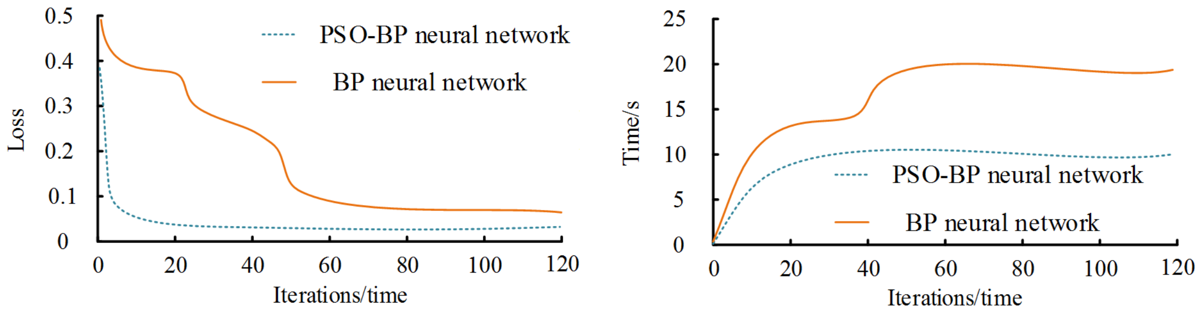


FIGURE 9. Comparison of convergence between BP neural network and PSO-BP neural network

The BP neural network completed convergence at the 50th iteration, while the PSO-BP neural network completed convergence at the 10th iteration. After the improvement of PSO, the convergence speed of the BP neural network algorithm has been significantly improved, and the running time of the PSO-BP neural network has also been significantly reduced. The improvement of BP neural network through research is effective. Moreover, this paper selects three decision variables: no information sharing, low information sharing, and high information sharing, and three indicators that reflect the inventory status of the three links in the FAP supply chain: supplier inventory, wholesaler inventory, and retailer inventory. Through the simulation of the system, the simulation results shown in Figure 10 are obtained.

From the above system simulation results, it can be seen that whether suppliers, wholesalers and retailers in the FAP supply chain system share information, and the degree of information sharing, has a significant impact on their respective inventory conditions. In the early stage of implementing the information sharing strategy in the supply chain system, due to changes in their respective ordering patterns, the inventories of suppliers, wholesalers and retailers fluctuated to a large extent. However, after a period of adaptation and adjustment, the inventories of suppliers, wholesalers and retailers tend to be stable, and the overall inventory level has dropped significantly. With the improvement of information sharing, the effect is more significant.

4. **Conclusion.** Fresh products are different from general commodities, and have the characteristics of short shelf life, perishable and perishable. In the actual operation process, the retail terminal's awareness of FAP inventory management is relatively weak. Moreover, the ordering strategy only relies on the work experience accumulated at ordinary times, and lacks accurate prediction of market demand, so the phenomenon of slow sales is more common. This paper combines the neural network to analyze the integrated inventory optimization of FAP supply chain. The simulation experiment verified that the integrated inventory optimization effect of FAP supply chain based on neural network is obvious. However, in inventory optimization, only the factor of whether information is shared is considered in this study, without considering other possible impacts on FAP supply chain inventory. In the future study, factors such as season and production can be considered to affect the comprehensive inventory of the FAP supply chain.

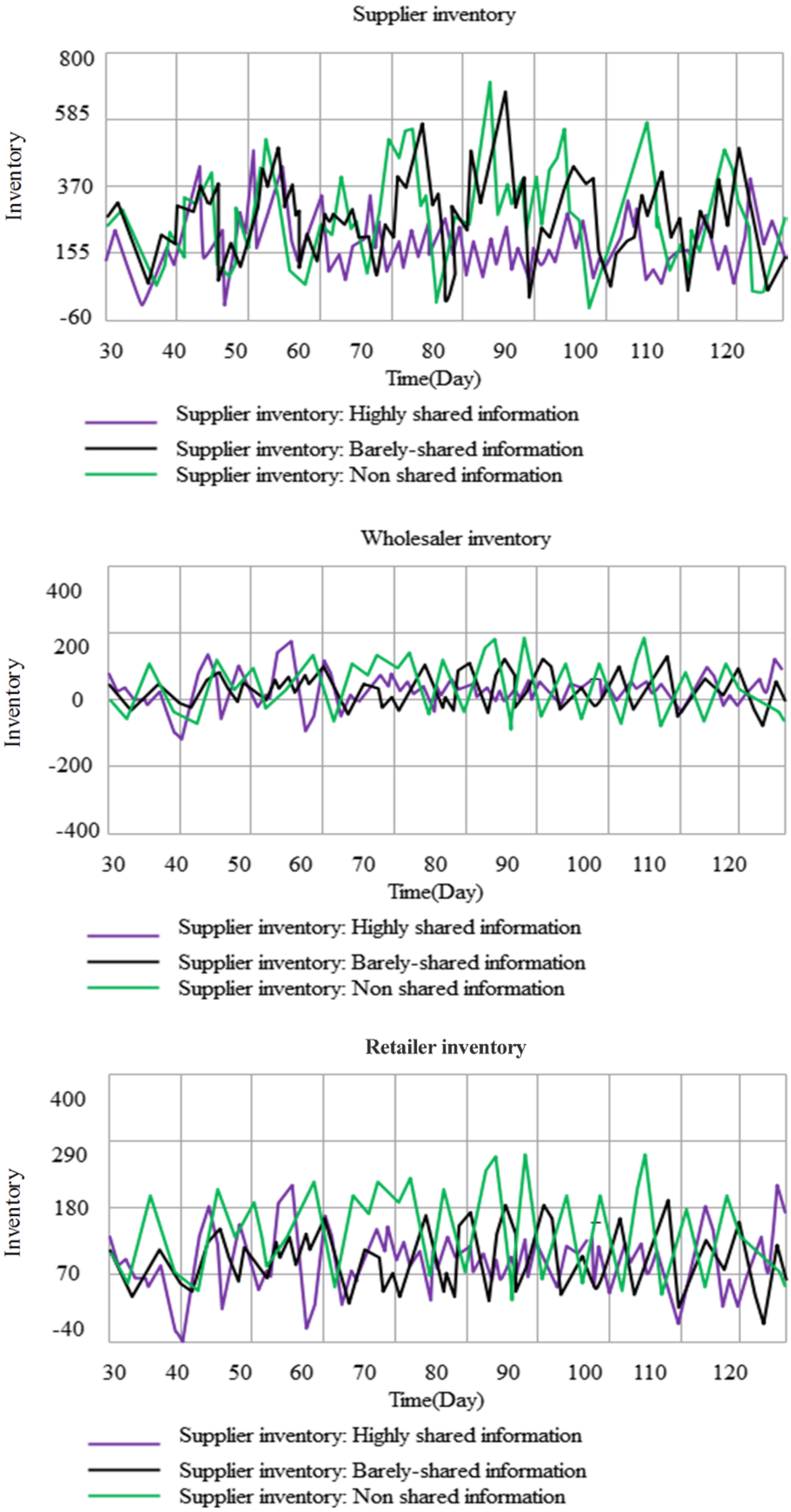


FIGURE 10. Simulation diagram of supplier, wholesaler and retailer inventory simulation

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