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Optimal Decision-Making Model of Agricultural Product Information Based on Three-Way Decision Theory

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Abstract: As an effective heuristic method, three-way decision theory gives a new semantic interpretation to the three fields of the rough set, which has a huge application space. To classify the information of agricultural products more accurately under certain thresholds, this paper first makes a comprehensive evaluation of the decision, particularly the influence of the attributes of the event itself on the results and their interactions. By using fuzzy sets corresponding to membership and non-membership degree, this paper analyzes and puts forward two cases of proportional correlation coefficients in the transformation of a delayed decision domain, and selects the corresponding coefficients to compare the results directly. Finally, consumers can conveniently grasp product attribute information to make decisions. On this basis, this paper analyzed the standard data to verify the accuracy of the model. After that, the proposed algorithm, based on three decision-making agricultural product information classification processing, is applied to the relevant data of agricultural products. The experimental results showed that the algorithm can obtain more accurate results through a more straightforward calculation process. It can be concluded that the algorithm proposed in this paper can enable people to make more convenient and accurate decisions based on product attribute information.

Keywords: three-way decision; information analysis; fuzzy set; optimization algorithm

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1. Introduction

Agricultural production plays a key role in national economic development, social stability, and food safety. It is essential to use new technology to deal with the relevant information of agricultural products [1,2]. In recent years, producers and distributors of agricultural products have attached great importance to the classification and improvement of product quality, because consumers pay more attention to the quality evaluation of agricultural products, which directly affects their purchasing decisions. Against the background of the increasing demand for evaluations of agricultural products, the purpose of solving this kind of problem is to classify the relevant information of agricultural products with appropriate algorithms. This processing includes identifying, rating, and classifying between the same variety, different varieties, and different products [3–5].

Nevertheless, the information that people obtain in the constantly changing and developing objective world is likely to be incomplete, unstable, and random [6]. People have explored many theories and methods in order to overcome the limitations of the ability to analyze these data as much as possible, such as rough set theory [7], fuzzy set theory [8], D-S theory [9,10], non-classical logic [11,12], probability theory method [13], probability graph method [14], etc. However, the collated data and information often lead to difficult decision-making due to too many options or uncertain consequences. To solve this problem, Canadian professor Yao first gave the concept of three-way decision at the 5th International Conference on Rough Sets and Knowledge Technology in 2009 [15], and formally proposed three-way decision theory in 2010 [16]. The traditional two-way decision-making must decide to accept or reject at the end of information processing even if the information is incomplete or unreliable, the risk of this decision-making strategy was often high and the boundary information cannot be processed. Three-way decision theory gave the rough set a new semantic interpretation based on rough set and decision rough set [17], which overcame the limitation that rough set theory was only applicable to knowledge acquisition in a complete information system, its core is to divide the solution space of decision-making problems into the positive domain, boundary domain, and negative domain. The positive domain corresponds to a positive acceptance decision result, the negative domain corresponds to a negative rejection decision result, and the boundary domain corresponds to an uncertain delayed decision result. Delayed decision-making in the boundary domain is a process of reprocessing boundary information, through further observation and research on the delayed decision, the delayed decision can be converted into an acceptance or rejection decision when sufficient information is obtained, so as to reduce misclassification and decision cost, such as time, consumables, capital, etc.

In recent years, there has been more theoretical research on and applications of three-way decision-making, a three-level conceptual model of perception–cognition–action (PCA) has been proposed [18], which is intended to be applied to intelligent data analysis, intelligent systems, and human understanding, thus opening up a broader application space for three-way decision theory. Li et al. [19] constructed an image information hybrid system combined with practical application scenarios, and extended the three-way decision-making model to solve the problem of medical diagnosis. Luo [20] proposed a scheme based on multi-granularity three-way decision-making of hesitant fuzzy language, including measurement to manage and sort municipal solid waste management, but the discussion on the use of hesitation to solve delayed decision-making complicates the operation. Gao [21] used the target threat assessment method of three-way decision-making based on intuitive fuzzy multi-attribute decision-making to solve the important requirements of complex battlefield situations and uncertain information processing. Adding to the discussion of multiple attributes, Wang [22] put forward a new three-way decision model based on probability dominance relation, summarized the application of related models, and presented the latest improved scheme, which makes the application of three-way decision-making more flexible and extensive. At the same time, three-way decision-making theory is also reflected in multi-party game methods. Zuo and Li [23] described three behaviors of the government according to the three situations of decision-making in order to verify the rationality and effectiveness of the subsidy mechanism of new energy technology, and finally get a scientific policy implementation plan. In the field of deep learning, three-way decision theory can also be used to judge and correct experimental results. Wang and Miao [24] used three-way decision theory to correct pedestrian detection results, and the results show that compared with the single tracker and detector, this method can significantly improve tracking accuracy. In addition, three-way decision theory and deep convolution neural network (CNN) have been combined for incremental analysis and screening to achieve accurate facial recognition results at low cost [25].

In the field of agriculture, Sezer et al. [26] evaluated the effects of bread wheat quality due to different water table depths and groundwater salinity levels and determined the most suitable irrigation scheme. Zhang [27] proposed a recognition method based on genetic algorithm and feature correlation for diseases, such as apple leaf disease, powdery mildew, mosaic disease, and rust, and achieved more than 90% correct recognition. Mesa et al. [28] used the combined strengths of RGB and hyperspectral imaging in grading bananas, and this can serve as a paradigm for grading other horticultural crops. Bhargava [29] and others classified and detected multiple varieties of apples based on freshness through image segmentation. Similarly, Arun et al. [30] used an artificial neural network to detect and grade the quality of grapefruit. Because different varieties of the same kind of agricultural products have their own unique agronomic, processing, and nutritional characteristics, this is also valuable for the identification and decision-making of different varieties. Arakeri et al. [31] developed image processing software to analyze the defects and maturity of fruits to solve the problem that manual quality inspection and grading can damage agricultural products. Xie et al. [32] used visible and near-infrared hyperspectral imaging techniques to classify mung beans. Kurtulmuş et al. [33] combined a neural network with computer vision to create a low-cost multilayer perceptron model, which realized the accurate classification of eight pepper seeds. Gomiero [34] reviewed the quality of organic agricultural products from the farming to production stages.

This paper studies the application of three-way decision-making to agricultural products and puts forward a more convenient model algorithm based on the traditional theory of three-way decision-making. The final result of the three-way decision is the two-way decision. According to the discussion of the second decision-making of the three-way decision, the decision model is refined, and a method that is closer to the two-way decision is obtained. Simultaneously, there is a limited discussion of the three-way decision of the infinite cycle, and the result of the final decision is defined. In this paper, the analysis of the practical application data is carried out through experiments, and the accuracy of the model is proved. Finally, the relevant data of agricultural products are brought into the algorithm based on three decision-making agricultural product information classification processing, and more accurate results are obtained through a simpler operation process. The experimental results show that the algorithm not only improves the time efficiency of processing products, but also verifies the practicability of the model in classifying agricultural product information.

2. Materials and Methods

2.1. Model Definition

A great deal of the theoretical basis of three-way decision-making basically comes from the idea of the rough set. In more detail, the positive, negative, and boundary domains are the selections for decision-makers for accepted, rejected, and delayed decision actions. Set a space (U, A) where U is the object domain, a finite non-empty set of event objects; O is used to filter the condition set, and D is the decision scheme set. In order to carry out classification processing in the domain, let the equivalent partition $\partial = U/O$, and $[x] \in \partial$ refers to the class of the object x under the condition of partition. Set X, with the maximum and minimum value in the X range represented as follows [35]:

$$f_1(X) = \{x \in U|\,[x] \cap X \neq \varnothing\}$$

$$f_2(X) = \{x \in U|\,[x] \subseteq X\}$$

In this way, U can be divided into three domains: positive, boundary, and negative domains, corresponding to the following formulas, respectively:

$$POS(X) = f_2(X) = \{x \in U|\,[x] \subseteq X\}$$

$$POS(X) = f_2(X) = \{x \in U|\,[x] \subseteq X\}$$

$$NEG(\,X) = U - f_1(X) = \{x \in U|\,[x] \cap X \neq \varnothing\}$$

The conditional probability formula $P(X\,[x]) =|\,X\ \cap\,[x]|/|[x]|$ indicates the probability that an event object belongs to [x], but, at the same time, is under the condition of X. In this way, it can be obtained

$$POS_{(n,m)}(X) = \{x \in U|P(X|[x]\,) = 1\}$$

$$BND_{(n,m)}(X) = \{x \in U|0 < P(X|[x]\,) < 1\}$$

$$NEG_{(n,m)}(X) = \{x \in U|P(X|[x]\,) \neq \varnothing\}$$

If a pair of thresholds n and m are introduced, the three domains depend on (m < n) and $0 \leq m < n \leq 1$, and the definition is as follows:

$$\mathrm{POS}_{(n,m)}(X) = \{x \in U | P(X|[x]) \geq n\}$$

$$\mathrm{BND}_{(n,m)}(X) = \{x \in U | m < P(X|[x]) < n\}$$

$$\mathrm{NEG}_{(n,m)}(X) = \{x \in U | P(X|[x]) \leq m\}$$

The following can be concluded:

When the possibility that x belongs to x is greater than n, then x is in the positive domain, corresponding to

$$\{x \in U | P(X|[x]) \geq n\}$$

When the possibility that x belongs to X is between n and m, then x is in the boundary domain, corresponding to

$$\{x \in U | m < P(X|[x]) < n\}$$

When the possibility that x belongs to X is less than m, then x is in the negative domain, which corresponds to

$$\{x \in U | P(X|[x]) \leq m\}$$

2.2. Classification of Objective Information

When people receive objective information, they use each part of the information to compare the standards that they have prepared, including the criteria that they will choose to accept, the criteria that they will choose to reject, and the criteria that they will wait and see about; that is, a three-way decision-making analysis that is intuitively vague about objective information.

Then set the objective information object set U, where x is any component of this collection, and the decision-maker, after receiving the objective information, will have two attitudes regarding the event object x, that either x should belong to U or the opposite, but the relationship of $x \in U$ is unchanged. This "attitude" can be regarded as the two states of membership degree and non-membership degree of event object x according to a certain decision-making behavior. In this paper, POS(P) is used to represent the membership state and NEG(N) the non-membership state. At the same time, set U is divided into membership state set K and non-membership state set K^-. This is for more detailed analysis when people are uncertain, that is, delayed decision-making. Here, first, use the decision cost matrix based on the three-way decision model of the decision rough set [36], as shown in Table 1.

Table 1. Decision cost matrix in two states.

Decision Action	Event Object	
	Membership State (P)	**Non-Membership State (N)**
Accept event object (w_P)	γ_{PP}	γ_{PN}
Reject event object (w_N)	γ_{NP}	γ_{NN}
Delay decision (w_B)	γ_{BP}	γ_{BN}

In Table 1, w_P means that event object x belongs to the positive domain, which means the event is accepted, and in this case, $x \in K$; w_N means that event object x belongs to the negative domain, which means the event is rejected, and in this case, $x \in K^-$; w_B means that event object x belongs to the boundary domain, which means the decision on this event is delayed, and it is not clear whether event object x belongs to K or K^-. At this point, in order to discuss the state of object X when there is a delayed decision, let the evaluation function $F(w_x|x)$, where w_x is the decision action of event object x, then it can be clearly obtained that when $x \in K$, the evaluation cost of the function is the corresponding $\gamma_{PP}, \gamma_{NP}, \gamma_{BP}$ when the three decision actions are carried out in the membership state. On the other hand, when $x \in K^-$, the evaluation cost of the function is the corresponding $\gamma_{PN}, \gamma_{NN}, \gamma_{BN}$ when the three decision actions are carried out in the non-membership state. In addition, let $\delta(x)$ be the membership degree and $\theta(x)$ the non-membership degree of event object x.

According to the introduction of the three-way decision in Section 2.1, and in order to better reflect the function of the function, it is considered that $0 \leq \gamma_{PP} \leq \gamma_{BP} \leq \gamma_{NP}$, $\gamma_{PN} \geq \gamma_{NN} \geq \gamma_{BN} \geq 0, 1 \geq \delta(x) + \theta(x) \geq 0$. To sum up, for the price function $F(w_x|x)$, it can be concluded that:

The cost of accepting event object x is $F(w_P|x) = \gamma_{PP} \times \delta(x) + \gamma_{PN} \times \theta(x)$.

The cost of rejecting event object x is $F(w_N|x) = \gamma_{NP} \times \delta(x) + \gamma_{NN} \times \theta(x)$.

The cost of delaying event object x is $F(w_B|x) = \gamma_{BP} \times \delta(x) + \gamma_{BN} \times \theta(x)$.

According to normal situations where people are faced with choices, they are more likely to accept options that cost less, so the following can be obtained: When $F(w_P|x) \leq F(w_N|x)$ and $F(w_P|x) \leq F(w_B|x)$, it means that event object x is in the positive domain of the three-way decision theory and is accepted by the decision-maker. When $F(w_N|x) \leq F(w_P|x)$ and $F(w_N|x) \leq F(w_B|x)$, it means that event object x is in the negative domain and is rejected by the decision-maker. When $F(w_B|x) \leq F(w_P|x)$ and $F(w_B|x) \leq F(w_N|x)$, it means that event object X is in the boundary domain and the decision is delayed.

$$\begin{cases} F(w_P|x) \leq F(w_N|x) \\ 1 \geq \delta(x) + \theta(x) \geq 0 \end{cases}$$

The rules of the three decision-making modes can be obtained through the two constraints of $F(w_P|x) \leq F(w_N|x)$ and $1 \geq \delta(x) + \theta(x) \geq 0$:

1. When the decision is accepted, it conforms to

$$\left(\delta(x) \leq \frac{\gamma_{NN} - \gamma_{PN}}{(\gamma_{PP} - \gamma_{NP}) + (\gamma_{PN} - \gamma_{NN})}\right) \cap \left(\delta(x) \leq \frac{\gamma_{BN} - \gamma_{PN}}{(\gamma_{PP} - \gamma_{BP}) + (\gamma_{PN} - \gamma_{BN})}\right)$$

2. When the decision is rejected, it conforms to

$$\left(\delta(x) \leq \frac{\gamma_{PN} - \gamma_{NN}}{(\gamma_{NP} - \gamma_{PP}) + (\gamma_{PN} - \gamma_{NN})}\right) \cap \left(\delta(x) \leq \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{NP} - \gamma_{BP}) + (\gamma_{BN} - \gamma_{NN})}\right)$$

3. When the decision is deferred, it conforms to

$$\left(\delta(x) \leq \frac{\gamma_{PN} - \gamma_{BN}}{(\gamma_{PN} - \gamma_{BN}) + (\gamma_{BP} - \gamma_{PP})}\right) \cap \left(\delta(x) \geq \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{BN} - \gamma_{NN}) + (\gamma_{NP} - \gamma_{BP})}\right)$$

Then set

$$\alpha = \frac{\gamma_{PN} - \gamma_{BN}}{(\gamma_{PN} - \gamma_{BN}) + (\gamma_{BP} - \gamma_{PP})}$$

$$\beta = \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{BN} - \gamma_{NN}) + (\gamma_{NP} - \gamma_{BP})}$$

$$\partial = \frac{\gamma_{PN} - \gamma_{NN}}{(\gamma_{NP} - \gamma_{PP}) + (\gamma_{PN} - \gamma_{NN})}$$

From the above delayed decision satisfying conditions, it can be known that $\alpha > \beta$, so it can be concluded that

$$\frac{\gamma_{BP} - \gamma_{PP}}{\gamma_{PN} - \gamma_{BN}} < \frac{\gamma_{NP} - \gamma_{PP}}{\gamma_{PN} - \gamma_{NN}} < \frac{\gamma_{NP} - \gamma_{BP}}{\gamma_{BN} - \gamma_{NN}}$$

Therefore, $0 \leq \beta < \partial < \alpha \leq 1$. When $\delta(x) \geq \alpha$, event object x is in the positive domain of the three-way decision, that is, it is accepted by the decision-maker. When $\delta(x) \leq \beta$, event object x is in the negative domain and is rejected. When $\alpha < \delta(x) < \beta$, event object x is in the marginal domain and the decision is delayed. Finally, the basic model of three-way decision-making combined with intuitive fuzzy evaluation can be obtained:

$$F(x) = \begin{cases} w_P & \delta(x) \geq \alpha \\ w_B & \alpha < \delta(x) < \beta \\ w_N & \delta(x) \leq \beta \end{cases}$$

The model shows that the decision-maker's choice is related to the membership degree $\delta(x)$ and threshold (α, β) of event object x, which can be used to process the information of the three-way decision.

2.3. Comprehensive Judgment of Multiple Attributes of Agricultural Products

Agricultural products in daily life are basically classified as vegetables and fruits, and the individual products also have many attributes, such as their origin, variety, shelf life, purchase evaluation, and so on. These factors often become important reference indicators for growers to distribute categories and consumers to choose products. Therefore, when analyzing certain kinds of agricultural products, it is necessary to judge and choose specific products based on the indicators of their own attributes, that is, to carry out a fuzzy comprehensive evaluation.

The setting is used to evaluate the attribute set of the product itself, $M = \{m_1, m_2, m_3, m_4 \ldots\ldots m_i\}$, where m_n $(n \leq i)$ is the index of the *n*th self-attribute and i is the number of self-attribute indices; set the result to evaluate the self-attribute of product $Y = \left\{y_1, y_2, y_3, y_4 \ldots\ldots y_j\right\}$, where $y_s (s \leq j)$ is the result of the *s*th evaluation of the product's attributes and j is the number of results of the evaluation of the product's attributes, and the result can be either a constant or a grade (for example, 1.33 or better). In order to determine the membership degree of an attribute to a result, it is necessary to calculate the membership degree of two elements. First, a fuzzy evaluation is carried out on a certain self-attribute m_n, and its membership degree to the *s*th result y_s is p_{ns}. The fuzzy evaluation of this single element is $P_n = \{P_{n1}, P_{n2}, P_{n3} \ldots P_{nj}\}$. If all the factors of the evaluation results are evaluated, then the judgment matrix can be obtained:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1j} \\ P_{21} & P_{22} & \ldots & P_{2j} \\ \vdots & \ldots & \ldots & \vdots \\ P_{n1} & & & P_{nj} \end{bmatrix}$$

Set another set of weight vectors Z = $\{z_1, z_2, z_3 \ldots\ldots z_i\}$, where z_n represents the importance of attribute m_n in the product attributes. The importance of m_n is quantitatively satisfied by $\sum_{n=1}^{i} z_n = 1, n = 1, 2, 3, 4, \ldots\ldots, i$. Finally, vector set Z is set into judgment matrix P, $L = Z \circ P = \{l_1, l_2, l_3, \ldots\ldots, l_j\}$. This is the result of fuzzy evaluation.

2.4. Comprehensive Judgment of Decision-Making

In the previous section, the fuzzy comprehensive evaluation method was used to sort, or qualitatively evaluate, the objective information. It is too troublesome to divide the result set into three domains by using three-way decision, so the method in the previous section is directly applied to the comprehensive judgment of decisions.

First, set the decision action set F(x) = $\{f_1, f_1 \ldots\ldots f_n\}$ and event membership set $\delta(x) = \{\delta_1, \delta_2 \ldots\ldots \delta_n\}$, and also set a weight vector set G = $\{g_1, g_2, g_3 \ldots\ldots g_n\}$. Determination matrix Q can be obtained, and there is a quarrel matrix in order to reduce the error.

$$Q = \begin{bmatrix} \delta_{11} & \delta_{12} & \cdots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ \delta_{n1} & & & \delta_{nn} \end{bmatrix} = \begin{bmatrix} (\delta_{11}^-, \delta_{11}^+) & (\delta_{12}^-, \delta_{12}^+) & \cdots & (\delta_{1n}^-, \delta_{1n}^+) \\ (\delta_{21}^-, \delta_{21}^+) & (\delta_{221}^-, \delta_{22}^+) & \cdots & (\delta_{2n}^-, \delta_{2n}^+) \\ \vdots & \cdots & \cdots & \vdots \\ (\delta_{n1}^-, \delta_{n1}^+) & & & (\delta_{nn}^-, \delta_{nn}^+) \end{bmatrix}$$

The fuzzy result $C = G \circ Q = \{c_1, c_2, c_3, \ldots\ldots, c_n\}$ can be obtained by setting the membership set $\delta(x)$ into matrix Q, then every two interval numbers in the fuzzy result C are compared, respectively, and possibility matrix V can be constructed:

$$V = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1n} \\ V_{21} & V_{22} & \cdots & V_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ V_{n1} & & & V_{nn} \end{bmatrix}$$

Calculate the row vector sum of the possibility matrix V, $V_i = \sum_{j=1}^{n} V_{ij} (j = 1, 2, 3, 4 \ldots\ldots n)$, and $V_i(i = 1, 2, 3, 4 \ldots\ldots n)$ needs to be normalized. A sequence of decision-making actions can be calculated, and the first order is the best solution under the decision-making scheme.

However, there is always the choice of acceptance or rejection in the delay decision. That is, the delay decision should be transformed into an acceptance or rejection decision. Set the decision-making actions of the decision-maker to accept, reject, or delay as f_P, f_N, f_B, then possible schemes V_P, V_N, V_B can be obtained. In this case, if the probability of a certain decision action being selected is K, the probability of the accepted decision action is $K_P = \frac{V_P}{V_P+V_N+V_B}$, the probability of the rejected decision action is $K_P = \frac{V_P}{V_P+V_N+V_B}$, and the probability of the delay decision action is $K_B = \frac{V_B}{V_P+V_N+V_B}$.

At this point, the following can be concluded:

When $V_P > V_N > V_B$ or $V_P > V_B > V_N$, the decision-maker will make the acceptance decision f_P.

When $V_N > V_B > V_P$ or $V_N > V_P > V_B$, the decision maker will make the rejection decision f_N.

When $V_B > V_N > V_P$ or $V_B > V_P > V_N$, the decision-maker will make a delayed decision f_B.

At this time, in order to obtain the next decision of the delayed decision, it is set that when the decision-maker delays the decision, the action of accepting the decision is further selected as V_{BP}. Then, after the decision-maker has delayed the decision, the action of rejection is further selected as V_{BN}, and $V_B = V_{BP} + V_{BN}$. Obviously, when $V_{BP} > V_{BN}$, the next action to delay the decision is to accept; when $V_{BP} < V_{BN}$, the next action to delay the decision is to reject; and when $V_{BP} = V_{BN}$, the next action to delay the decision is to delay, so a new round of operations is needed. In Section 2.2, δ (x) is the membership degree and θ (x) is the non-membership degree of event object x, so the absolute value of the difference between δ (x) and θ (x) can be used to determine the possibility that event object x belongs to the set, so the proportional relationship between V_{BP} and V_{BN} in V_B can be defined. In this case, when $\delta(x) > \theta(x)$, and let the proportional coefficient be ε, then $\varepsilon = \frac{|\delta(x)-\theta(x)|}{\delta(x)}$, $V_{BP} = V_B \times \varepsilon$, and $V_{BN} = V_B \times (1-\varepsilon)$, so when $\varepsilon > 0.5$, the decision-maker delayed the decision and further chose to accept decision action f_P; when $\varepsilon < 0.5$, the decision-maker delayed the decision and further chose to reject decision action f_N; and when $\varepsilon = 0.5$, the decision-maker could not choose to accept or reject the decision after delaying the decision. When $\delta(x) > \theta(x)$, and let the proportional coefficient be $\varepsilon^\sim$, then $\varepsilon^\sim = \frac{|\delta(x)-\theta(x)|}{\theta(x)}$, and when $\varepsilon^\sim > 0.5$, the decision-maker delayed the decision and further chose to reject decision action f_N; when $\varepsilon^\sim < 0.5$, the decision-maker delayed the decision and further chose to accept decision action f_P; and when $\varepsilon^{\sim} = 0.5$, the decision-maker could not choose to accept or reject the decision after delaying the decision. It is worth discussing that when $\varepsilon = 0.5$ or $\varepsilon^{\sim} = 0.5$, the value of ε or $\varepsilon^{\sim}$ will still be 0.5 for each new round of judgment, so, in this case, the decision-maker's decision tends to be infinitely delayed, which will greatly increase the cost. Therefore, this paper defines it as the decision-making behavior of choosing rejection after delaying decision-making.

3. Results

3.1. Correctness Verification

First, this section uses Zhu's dataset to make a confirmatory analysis of water pollution [37]. The set of pollutants that affect the pollution level (cause set) is Z, $Z = \{X_1, X_2, X_3, \ldots, X_n\}$, where k_i is the ith product attribute, and $i = 2$. The set of sampling points is L, $L = \{m_1, m_2, m_3, \ldots, m_n\}$, where m_j is the product of the jth product location, and $j = 2$. Using Zhu's research data, the fuzzy relationship of the product itself is set and the set of origin is obtained: $R\,(Z \to L) = (\delta_R(X_i, m_i)\,, \theta_R\,(X_i, m_i))$, where $\delta_R(X_i, m_i)$ is the degree of membership and $\theta_R\,(X_i, m_i)$ is the degree of non-membership, so

$$R = \begin{bmatrix} (0.5, 0.2)(0.6, 0.2)(0.3, 0.6)(0.8, 0.1)(0.7, 0.2)(0.5, 0.3)(0.6, 0.2) \\ (0.6, 0.3)(0.7, 0.2)(0.3, 0.6)(0.9, 0.1)(0.7, 0.2)(0.4, 0.3)(0.7, 0.2) \end{bmatrix}$$

Explained by the first set of data, 0.5 represents the membership degree and 0.2 represents the non-membership degree of the product of the first origin to the first product attribute. In Zhu's work, the relevant experts discussed and formulated that the weight of the evaluation is $A = ((0.1, 0.25), (0.5, 0.3))$, explained by the first set of data, where 0.1 represents the membership degree and 0.25 represents the non-membership degree of the first product attribute relative to other product attributes. Then, build the intuitive blurry set and calculate the water samples of one of the sample points m_1:

$$\delta_R(A, Y_1) = \vee((0.5, 0.1) \wedge (0.6, 0.5)) = \vee((0.1) \wedge (0.5)) = 0.5$$

$$\theta_R\,(A, Y_1) = \vee((0.2, 0.25) \wedge (0.3, 0.3)) = \vee((0.2) \wedge (0.3)) = 0.3$$

By the same token, by calculating $m_2, m_3, m_4\,, m_5, m_6\,, m_7$, the intuitive fuzzy sets can be obtained:

$$B = ((0.5, 0.3), (0.5, 0.2), (0.3, 0.3), (0.5, 0.1), (0.5, 0.2), (0.4, 0.3), (0.5, 0.3))$$

In this case, in order to better compare within the threshold range, the relative set can be obtained by $\delta(x_i) + \theta(x_i) = 1$:

$$B^{\sim} = ((0.63, 0.37), (0.71, 0.29), (0.5, 0.5), (0.83, 0.17), (71, 0.29)(0.57, 0.43), (0.63, 0.37))$$

Table 2 shows the results according to the reasonable evaluation cost function recommended in this example.

Table 2. Evaluation cost function.

Evaluation Cost Function	γ_{PP}	γ_{BP}	γ_{NP}	γ_{PN}	γ_{NN}	γ_{BN}
Function value	0.18	0.75	1.90	1.80	0.08	0.55

By calculation:

$$\alpha = \frac{\gamma_{PN} - \gamma_{BN}}{(\gamma_{PN} - \gamma_{BN}) + (\gamma_{BP} - \gamma_{PP})} = 0.599$$

$$\beta = \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{BN} - \gamma_{NN}) + (\gamma_{NP} - \gamma_{BP})} = 0.290$$

According to the relative membership degree in $B^{\sim}$, the above three cases of $\delta(x) \geq \alpha$, $\alpha < \delta(x) < \beta$, and $\delta(x) \leq \beta$ can be used to judge and draw a conclusion: Water sample m_1, m_2, m_4, m_5, m_7 of the sampling point is the polluted water sample, and the water quality of the sampling point needs to be treated, but whether m_3 and m_6 are polluted water samples needs to be further analyzed.

$$m_3: \ \varepsilon = \frac{|\delta(x) - \theta(x)|}{\theta(x)} = 0.33 < 0.5$$

$$m_6: \ \delta(x) - \theta(x) = 0$$

That is, m_3 and m_6 are uncontaminated water samples.

This conclusion is consistent with the conclusions in this verification case, and to convert for delay decisions, this paper is more concise in the way in which the membership degree and non-membership degree of the non-membership are simpler and more convenient.

3.2. Decision Analysis of Agricultural Product Data

After verifying the effectiveness and scientific nature of the proposed model, this section further uses evaluation cases of agricultural products for analysis.

3.2.1. Case Decision Analysis of Apple

This section uses data collected by the upstream supply chain of apples for analysis [38]. The self-attribute set that affects product quality is Z, $Z = \{X_1, X_2, X_3, \ldots, X_n\}$, where X_i is the ith product attribute and $i = 5$, X_1 is variety, X_2 is sweetness, X_3 is fruit type, X_4 is hardness, and X_5 is pesticide residue quantity. The set of origin is L, $L = \{Y_1, Y_2, Y_3, \ldots, Y_n\}$, where Y_j is the product of the jth product location and $j = 4$. Through the expert rating and Delphi method applied in the literature [39], the fuzzy relation R between the product's own attribute set and the place of origin set can be obtained: $R\,(Z \to L) = (\delta_R(X_i, Y_i)\,, \theta_R\,(X_i, Y_i))$, where $\delta_R(X_i, m_i)$ is the degree of membership and $\theta_R\,(X_i, m_i)$ is the degree of non-membership, so

$$R = \begin{bmatrix} (0.833, 0.083) & (0.333, 0.167) & (0.667, 0.250) & (0.733, 0.083) \\ (0.416, 0.416) & (0.500, 0.083) & (0.583, 0.000) & (0.333, 0.500) \\ (0.750, 0.167) & (0.250, 0.333) & (0.500, 0.500) & (0.750, 0.250) \\ (0.916, 0.083) & (1.000, 0.000) & (0.083, 0.916) & (0.500, 0.416) \\ (1.000, 0.132) & (0.416, 0.516) & (0.250, 0.316) & (0.100, 0.223) \end{bmatrix}$$

Explained by the first set of data, 0.833 represents the membership degree and 0.083 represents the non-membership degree of the product of the first origin to the first product attribute. After consulting relevant experts and revising the values many times, the weights of the five indicators are $A = ((0.4, 0.1), (0.15, 0.65), (0.1, 0.35), (0.15, 0.45), (0.2, 0.6))$, explained by the first set of data, where 0.4 represents the membership degree and 0.1 represents the non-membership degree of the first product attribute relative to other product attributes.

Then the intuitive fuzzy set is constructed to calculate the product Y_1 of one of the producing areas:

$$\begin{aligned} \delta_R(A, Y_1) &= \vee((0.2, 0.4) \wedge (0.4, 0.15) \wedge (0.8, 0.1) \wedge (0.9, 0.15) \wedge (1, 0.2)) \\ &= \vee((0.4) \wedge (0.15) \wedge (0.1) \wedge (0.15) \wedge (0.2)) = 0.4 \end{aligned}$$

$$\begin{aligned} \theta_R\,(A, Y_1) &= \vee((0.1, 0.1) \wedge (0.4, 0.7) \wedge (0.2, 0.4) \wedge (0.1, 0.5) \wedge (0.1, 0.6)) \\ &= \vee((0.1) \wedge (0.4) \wedge (0.2) \wedge (0.1) \wedge (0.1)) = 0.4 \end{aligned}$$

By the same calculation of Y_2, Y_3, Y_4, can get the intuitionistic fuzzy set:

$$B = ((0.4, 0.4), (0.3, 0.5), (0.4, 0.3), (0.3, 0.5))$$

In this case, in order to better compare within the threshold range, the relative set can be obtained by $\delta(x_i) + \theta(x_i) = 1$:

$$B^{\sim} = ((0.5, 0.5), (0.4, 0.6), (0.6, 0.4), (0.4, 0.6))$$

According to the advice of relevant experts, the reasonable evaluation cost function mentioned in Section 2.2 of this paper is given in Table 3.

Table 3. Evaluation cost function.

Evaluation Cost Function	γ_{PP}	γ_{BP}	γ_{NP}	γ_{PN}	γ_{NN}	γ_{BN}
Function value	0.27	0.79	1.03	1.20	0.42	0.56

By calculation,

$$\alpha = \frac{\gamma_{PN} - \gamma_{BN}}{(\gamma_{PN} - \gamma_{BN}) + (\gamma_{BP} - \gamma_{PP})} = 0.55$$

$$\beta = \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{BN} - \gamma_{NN}) + (\gamma_{NP} - \gamma_{BP})} = 0.35$$

According to the relative membership degree in $B^{\sim}$, the above three cases of $\delta(x) \geq \alpha$, $\alpha < \delta(x) < \beta$, and $\delta(x) \leq \beta$ can be used to judge and draw a conclusion. The apple quality of Y_3 is better, and the apple quality of Y_1, Y_2, and Y_4 is normal. In the case of only considering the quality factor, it is obvious that apples from Y_3 can be bought, but we need to analyze further whether or not to buy the apples from Y_1, Y_2, and Y_4 in the end:

$$Y_2, Y_4 : \ \varepsilon^{\sim} = \frac{|\delta(x) - \theta(x)|}{\theta(x)} = 0.3 < 0.5$$

$$Y_1 : \delta(x) - \theta(x) = 0$$

That is, apples from Y_2 and Y_4 will also be selected for purchase, but not apples from Y_1.

3.2.2. Case Decision Analysis of Wheat

The data of each wheat site [39] are selected for analysis, and the attribute set that affects the product quality is $Z, Z = \{X_1, X_2, X_3, \ldots, X_n\}$, where X_i is the ith product attribute and $i = 3$, X_1 is the wheat grain weight, X_2 is the wheat ear length, and X_3 is the grain size. The set of origin is $L, L = \{Y_1, Y_2, Y_3, \ldots, Y_n\}$, where Y_j is the product of the jth product location and $j = 4$. Through the research data of the selected wheat case, the fuzzy relationship of the product set and the origin set is obtained, $R\,(Z \to L) = (\delta_R(X_i, Y_i), \theta_R\,(X_i, Y_i))$, where $\delta_R(X_i, m_i)$ is the degree of membership and $\theta_R\,(X_i, m_i)$ is the degree of non-membership, so

$$R = \begin{bmatrix} (0.57, 0.40) & (0.67, 0.28) & (0.60, 0.30) & (0.67, 0.15) \\ (0.64, 0.28) & (0.69, 0.30) & (0.74, 0.10) & (0.73, 0.11) \\ (0.65, 0.23) & (0.61, 0.33) & (0.50, 0.27) & (0.68, 0.18) \end{bmatrix}$$

As explained by the first set of data, 0.57 represents the membership degree and 0.40 represents the non-membership degree of the product of the first origin to the first product attribute. After consulting relevant experts and revising the values many times, the weight of the three indicators is $A = ((0.67, 0.10), (0.28, 0.25), (0.05, 0.65))$. As explained by the first set of data, 0.4 represents the membership degree and 0.1 represents the non-membership degree of the first product attribute relative to other product attributes. Then the intuitive fuzzy set is constructed to calculate the product Y_1 of one of the producing areas:

$$\delta_R(A, Y_1) = \vee((0.57, 0.67) \wedge (0.64, 0.28) \wedge (0.65, 0.05)) = \vee((0.57) \wedge (0.28) \wedge (0.05)) = 0.57$$

$$\theta_R\ (A, Y_1) = \vee((0.40, 0.10) \wedge (0.28, 0.25) \wedge (0.23, 0.65)\ = \vee((0.10) \wedge (0.25) \wedge (0.23)) = 0.28$$

By the same calculation of Y_2, Y_3, Y_4, can get an intuitive fuzzy set:

$$B = ((0.6, 0.3), (0.7, 0.3), (0.6, 0.3), (0.7, 0.2))$$

In this case, in order to better compare within the threshold range, the relative set can be obtained by $\delta(x_i) + \theta(x_i) = 1$:

$$B^{\sim} = ((0.67, 0.33), (0.70, 0.30), (0.67, 0.33), (0.78, 0.22))$$

According to the advice of relevant experts, the reasonable evaluation cost function mentioned in Section 2.2 of this paper is given in Table 4.

Table 4. Evaluation cost function.

Evaluation Cost Function	γ_{PP}	γ_{BP}	γ_{NP}	γ_{PN}	γ_{NN}	γ_{BN}
Function value	0.60	1.12	1.38	1.63	0.20	0.43

By calculation:

$$\alpha = \frac{\gamma_{PN} - \gamma_{BN}}{(\gamma_{PN} - \gamma_{BN}) + (\gamma_{BP} - \gamma_{PP})} = 0.698$$

$$\beta = \frac{\gamma_{BN} - \gamma_{NN}}{(\gamma_{BN} - \gamma_{NN}) + (\gamma_{NP} - \gamma_{BP})} = 0.469$$

According to the relative membership degree in $B^{\sim}$, the above three cases of $\delta(x) \geq \alpha$, $\alpha < \delta(x) < \beta$, and $\delta(x) \leq \beta$ can be used to judge and draw a conclusion: the quality of wheat from Y_2 and Y_4 was better, while that from Y_1 and Y_3 was not so good. However, when only considering the quality factors when deciding whether to buy, it is obvious that one can buy wheat from producing areas Y_2 and Y_4, but the final purchase of wheat from producing areas Y_1 and Y_3 still needs further analysis. It can be seen that the $\delta(x)$ and $\theta(x)$ values of the two producing areas are the same:

$$\varepsilon^{\sim} = \frac{|\delta(x) - \theta(x)\,|}{\theta(x)} = 0.51 > 0.5$$

So, wheat from producing areas Y_1 and Y_3 can also be purchased, and its quality is acceptable.

Compared with the ranking of crop growth conditions mentioned in this selected wheat case, through another scheme of three-way decision-making, this paper makes a detailed definition of crop quality that is only ranked but cannot be measured, and obtains more accurate results.

4. Discussion

With the development of society, people are capable of more conveniently using computer methods, or real-time physical and chemical testing, to obtain attribute values of agricultural products. At the same time, it is imperative to use such numbers to evaluate the quality of agricultural products reasonably and efficiently [40–44]. In this paper, according to the combination of three-way decision-making and intuitive fuzzy evaluation, the calculation process of transforming a three-way decision into a two-way decision is significantly simplified, and the optimal treatment of decision-making behavior is realized. Through the use of an example, this paper verifies the correctness of the model and its applicability in the field of agricultural products. The results show that the model can get more accurate evaluation results better and faster.

In this study, when solving the objective information processing, the membership state of the event object is discussed, and then combined with the division threshold of the three-way decision to get the decision cost estimation, which fuses the subjective and objective factors influencing the decision-maker. While the work of Li et al. [45] uses the method of grey relational analysis to judge the fit between the objective evaluation value and the subjective preference value of the decision-maker to evaluate the risk of decision-making, this method can get more accurate correlation parameters and better judge the risk of decision-making, but the calculation process is more complex. In the comprehensive evaluation of multiple attributes in this paper, it is necessary to judge and select based on the indicators of the attributes of the object to be evaluated, that is, fuzzy comprehensive evaluation. In the work of Li and Wei [46], similar methods were used to evaluate accounting informationization, and they also combined them with entropy crossings to determine the weight of experts to reduce errors caused by individual subjective bias. This paper mainly blurs comprehensive evaluation and combines decision-making options, providing new solutions, but does not provide programs for weights, and analyzes the weights given directly in the decision analysis of the instance. However, this paper mainly combines fuzzy comprehensive evaluation with decision selection, which provides a new idea to solve this problem; it does not solve the weight problem, but directly applies the weight given in the example to the case decision analysis.

In the final construction of the model, this paper discusses the changing characteristics of the proportional coefficient between membership degree and non-membership degree, which makes the decision analysis process more flexible, which also guarantees that the model will be suitable for evaluating all kinds of agricultural products. However, there is also a deficiency: according to the actual situation, two or more levels of attribute indicators should be established in the future, and the interactions between and within levels should be discussed. At the same time, a widely applicable method for calculating the weight of product attributes is put forward as much as possible, and efforts were made to weigh the influence of subjective and objective factors on the parameters of the model. Similarly, the evaluation function used to determine the threshold also needs to accumulate more relevant expert advice and model experience in order to make it more accurate.

5. Conclusions

In order to meet the demand for comprehensively judging many aspects of agricultural products, this paper first expounds on the basic model of three-way decision-making, and then introduces the method of intuitive fuzzy evaluation to deal with the problem of multiple attributes and mutual influence of a single event. This paper attempts to use the relative fuzzy set to compare the data based on the fuzzy set, and puts forward a method of generating the proportional coefficient between membership degree and non-membership degree. At the same time, the value of the proportional coefficient changes according to the change of membership and non-membership degree, which enriches the processing and analysis of delayed decision transformation in three-way decision-making. On this basis, this paper analyzes the application of practical data, and proves the accuracy of the model. Finally, the relevant data of agricultural products are brought into the algorithm based on the three-way decision agricultural product information classification processing proposed in this paper. The experimental results show that the algorithm proposed in this paper can obtain more accurate results through a simpler operation process. It can enable relevant decision-makers to make more convenient and accurate decisions according to the product's attribute information. In this paper, the current threshold calculation method and product attribute weight distribution method are relatively single, because they are limited by the level of mathematical logic research. Future research will focus on multi-level attribute impact research, as well as threshold calculation and weight calculation methods with strong generalization capabilities, in order to continuously enrich and improve the three decision-making theories to enable them to play a huge role in application potential.

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