Automatic Severity Assessment of the Avian Influenza Disease in the Chicken Farming

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Abstract: The states of the avian influenza diseases can be divided into several levels according to the disease severities. The diseases with different severity levels should be treated differently in order to avoid wasting the valuable medical resources. The paper tries to design an automatic diagnosis and severity assessment system to assist farmers in making decisions timely. Firstly, we select the typical and scientific indicators of the avian influenza which is the basis of the algorithm. Secondly, we collect the indicator data of the samples using the hesitant fuzzy linguistic term set which can keep the most data details and also accord with the practical expression habits. Thirdly, we propose the algorithm based on the complex proportional assessment algorithm to aggregate the indicator information and point out the specific steps, we give an example to illustrate the automatic diagnosis and severity assessment of the avian influenza disease in the poultry farms subsequently. Fourthly, we compare the algorithm proposed in the paper with two well-known classic algorithms and point out the similarities and advantages over them. In the end, the paper also points out the future research directions.

Key words: Avian Influenza, Chicken Farming, Hesitant Fuzzy Linguistic Term Set, Complex Proportional Assessment

1. Introduction

The avian influenza is a highly pathogenic infectious disease, which is mainly transmitted by birds or chicken. It is very harmful to the poultry farming and can cause very high fatality rate. While, we has not yet developed a very effective drug for the treatment of the avian influenza disease, so we must do a good job in the daily preventive measures and detect the symptoms and assess the severity timely.

The states of the avian influenza can be roughly classified into six levels according to the severity of the disease, and they are the normal level, the mild level, the moderate level, the severe level, the serious level and the terrible level respectively. Moreover, the avian influenza disease is infectious, so different measures will be taken according to the severity levels in order to avoid wasting valuable medical resources and causing public panic.

We try to design a severity assessment system to classify the epidemic situations into different levels automatically. The severity assessment system can help poultry farmers make judgments timely and it can also reduce labor costs and improve work efficiency. The system is consisted of the support indicator system and the assessment process system. For the support indicator system, it always exist many symptoms of the avian influenza disease. The selection of the typical and scientific symptoms is the basis of the system. While for the assessment process system, we must find the appropriate data structure, data processing algorithms and the system model.

On the aspect of the research of the data structures, in the severity assessment process, it is vital to describe each indicator clearly and accurately. The poultry farmers are always inclined to give his/her opinion with linguistic evaluation rather than real numbers for the most of indicators. This has proposed a difficult problem for the subsequent algorithms to process the data. In order to solve the problem, the fuzzy linguistic approach is proposed by Zadeh, which can record and process the single linguistic values effectively. However, sometimes the poultry farmers hesitate among several linguistic values in the evaluation process and can't give the unique value for the indicators. While, the fuzzy linguistic approach proposed by Zadeh can't handle it. Rodríguez et al. proposed the definition of the hesitant fuzzy linguistic term set (HFLTS) on the basis of the fuzzy linguistic idea, which can solve the hesitation effectively. Then, Liao et al. gave the mathematical definition of the HFLTS, which can make it more convenient for mathematical calculation and algorithmic batch processing [1].

On the aspect of the research of the data processing algorithms, scholars have proposed several algorithms based on the HFLTS theory from different perspectives. The typical algorithms such as, Beg and Rashid designed the "Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)" algorithm to aggregate the evaluations of all the indicators. Wei et al. developed the "Tomada de Decisión Inerativa Multicritero (TODIM)" method and applied it in the hesitant fuzzy decision-making field [2]. Fahmi et al. improved the classic "Elimination et Choice Translating Reality (ELECTRE)" approach and has also extended this approach into the hesitant fuzzy decision-making field [3].

The "Complex Proportional Assessment (COPRAS)" algorithm is also an effective algorithm to comprehensively aggregate the various information. The classic COPRAS algorithm can only handle the real numbers, while, considering the data used in the system are in the form of hesitant fuzzy sets, we propose the "Hesitant Fuzzy Linguistic-Complex Proportional Assessment (HFL-COPRAS)" algorithm on the basis of the classic COPRAS algorithm to solve the problem.

2. Preliminary

2.1. The Selection of the Typical Indicators

There are many symptoms in the avian influenza disease, many indicators will be difficult to highlight the main features, while, few indicators may tend to overlook the details. We must establish the scientific and typical indicator system. The indicator system used in the paper is shown in Table 1.

Table 1. The indicator system

Feed consumption (C_1)	Decrease in feed consumption is one of the typical symptoms
Weight (C_2)	The weight is significantly lighter compared with normal weight
Egg production (C_3)	Egg production decreased significantly
Cough and sneeze (C_4)	Repeated, long-time cough and sneeze are also typical symptoms
Spiritual state (C_5)	Poor mental state and lethargy
Head and face edema (C_6)	Edema on the head and face
Diarrhea (C_7)	Gradually aggravated diarrhea symptoms

2.2. The Definition and Related Theory of the HFLTS

The definition of the HFLTS is first linguistically introduced by the Rodríguez et al., while, he failed to give the mathematical definition. Liao et al. firstly proposed the mathematical definition of the HFLTS on the basis of the description of Rodríguez et al. The mathematical definition of the HFLTS can be defined as:

$$H = \{< x_i, h(x_i) > | x_i \in X\} \tag{1}$$

Where the X is a fixed set contained certain number of elements and the x_i is one of elements of the fixed set X . The $h(x_i)$ contains several values in the S and the $h(x_i)$ can be expressed mathematically as $h(x_i) = \{s_{\phi_l}(x_i) | s_{\phi_l}(x_i) \in S, l = 1, \ldots, L\}$. The S is the total range of values, which can be denoted mathematically as $S = \{s_t | t = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$. The L is the total number of terms of the $h(x_i)$. The symbol ϕ_l is the subscript of the linguistic terms. The $h(x_i)$ records all the possible estimations of the indicator x_i .

Recently, the related studies of HFLTS develop rapidly on the basis of the mathematical definition. Liao et al. firstly proposed the similarity and distance measure methods of the HFLTS. Liu and Rodríguez developed the HFLTS theory and applied it in the words processing field. Wei et al. tried to combine the HFLTS theory with the TODIM method. Wang et al. proposed the definition of the systematic comparisons and applied it in the HFLTS optimal model.

2.3. The Classic COPRAS Algorithm

The classic COPRAS algorithm has been widely used in solving various kinds of assessment problems. Kaklauskas et al. applied this algorithm to seek the optimal construction plan. Mulliner et al. obtained the assessment of housing affordability by using the classic COPRAS algorithm and then compared several different algorithms. Pitchipoo et al. sought the most suitable spot by building the COPRAS optimal model. Peng and Selvachandran modified the classic COPRAS algorithm and then used it in the Pythagorean fuzzy environment [4, 5].

The specific implementation steps of the classic COPRAS algorithm can be described roughly as follows:

Step 1. Construct the assessment matrix $X = \{x_{ij} | i = 1, \cdots, m; j = 1, \cdots, n\}$. The symbol m is the total number of the assessment indicators. The symbol n is the total number of samples. The symbol x_{ij} indicates the estimation of the samples j under the indicator i estimated by the experts. While, the value of the x_{ij} is a single real number.

Step 2. Construct the normalized assessment matrix $D=\{d_{ij} \mid i=1,\cdots,m; j=1,\cdots,n\}$. The value of the d_{ij} can be obtained by the equation (2). The q_i is the weight of the indicator i.

$$d_{ij}=\frac{x_{ij}\cdot q_i}{\sum_{j=1}^{n} x_{ij}} \tag{2}$$

Step 3. Calculate the maximum values S_j^+ and the minimum values S_j^- under each indicator respectively according to the equation (3) and (4).

$$S_j^+=\max_{i=1}^{m}(d_{ij}) \tag{3}$$

$$S_j^-=\min_{i=1}^{m}(d_{ij}) \tag{4}$$

Step 4. Calculate the total estimation value Q for each sample according to the equation (5) and the equation (6).

$$S_{\min}^-=\min_{j=1}^{n}(S_j^-) \tag{5}$$

$$Q_j=S_j^+ + \frac{S_{\min}^-\cdot\sum_{j=1}^{n} S_j^-}{S_j^-\cdot\sum_{j=1}^{n}\frac{S_{\min}^-}{S_j^-}} \tag{6}$$

Step 5: Rank the samples according to the total estimation value Q. Classify the samples into several severity levels by setting thresholds.

However, the classic COPRAS algorithm mentioned above mainly focused on the application under the real number environment. Some scholars have also tried to use this algorithm into different environments. Such as, Rabbani et al. tried to adopt the COPRAS algorithm to rank the alternatives under the linguistic variables. Zavadskas et al. proposed the modification of the classic COPRAS algorithm to assess the living environments [6].

From the above analysis, we can notice that there is few research combining the classic COPRAS algorithm with the hesitant fuzzy linguistic terms. The paper will attempt on the theme and try to propose a new algorithm.

3. The Hesitant Fuzzy Linguistic-Complex Proportional Assessment Algorithm

The severity assessment problem can be described mathematically as follow. Let the $A=\{A_j \mid j=1,2,..,n\}$ be the sample set and the $C=\{C_i \mid i=1,2,...,m\}$ be the assessment indicator set. We want to classify the samples into different severity levels automatically according to the assessment indicators. The indicators can be divided into two category, that is the beneficial indicators and the cost indicators according to the objective function. The beneficial indicators can be recorded as $C^+=\{C_i^+ \mid i=1,2,\dots,k\}$ and the cost indicators can be recorded as $C^-=\{C_i^- \mid i=1,2,\dots,p\}$. The weight vector of the indicators $C=\{C_i \mid i=1,2,...,m\}$ can be recorded as $\omega=(\omega_1,\omega_2,...,\omega_m)^T$, the value of ω_i satisfies $\omega_i\in[0,1]$ and $\sum_{i=1}^{m}\omega_i=1$, the weight ω_i indicates the relative importance of the indicator C_i, the larger the value is, the more important the corresponding indicator data is. Generally, there are two methods to obtain the values of the weights, the first method is that the weight values will be given by experts directly, and the second method is that the weight values will be obtained by calculating through the optimization model. The second method may be more realistic in most cases. The paper adopts the second method to obtain the optimal weight values.

3.1. The Hesitant Fuzzy Linguistic Decision Matrix

Firstly, we construct the hesitant fuzzy linguistic decision matrix H which can be denoted as follows. The matrix can be indicated as $H=\{h^{ij} \mid i=1,\cdots,m.j=1,\cdots,n\}$, the m indicates the total number of indicators and the n indicates the total number of samples.

$$H = \begin{bmatrix} h^{11} & h^{12} & \cdots & h^{1n} \\ h^{21} & h^{22} & \cdots & h^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ h^{m1} & h^{m2} & \dots & h^{mn} \end{bmatrix}_{m\times n} \tag{7}$$

$$h^{ij} = \{< l_t^{ij}, s_{\delta_t}^{ij} > | \, t = 1, 2, \cdots, b\} \tag{8}$$

The h^{ij} is the element of the hesitant fuzzy linguistic decision matrix. The element h^{ij} shows the possible membership that the sample A_j satisfies the indicator C_i, The $s_{\delta_t}^{ij}$ indicates the score values, the b indicates the total number of score values ,the $l_t^{ij} (0 \le l_t^{ij} \le 1)$ is the probability for the corresponding score values. The δ_t is a fixed set which includes all the possible score values and it is given by experts in advance.

Let's give an simple example to illustrate the theory discussed in the section, Assume that the score values include 6 levels in total, they are the normal level, the mild level, the moderate level, the severe level, the serious level and the terrible level, and it can be indicated as $s = \{s_0, s_1, s_2, s_3, s_4, s_5\}$ mathematically. If an expert judges that the symptom is severe but he is not total sure, he hesitates between the severe level s_3 and the serious level s_4, and he judges the probability of the severe level is 0.6 and the probability of the serious level is 0.4. So the expert can gives his estimation as $\{< 0.6, s_3 >, < 0.4, s_4 >\}$ with the help of the technology of the hesitant fuzzy linguistic term set. It can avoid losing any detail information compared with other data structure.

3.2. The Calculation of the Optimal Weights

The calculation of the optimal weights is an important and fundamental problem in the assessment problem. Different indicators must be given different weights according to their importance. Some people try to obtain the accurate weights by the big data analysis, while, we have found the fact that it is nearly impossible to achieve the goal because of the complexity and the information limitation.

The optimal-solution-based approach is one of the classic weight calculation methods and it can obtain the optimal weights. However, the problem discussed in the paper is different and it mainly calculates the weights based on the severity of indicators [7]. Thus, we must transform the positive solution to the negative solution in the optimal-solution-based approach. So, we propose a new approach of computing the optimal weights based on the negative optimal solution under the hesitant fuzzy linguistic term set environment [8].

Based on the definition of the element of the hesitant fuzzy linguistic decision matrix $(h^{ij})_{m\times n}$ mentioned above, the paper proposes the following nonlinear optimal model to calculate the optimal weights.

$$\begin{aligned} &\text{Min } \ \overline{f}(\omega) = \sum_{i=1}^{m}\sum_{j=1}^{n} \omega_i^2 d^2(h^{ij}, (h^i)') \\ &\text{s.t.} \ \ \sum_{i=1}^{m} \omega_i = 1, \ \ i = 1, 2, \dots, m \end{aligned} \tag{9}$$

where $(h^i)'$ indicates the optimal-ideal-solution under the indicator C_i, and $d(h^{ij}, (h^i)')$ indicates the distance between h^{ij} and $(h^i)'$ which can be calculated by the equation (10).

$$d(h^{ij}, (h^i)') = \frac{1}{b}\sum_{t=1}^{b} (l_t^{ij} \times \frac{|\delta_t^{ij} - (\delta^i)'|}{\tau + 1}) \tag{10}$$

We solve the optimal model by constructing the Lagrange function which is shown as follows:

$$L(\omega, \lambda) = \overline{f}(\omega) + 2\lambda(\sum_{i=1}^{m} \omega_i - 1) \tag{11}$$

We can acquire the following equations according to the principle of that the partial derivatives will be zero when the weights reach the optimal values.

$$\begin{cases} \dfrac{\partial L(\omega, \lambda)}{\partial \omega_i} = 2\sum_{j=1}^{n} \omega_i d^2(h^{ij}, (h^i)' + 2\lambda = 0 \\ \dfrac{\partial L(\omega, \lambda)}{\partial \lambda} = \sum_{i=1}^{m} \omega_i - 1 = 0 \end{cases} \tag{12}$$

We can easily obtain the optimal weights by solving the equations above, the optimal weights are shown as follows:

$$\omega_i = \frac{1}{(\sum_{i=1}^{m} \frac{1}{\sum_{j=1}^{n} d^2(h^{ij},(h^i)')})(\sum_{j=1}^{n} d^2(h^{ij},(h^i)'))} \tag{13}$$

3.3. The Information Aggregation Operator

It is always difficult to make precise judgment according to several separated "hesitant fuzzy linguistic elements (HFLE)" [9]. The information aggregation operator can gather all the separated information together and it is more advantageous for selecting the optimal sample [10]. We introduce a basic information aggregation operator, which is named "hesitant fuzzy linguistic weighted averaging (CIHFLWA)" operator. The mathematical expression of the CIHFLWA operator is shown as follows:

$$CIHFLWA(h^1,h^2,\ldots,h^m) = \bigcup_{s_{\delta_t}^1 \in h^1, s_{\delta_t}^2 \in h^2, \ldots, s_{\delta_t}^m \in h^m} \{\sum_{i=1}^{m} \omega_i (l_t^i \cdot \delta_t^i)\} (t = 1,2,\cdots,b) \tag{14}$$

We will take an simple example to illustrate the specific calculation steps under the hesitant fuzzy linguistic environment [11].

Example 1. We assume that there are two experts estimating the same thing respectively. The weight of the first expert is 0.4, while the second expert is more sophisticated and his weight is 0.6. The estimation of the first expert is $h^1 = \{< 0.2, s_2 >, < 0.5, s_3 >, < 0.3, s_4 >\}$ and the estimation of the second expert is $h^2 = \{< 0.5, s_1 >, < 0.3, s_2 >, < 0.2, s_3 >\}$. We aggregate the opinions of the two experts comprehensively by using the CIHFLWA operator, which is shown as follows:

$$CIHFLWA(h^1,h^2) = \begin{Bmatrix} 0.4\times(0.2\times2)+0.6\times(0.5\times1), 0.4\times(0.2\times2)+0.6\times(0.3\times2), \\ 0.4\times(0.2\times2)+0.6\times(0.2\times3), 0.4\times(0.5\times3)+0.6\times(0.5\times1), \\ 0.4\times(0.5\times3)+0.6\times(0.3\times2), 0.4\times(0.5\times3)+0.6\times(0.2\times3), \\ 0.4\times(0.3\times4)+0.6\times(0.5\times1), 0.4\times(0.3\times4)+0.6\times(0.3\times2), \\ 0.4\times(0.3\times4)+0.6\times(0.2\times3) \end{Bmatrix}$$
$$= \{0.46, 0.52, 0.52, 0.9, 0.96, 0.96, 0.78, 0.84, 0.84\}$$

3.4. The HFL-COPRAS Algorithm for the Severity Assessment

We will discuss the specific steps of assessing the severity by using the HFL-COPRAS algorithm in this section [12].

Step 1: Select m scientific and typical indicators. Find n typical samples to be tested.

Step 2: Estimate the value of the indicators and obtain the decision matrix $H = (h^{ij})_{m\times n}$ by using the form of the hesitant fuzzy linguistic elements. All the indicators adopt the uniform linguistic scale which is $S = \{s_\delta \,|\delta = 0,1,2,3,4,5,6\}$.

Step 3: Calculate the optimal weights by the simulation of the model 1.

Step 4: Aggregate the beneficial indicators and the cost indicators respectively. Firstly, we must divide the indicators into the beneficial indicators and the cost indicators according to the objective function. The T_+^j indicates the total beneficial aggregation of the j th sample, while The T_-^j indicates the total cost aggregation of the j th sample. Assume that there are k beneficial indicators and p cost indicators in total respectively, the parameter k and the parameter p satisfy $k + p = m$. The T_+^j and the T_-^j can be obtained by the calculation of the equation (15) and the equation (16).

$$T_+^j = CIHFLWA(h_+^{1j}, h_+^{2j}, \ldots, h_+^{kj}) \tag{15}$$

$$T_-^j = CIHFLWA(h_-^{1j}, h_-^{2j}, \ldots, h_-^{pj}) \tag{16}$$

Step 5: Obtain the aggregated score values of the beneficial indicators and the cost indicators respectively according to the equation (17) - the equation (20). The $\mathbb{F}(T_+^j)$ indicates the aggregated score values of the beneficial indicators of the j th sample, while the $\mathbb{F}(T_-^j)$ indicates the aggregated score values of the cost indicators of the j th sample.

$$\mathbb{F}(T_+^j) = \bar{\delta} - \frac{\frac{1}{\#h(T_+^j)}\sum_{k=1}^{\#h(T_+^j)}(\delta_k - \bar{\delta})^2}{\mathrm{var}(\tau)} \quad (17)$$

$$\mathbb{F}(T_-^j) = \bar{\delta} - \frac{\frac{1}{\#h(T_-^j)}\sum_{k=1}^{\#h(T_-^j)}(\delta_k - \bar{\delta})^2}{\mathrm{var}(\tau)} \quad (18)$$

$$\bar{\delta} = \frac{1}{\#h(T^j)}\sum_{k=1}^{\#h(T^j)}\delta_k \quad (19)$$

$$\mathrm{var}(\tau) = \frac{(0-\tau/2)^2 + \ldots + (\tau-\tau/2)^2}{\tau+1} \quad (20)$$

Step 6: Integrate the total scores of each sample according to the equation (21). The M_j indicates the total scores of the j th sample.

$$M_j = \mathbb{F}(T_-^j) + \frac{\sum_{j=1}^{n}\mathbb{F}(T_+^j)}{\mathbb{F}(T_+^j)\cdot\sum_{j=1}^{n}\frac{1}{\mathbb{F}(T_+^j)}} \quad (21)$$

The total scores M is negatively correlated with the beneficial aggregated score values $\mathbb{F}(T_+)$ and positively correlated with the cost aggregated score values $\mathbb{F}(T_-)$ according to the equation (21).

Step 7: Rank the samples according to the values of $M_j\,(j=1,2,...,n)$ from large to small. The bigger the M value is, the more serious the avian influenza is.

4. The Severity Assessment for the Avian Influenza Disease

The specific processes of the severity assessment for the avian influenza disease will be introduced in this section.

Step 1: Assume that there are three poultry farms (F_1, F_2, F_3) with different avian influenza symptoms and will be assessed automatically by a severity assessment system. The poultry farmers give his own observation information about the disease respectively using the form of HFLEs and put the information into the indicator system: feed consumption (C_1), weight (C_2), egg production (C_3), cough and sneeze (C_4), spiritual state (C_5), head and face edema (C_6), diarrhea (C_7). The indicator weight vector $\omega = (\omega_1, \omega_2, ..., \omega_7)^T$ can be obtained by the optimal-ideal-solution-based model mentioned above. Moreover, the linguistic scale of all the indicators is $S=\{s_0, s_1, s_2, \cdots, s_6\}$, where the s_0 indicates the normal level and the s_6 indicates the terrible level. The C_1, C_2, C_3, C_5 belong to cost indicators, while the C_4, C_6, C_7 belong to beneficial indicators.

Step 2: Estimate the value of the indicators and obtain the decision matrix $H = (h^{ij})_{m\times n}$ by using the form of the hesitant fuzzy linguistic elements which is shown in the table 2.

Table 2. The hesitant fuzzy linguistic decision matrix

	F_1	F_2	F_3
C_1	$\{<0.4,s_4>,<0.6,s_5>\}$	$\{<0.5,s_4>,<0.5,s_5>\}$	$\{<0.7,s_4>,<0.3,s_5>\}$
C_2	$\{<0.5,s_4>,<0.5,s_5>\}$	$\{<0.6,s_4>,<0.4,s_5>\}$	$\{<0.2,s_5>,<0.8,s_6>\}$
C_3	$\{<0.4,s_4>,<0.6,s_5>\}$	$\{<0.7,s_3>,<0.3,s_4>\}$	$\{<0.5,s_4>,<0.5,s_5>\}$
C_4	$\{<0.3,s_2>,<0.7,s_3>\}$	$\{<0.5,s_1>,<0.5,s_2>\}$	$\{<0.8,s_5>,<0.2,s_6>\}$
C_5	$\{<0.5,s_5>,<0.5,s_6>\}$	$\{<0.4,s_3>,<0.6,s_4>\}$	$\{<0.8,s_4>,<0.2,s_5>\}$
C_6	$\{<0.7,s_3>,<0.3,s_4>\}$	$\{<0.3,s_4>,<0.7,s_5>\}$	$\{<0.6,s_2>,<0.4,s_3>\}$
C_7	$\{<0.6,s_1>,<0.4,s_2>\}$	$\{<0.5,s_1>,<0.5,s_2>\}$	$\{<0.8,s_2>,<0.2,s_3>\}$

Step 3. Obtain the optimal weights by the simulation of the model 1. The optimal weights are shown in the table 3.

Table 3. The optimal weights of the assessment indicators

Indicators	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ω_i	0.1867	0.2486	0.1128	0.0653	0.1325	0.074	0.1801

Step 4. Aggregate the beneficial indicators and the cost indicators respectively which are shown as follows:

$$T_-^1 = \begin{pmatrix} s_{1.3077}, s_{1.3739}, s_{1.4656}, s_{1.5318}, \\ s_{1.4320}, s_{1.4982}, s_{1.5899}, s_{1.6561}, \\ s_{1.5690}, s_{1.6353}, s_{1.7270}, s_{1.7932}, \\ s_{1.6933}, s_{1.7596}, s_{1.8513}, s_{1.9175} \end{pmatrix}$$

$$T_+^1 = \left(s_{0.3026}, s_{0.3387}, s_{0.2360}, s_{0.2721}, s_{0.4006}, s_{0.4366}, s_{0.3340}, s_{0.3700}\right)$$

$$T_-^2 = \begin{pmatrix} s_{1.3659}, s_{1.5249}, s_{1.2644}, s_{1.4234}, \\ s_{1.2665}, s_{1.4255}, s_{1.1650}, s_{1.3240}, \\ s_{1.4593}, s_{1.6183}, s_{1.3578}, s_{1.5168}, \\ s_{1.3598}, s_{1.5188}, s_{1.2583}, s_{1.4173} \end{pmatrix}$$

$$T_+^2 = \left(s_{0.2115}, s_{0.3016}, s_{0.3817}, s_{0.4718}, s_{0.2442}, s_{0.3342}, s_{0.4144}, s_{0.5044}\right)$$

$$T_-^3 = \begin{pmatrix} s_{1.4210}, s_{1.1295}, s_{1.4774}, s_{1.1859}, \\ s_{2.3656}, s_{2.0741}, s_{2.4220}, s_{2.1305}, \\ s_{1.1783}, s_{0.8868}, s_{1.2347}, s_{0.9432}, \\ s_{2.1229}, s_{1.8314}, s_{2.1793}, s_{1.8878} \end{pmatrix}$$

$$T_+^3 = \left(s_{0.6382}, s_{0.4581}, s_{0.6382}, s_{0.4581}, s_{0.4553}, s_{0.2752}, s_{0.4553}, s_{0.2752}\right)$$

Step 5: Obtain the aggregated score values of the beneficial indicators and the cost indicators for each sample respectively which are shown as follows:

$$\mathbb{F}(T_-^1) = 1.5983\ ,\ \mathbb{F}(T_+^1) = 0.3298\ ,\ \mathbb{F}(T_-^2) = 1.3869$$

$$\mathbb{F}(T_+^2) = 0.3512\ ,\ \mathbb{F}(T_-^3) = 1.6249\ ,\ \mathbb{F}(T_+^3) = 0.4473$$

Step 6: Integrate the total scores of each sample which are shown as follows:

$$M_1 = 1.7998,\ M_2 = 2.0453,\ M_3 = 1.8933$$

Step 7. Rank the severity of the avian influenza disease according to the M value. The severity ranking of the three samples is shown as follows:

$$S_2 \succ S_3 \succ S_1$$

The disease of the second sample is most serious which we must pay more attention to it. The state of the first sample is relatively least serious and the state of the third sample is in the middle. Certainly, we can also classify samples into different severity levels by setting thresholds.

5. The Comparison with Other Typical Algorithm

The TOPSIS algorithm and the TODIM algorithm are two of the most commonly used assessment algorithms. We will compare the algorithm proposed in the paper with the “hesitant fuzzy linguistic TOPSIS (HFL-TOPSIS)” algorithm and the “hesitant fuzzy linguistic TODIM (HFL-TODIM)” algorithm.

The similarities of the three algorithms is that all the algorithms should find the optimal solution which should be close to the ideal best solution as near as possible and be far away from the ideal worst solution as far as possible.

The main advantages of the algorithm proposed in the paper compared with the HFL-TOPSIS algorithm and the HFL-TODIM algorithm:

(1) The algorithm proposed in the paper has considered the important role of the weights, however, the HFL-TOPSIS algorithm fails to take the weights into consideration.

(2) The algorithm proposed in the paper has more operability compared with the HFL-TODIM algorithm, especially when there are large number of indicators. Moreover, the computation is also relatively small compared with other algorithms.

(3) The algorithm proposed in the paper calculates the effect of the beneficial indicators and the cost indicators respectively, it is more concise and flexible compared with the HFL-TOPSIS algorithm and the HFL-TODIM algorithm. The optimal solution can be obtained by processing the original data directly and do not need to seek the ideal worst solution and the ideal best solution.

6. Conclusions

The poultry farming is an effective means for farmers to get rid of poverty especially in the vast remote rural areas, however, avian influenza is a highly lethal disease and threaten farmers all the time. There are disadvantages such as lack of medical resources and long distance from urban hospitals in the vast remote rural areas and it is easy to cause the huge poultry deaths. We try to develop an automatic diagnosis and severity assessment system of the avian influenza disease for the poultry farms. The reference severity of the avian influenza can be assessed automatically only need input several key indicators.

We propose the HFL-COPRAS algorithm on the basis of the classic COPRAS algorithm and introduce the idea of the decision-making in the management to solve the problem. We adopt the hesitant fuzzy linguistic set to collect the indicator information in order to avoid losing information details, moreover, we also add the confidence level in the hesitant fuzzy linguistic elements which make it more fit the practical expression habits. We introduce the CIHFLWA operator for the information aggregation, then we compare the algorithm proposed in the paper with the HFL-TOPSIS algorithm and the HFL-TOPSIS algorithm. The algorithm proposed in the paper mainly has several advantages: (1)it has considered the important role of the indicator weights which is necessary; (2)it has more operability and less computation compared with other algorithms, especially when there are large number of indicators;(3)it calculates the effect of the beneficial indicators and the cost indicators respectively, it is more concise and flexible compared with other algorithms. We also give an example to illustrate the specific steps of the algorithm for the severity assessment of the avian influenza disease in the poultry farms.

We will focus on the theme of allocating the different severity diseases with appropriate medical institutions in the future.

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