An Intelligent Decision Algorithm for a Greenhouse System Based on a Rough Set and D-S Evidence Theory

Lina Wang, Mengjie Xu, Ying Zhang

***Abstract*—This paper presents a decision-making approach grounded in rough set theory and evidential reasoning to address the demand for expert decision-making in greenhouse environmental control systems. Furthermore, a decision-making model is developed by integrating the D-S evidence theory with an expert knowledge table for greenhouse environmental control systems. The model's reasoning process encompasses continuous attribute discretization, expert decision table formation, attribute reduction, and evidence combination reasoning. Firstly, the fuzzy C-means clustering algorithm is employed to discretize the original environmental data and cluster it. Subsequently, an attribute reduction algorithm based on information entropy is utilized to optimize the decision table by eliminating unnecessary conditional attributes in expert knowledge. The reduced indicators are then combined using evidential theory. Finally, suitable greenhouse control methods are determined by the confidence decision proposed by the D-S evidence theory. To assess the efficacy of this intelligent decision-making algorithm based on rough set and D-S evidence theory, its performance is compared with traditional SVM algorithms and small-shot learning algorithms. The results indicate that this proposed method significantly enhances the credibility of control decision-making processes, with an average running time of 0.002378s for the fusion decision algorithm and 0.017939s for the support vector machine (SVM) algorithm, respectively. The SVM accuracy rate after testing and training stands at 90.34%. Moreover, retraining based on information entropy attribute reduction leads to a correct decision rate increase of up to 100%. This method notably improves confidence levels in decision-making processes while reducing uncertainty and demonstrates reliability when applied in making decisions regarding greenhouse environments.**

***Index Terms*—Greenhouse systems control, Intelligent decision-making, Rough sets, D-S evidence theory**

I. INTRODUCTION

AGRICULTURE is an important pillar industry of the country, and the intelligent decision-making technology of the greenhouse influencing factors is the top priority of China's agricultural development[1].

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At present, the majority of greenhouse environmental control strategies are centered on the greenhouse's internal model, with the primary objective of regulating external conditions for crop growth[2,6]. Expert decision-making systems play an important role in regulating the greenhouse microclimate environment and should provide a suitable environment for each influencing factor and crop to ensure its good growth[7,8].

However, the seamless integration of the monitoring instrument with greenhouse decision-making processes is hindered by delays, switching issues, and other challenges. Therefore, to reduce uncertainty in decision-making, it is crucial to utilize the raw data from this instrument for regulating the greenhouse environment[9]. To enhance FRST applications and complement MCDM studies, we propose fuzzy rough set theory (FRST). By building upon this foundation, we introduce new predictive decision-making models that combine fuzzy theory to effectively address complex problems encountered in such models[10]. This paper presents a novel approach to predictive decision-making that utilizes rough set theory for solving multi-attribute decisions through cluster analysis to identify categorical features and predict specific outcomes[11]. Rough sets have proven to be highly efficient in handling uncertain information, while also eliminating irrelevant data attributes[12]. They preserve the classification capability of information systems and significantly support simulated data across multiple computing stages[13]. However, when dealing with issues related to multi-source evidence, data fusion analysis fails to classify it accurately; even if streamlined information is obtained, uncertainty in decision-making arises from uncertain data, which makes accurate model building difficult[14]. D-S proof theory offers advantages in expressing uncertain and unknown situations, as well as leveraging knowledge or data from completely different sources. It establishes various aggregation rules within the field of decision-level data fusion and device intelligence research while addressing uncertainties associated with a basic probability distribution (BPA) required for threat assessment under the D-S proof theory[15].

In response to the aforementioned issues, this paper proposes a decision-making method that combines rough sets with Dempster-Shafer's (D-S) evidence theory[16]. D-S evidence theory is a novel mathematical tool designed to address issues related to fuzziness and imprecision, effectively handling data in uncertain situations[17]. Firstly, judgment indicators are reduced through attribute reduction recognition ability, eliminating irrelevant conditional attributes selected after D-S evidence theory reduction. Subsequently, the decision of basic credibility allocation is employed to assess the state of the greenhouse environment[18]. This facilitates the selection of appropriate control categories and enhances decision-making accuracy[19]. Rough sets are employed to construct basic probability distribution functions and calculate the degree of support among various influencing factors within the greenhouse[20]. The improved D-S evidence theory is then applied to compute the created BPA allocation matrix, constructing a confidence matrix that influences the combination of greenhouse factors. Finally, numerical examples are provided to verify the correctness and superiority of this method[21].

The first section introduces the fundamental concepts of rough set theory and D-S evidence theory, presenting a model for assessing greenhouse environments based on functional relationships. The second section provides an in-depth description of decision-making methods derived from rough set theory and evidence theory. The third section presents results obtained from the application of rough set-based techniques in conjunction with D-S evidence theory within a greenhouse system; these results are validated using experimental data. Finally, the fourth section concludes by demonstrating the feasibility of this fusion algorithm for controlling decisions related to greenhouse environments.

II. System Requirements And Parameters Analysis

A. Basic Concepts Of The Rough Set Theory

Polish scientist Z. Polack developed rough set theory, a novel mathematical approach capable of addressing ambiguity and imprecision in problems. Notably, this theory does not necessitate specifying the numerical description of certain properties in advance, but rather, directly originates from the set of descriptions of a given problem. It employs indistinguishable relationships and indistinguishable classes to determine the approximate domain of the problem and uncover the internal laws within. This has spurred significant advancements in data processing and analytics. Attribute reduction and rule reduction are essential research topics within rough set theory. Owing to the presence of redundant knowledge in the knowledge base, this information can consume resources and cause losses, as well as potentially interfere with accurate judgments made by humans or computers. The objective of attribute reduction is to ensure that the original data's decision classification capability remains unaltered, while unnecessary conditional attributes are removed. This process does not alter the dependency between decision attributes and conditional attributes[22].

Definition 1: Let I = (C∪D), where C and D represent conditional attributes and decision attributes, respectively. If c∈C, $\gamma_c(D) = \gamma_{c-[c]}(D)$, c is in C can be reduced, which means that any c∈C is not advisable. In this case, C is considered independent; otherwise, C is related. The sum kernel consists of all the irreducible relations in C and is referred to as the nuclear set or CORE(C). Knowledge divisions P and Q are derived on the domain U and X and Y, where X = U/ind(P) = $\{X_1, X_2, \cdots, X_n\}$, and Y=U/ind(Q)=$\{Y_1, Y_2, \cdots, Y_h\}$. Consequently, the probability distribution of P and Q on the algebra of subsets of the domain U can be denoted as σ[23].

$$[X:p] = \begin{bmatrix} X_1 & X_2 & \cdots & X_n \\ p(X_1) & p(X_2) & \cdots & p(X_n) \end{bmatrix}$$

$$[Y:p] = \begin{bmatrix} Y_1 & Y_2 & \cdots & Y_h \\ p(Y_1) & p(Y_2) & \cdots & p(Y_h) \end{bmatrix} \tag{1}$$

$p(X_i) = \frac{|X_i|}{|U|}, i = 1,2,\cdots,n; p(Y_j) = \frac{|Y_j|}{|U|}, j = 1,2,\cdots,h.$

Definition 2: The information entropy H(P) of knowledge P is defined as:

$$H(P) = -\sum_{i=1}^{n} p\,(X_i) \log\, p(X_i) \tag{2}$$

Definition 3: The conditional entropy H ((Q | P)) of knowledge Q relative to knowledge P is defined as:

$$H(\,Q \mid P\,) = -\sum_{i=1}^{n} p\,(X_i) \sum_{j=1}^{h} p\left(Y_j \mid X_i\right) \log p\left(Y_j \mid X_i\right) \tag{3}$$

where $P(Y_j \mid X_i) = \frac{|Y_j \cap X_i|}{|X_i|}$, $i = 1,2,\cdots,n,\ j = 1,2,\cdots,n.$

B. Basic Concepts Of The D-S Evidence Theory

G. Sanger introduced the concept of trust function into D-S evidence theory, representing a significant improvement over D-S evidence theory—an extension of probability theory. This novel approach possesses a weaker nature than probability theory, yet it enables objective reflection of uncertainties through rigorous logical reasoning, thereby establishing a set of scientific mathematical methods suitable for handling multi-data fusion. The Bayesian inference method serves as the foundation for D-S evidence theory, with Bayesian conditional probability playing a crucial role in its realization[24]. The concept of basic probability allocation (BPA) refers to the degree of trust assigned by the framework to each proposition, while m(A) represents the basic credible number that reflects the reliability of A. The two sources of evidence for the basic probability distribution function are m1 and m2. The calculation of this function is derived through the existing D-S evidence theory combination rule, which serves as the fundamental method for D-S evidence fusion[25].

Definition 1: Let U be the recognition framework. The function m: $2^u \rightarrow [0,1]$ satisfies the following conditions： $\mathrm{m}(\varphi) = 0, \sum_{A\subset U} \mathrm{m}\,(A) = 1, \mathrm{m}(A) = 0$. The basic assignment of A and m (A) = 0 denotes the degree of trust in A, also known as the mass function.

Definition 2: Belief Function

$$\mathrm{Bel}: 2^u \rightarrow [0,1] \tag{4}$$

$$\mathrm{Bel}(A) = \sum_{B\subset A} m(B) = 1 (\forall A \subset U) \tag{5}$$

The sum of the probability distribution functions representing all subsets of A.

Define 3: Synthesis of multiple trust functions

Let Bel_1, ⋯, and Bel_n be the trust functions on the same recognition framework Θ. The basic credibility of each proposition on the framework is assigned as m_1, ⋯, man. If $Bel_1 \oplus \cdots \oplus Bel_n$ is meaningful, we can calculate the basic credibility distribution after D-S evidence theory synthesis recorded as m for ∀A∈Θ, A≠ ϕ, A_1, ⋯, An∈Θ can be trusted by Eq. (6).

$$m(A) = \frac{1}{K} \sum_{A \cap A_2 \cap \cdots \cap A_n A} m_1(A_1) m_2(A_2) \cdots m_n(A_n)$$
$$K = \sum_{A \cap A_2 \cap \cdots A_n \neq \phi} m_1(A_1) m_2(A_2) \cdots m_n(A_n) \tag{6}$$

Decisions based on basic confidence allocation $\forall A_1, A_2 \in \Theta$.

$$m(A_1) = max\{m(A_i), A_i \in \Theta\} \tag{7}$$

$$m(A_2) = max\{m(A_i), A_i \in \Theta \text{ 且 } A_i \neq A_1\} \tag{8}$$

$$\begin{cases} m(A_1) - m(A_2) > \varepsilon_1 \\ m(\Theta) < \varepsilon_2 \\ m(A_1) > m(\Theta) \end{cases} \tag{9}$$

If equation (6) is satisfied, then A1 is the result of the verdict, where ε_1 and ε_2 are preset thresholds.

In D-S evidence theory, the primary concern is determining the fundamental probability distribution function of the focal element. Simultaneously, gathering evidence and distributing basic credibility depend on domain experts' experience or historical data, making subjectivity challenging to avoid. However, due to the characteristics of rough set theory, we can employ the concept of membership degree to enhance it. By analyzing an object's membership degree, rough set theory can be refined and utilized to identify a recognition framework that achieves obtaining a basic credibility distribution[26]. In summary, rough set theory is well-suited for integration with D-S evidence theory, as it aids in resolving significant issues associated with the challenges of evidence acquisition and also addresses errors resulting from expert judgment based on experience.

III. The Integration Of Rough Set And Evidence Theory

A. Discretization Method Based On Fuzzy C-Means Algorithm And Membership Degree Overlap

The data preprocessing method employed in this study is data regression, which typically involves dimensionality reduction and data compression. This implies that researchers can utilize smaller conditional attributes, value ranges, and less data to convey the same or similar information as the original dataset. The key feature of rough set theory is reducing conditional attributes by exchanging equivalence classes with objects for compressing data. By leveraging expert knowledge and considering factors affecting the greenhouse, we can eliminate both conditional attributes and redundant attributes through analysis of the expert table. The attribute reduction of the expert knowledge table data on greenhouse influence factors is carried out using rough set theory as the model frontier. Subsequently, the D-S evidence theory and various greenhouse influence factors are applied to obtain the essential confidence distribution of the combined result. The decision-making process based on the rough set and D-S evidence theory decision model is roughly divided into seven steps, as shown in Fig.1.

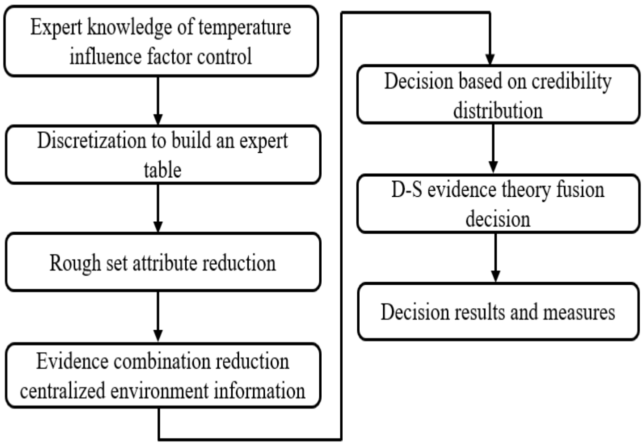

Fig.1. Decision model based on rough set and D-S evidence theory.

1)Discretization of continuous attributes: Rough set theory can only process attribute values with discrete characteristics, while environmental index data is usually continuous in expert knowledge. Therefore, before attribute reduction can be performed, the data must be discredited. In this paper, we propose a new method for continuous attributes based on the Fuzzy C-means clustering method. The fuzzy C-means clustering method is used to process continuous data by assigning them to clusters where all the data have the highest similarity within each cluster and different attribute values across clusters. The main difference between the fuzzy C-means clustering algorithm and the ordinary C-means clustering algorithm is that the fuzzy C-means clustering algorithm utilizes fuzzy partitioning. This means that each given data point uses a degree of membership ranging from [0, 1] to determine its extent of belonging to each group. The membership function is a function that indicates the extent to which an object x belongs to the set A, typically denoted as $\mu_A(x)$ its argument range encompasses all objects that may belong to set A, and the value range is [0,1], that is $0 \le \mu_A(x) \le 1$. The fuzzy C-means clustering algorithm divides n vectors (i=1, 2, . . . , n) into c fuzzy groups and finds the cluster center of each fuzzy group, then minimizes the value function of the dissimilarity index. Therefore, the value function of the fuzzy C-means clustering algorithm as Eq. (10):

$$J(U, c_1, \cdots, c_c) = \sum_{j=1}^{c} J_i = \sum_{j=1}^{c} \cdot \sum_{j}^{a} u_{ij}^m d_{ij}^2 \tag{10}$$

The basic principle of fuzzy C-means clustering algorithm is as follows: let X={x_1,x_2,⋯,x_n}∈R P is the object to be classified, where P is the dimension of the object and c is the number of clusters given by the user. C={c_1, c_2,⋯, c_i}, c_i is the clustering center of class I, and u_{ij} Is the degree of membership of the js object belonging to class I. The fuzzy C-means algorithm performs clustering by continuously adjusting the centroid and membership functions through iterative calculation of c_i and u_{ij}.

where u_{ij} is [0,1], C_i is the cluster center of I in the fuzzy C-means cluster, and $d_{ij} = ||c_i - x_j||$ Is the Euclidean jetties between the first cluster center and the jet data point. M>=1 is a weighted index. The calculation of the Center C_i is as Eq. (11):

$$C_i = \frac{\sum_{j-1}^{n} v_{ij}^{m} x_j}{\sum_{j=1}^{n} v_{ij}^{m}} \quad (11)$$

The membership degree is calculated as follows Eq. (12):

$$U_{ij} = \frac{1}{\sum_{k-1}^{c} (\frac{d_{ij}}{d_{ki}})^{2/(m-1)}} \quad (12)$$

2) Formation of Expert Decision Tables: The discredited expert knowledge can be expressed as S=(U, H, W, F), where S is the knowledge expression system corresponding to the greenhouse environment control expert knowledge. U={x1, x2,..., xn} is the domain, corresponding to the set of greenhouse environmental control objects; H=C∩D is the attribute set, C∩D=Ø, C={ck, k=1,2,..., m} is the conditional attribute set, corresponding to the greenhouse environment indicator attribute set; D={d} is the decision attribute set, corresponding to the greenhouse control decision attribute values; W is the set of all attribute ranges; F is the information function, which determines the value of each object in U under each attribute.

3)Attribute reduction is the process of representing the decision attributes of a decision system in their simplest form, without losing any information and considering their dependence or association with the set of conditional attributes. The reduction of a decision system may not be unique; there can be multiple sets of reductions, and the intersection of all reductions is referred to as the kernel. This article applies an attribute reduction algorithm based on information entropy to achieve the reduction of greenhouse environmental control decision tables.

4）Evidence combination reasoning: Based on the data reduction of the evidence theory, the basic confidence function of each attribute is combined into a smaller subregion. The fuzzy C-means clustering algorithm is then applied after continuous data discretization to determine the category with the highest membership degree for each original data point in the discretion sample. This process affects the discredited data sample and allows for more effective analysis as a discrete set. Finally, based on these synthesis results, the decision type is determined. The basic idea is as follows: (1) constructing a cognitive framework according to the problem; (2) establishing a reliability distribution function based on expert experience; (3) classifying each focal element based on data collected from different sources of evidence to determine its classification basis. (4) Synthesizing the basic confidence allocation value according to the principle of evidence consolidation, and (5) determining the final decision-making result based on the judgment criterion of basic confidence assignment[27].

B. Greenhouse influence factors control expert knowledge

The typical solar greenhouse selected in Northwest China is shown in Fig.2. This type of greenhouse consists of a wall and a single layer of transparent plastic film. The actuator includes a film rolling motor, a fan, and a wet curtain pump. Additionally, a special controller is added to collect environmental information within the greenhouse, implement decision-making methods based on rough sets and evidence theory, and drive the action of the actuator according to the decisions made. This leads to the creation of an expert knowledge table on factors that affect greenhouse control, as presented in Table I, consisting of a total of 12 sets of samples. Each group contains six greenhouse effect factors and determines a decision outcome based on these influencing factors. The greenhouse effect factors include temperature, humidity, light intensity, soil temperature, soil moisture, and CO_2 volume fraction all contributing to four possible decision results: opening the roller blind, opening the roller shutter and starting the fan, starting the fan only, or taking no action with regards to the wet curtain. Table I provides data on greenhouse influencing factor indicators along with their corresponding decision outcomes. However, it is challenging for users to comprehend the information contained within this data and utilize it directly for decision-making purposes.

Fig.2. Solar Greenhouse in Northwest China

TABLE I
EXPERT KNOWLEDGE TABLE ON GREENHOUSE IMPACT FACTOR CONTROL

Number	Temperature /°C	Humidity /%	Light intensity/klx	Soil temperature/ °C	Soil humidity/%	Carbon dioxide/ (μL · L-1)	Decision-making result
1	31.5	76.9	11.2	28.2	52	472	1
2	32.8	76.2	12.8	29.1	53	433	1
3	29.2	80.1	8.2	27.4	56	511	1
4	35.1	68.0	14.8	30.2	57	355	2
5	36.0	61.5	17.3	30.9	56	319	2
6	34.7	74.2	13.2	29.9	53	384	2
7	38.2	50.0	25.9	34.0	58	263	3
8	42.3	46.9	39.2	35.2	54	259	3
9	37.5	56.1	19.8	31.5	57	281	3
10	24.9	59.3	5.9	23.5	54	389	4
11	27.0	52.3	8.2	26.4	54	392	4
12	25.1	60.2	3.1	22.9	57	399	4

Note: The data presented in Table I encompasses greenhouse environmental indicators and their correlations. However, the implicit information within the data is not easily comprehensible to users, rendering it challenging for direct decision-making. Categories 1 to 4 denote curtain opening, curtain and door opening with fan initiation, fan activation alone, and curtain wetting without action, respectively. Employing the fuzzy C-means clustering algorithm, Table I is segmented into 4 clusters, each corresponding to a distinct number of decision outcome categories.

The algorithm generates a cluster center with a 4-level return value, and each sample's membership function is assigned to one of the 4 cluster centers. Consequently, classifying samples with the highest membership allows deriving their corresponding values and transmitting them from an initial continuous variable space to a discrete feature space. This spatial transformation facilitates the exportation of the corresponding decision table, as illustrated in Table II. It is noteworthy that Table II contains no incompatible samples, suggesting that the level of aggregation is a suitable balance.

TABLE II
GREENHOUSE IMPACT FACTOR CONTROL DECISION TABLE

Number	Temperature /°C	Humidity /%	Light intensity/klx	Soil Temperature / °C	Soil humidity/%	Carbon dioxide/ (μL · L-1)	Decision-making result
1	2	4	2	2	2	4	1
2	2	4	2	3	1	3	1
3	2	4	1	2	4	4	1
4	3	3	2	3	2	2	2
5	3	2	2	3	3	2	2
6	3	4	2	3	1	3	2
7	4	1	3	4	4	1	3
8	4	1	4	4	1	1	3
9	3	2	3	3	3	1	3
10	1	2	1	1	2	3	4
11	1	2	1	2	3	3	4
12	1	2	1	1	4	3	4

IV. ILLUSTRATIVE RESULTS

A. Intelligent Decision-Making Based On Rough Set And D-S Evidence Theory

For the sake of calculation convenience, symbols a, b, c, d, e, f, and g are employed to represent temperature, relative humidity, illuminance, soil temperature, soil moisture content, carbon dioxide volume fraction, and decision category. Table 2 is reduced using an attribute reduction algorithm based on information entropy. First, calculate the mutual information I(C, D) between the conditional attribute C and the decision attribute D as follows: I(C, D) = H(D) - H(D|C). Then calculate $CORE_D(C)$, which is the kernel of C relative to D. Let B = $CORE_D(C)$. Next,calculate I(B, D)=H(D)-H(D|B), For each calculate$\forall c_i \in (C \setminus B), I(c_i, D \mid B) = H(D \mid B) - H(D \mid B \cup \{c_i\}), c_m = \arg \max_{c_i \in C \setminus B} I(c_i, D \mid B)$. Update B by adding ci to it: let B=B∪{c_i}, The output property with the largest entropy reduction value is {c, f}, where c and B have 7 attribute combinations with f and B.

Finally, if I(B∪C, D)=I((B∪F, D)=I(C, D), then only the decision categories related to {temperature, illuminance} and {temperature, carbon dioxide volume fraction} are considered; other conditional properties are not relevant.

During the intelligent control decision of greenhouse influencing factors, the influencing factors in the whole framework indicate which control method should be adopted. Therefore, the whole framework can be written as {L(k),k=1,2,3,4} in Table 1, k is the result of four kinds of decisions. The power set of basic reliability distribution function under greenhouse affecting factors control decisions recognition framework expresses the support degree of the decision category in the greenhouse and m(ϕ)=0, $\sum_{A\subset\Theta} m(A)$=1, in which m (1), m (2), m (3), and m (4) represent the basic reliability distribution of greenhouse decision factors, and m (Θ) expresses the greenhouse effect of the uncertain factor of a basic probability distribution.

In this paper, the mean values of environmental indicators corresponding to each decision category in Table 1 are used to divide the basic confidence intervals. Let a, b, and c be temperature, light intensity, and CO_2 volume fraction respectively. Taking temperature as an example, the basic confidence interval is divided by the mean value of environmental indicators corresponding to each decision category. The sets of temperature values corresponding to M(1), M(2), M(3) and M(4) are

{31.5 ℃, 32.8 ℃, 29.2 ℃}, {35.1 ℃, 36.0 ℃, 34.7 ℃}, {38.2 ℃, 42.3 ℃, 37.5 ℃}, {24.9 ℃, 27.0 ℃, 25.1 ℃}. The average values of each set are calculated to be 31.2 ℃, 35.3 ℃, 39.3 ℃, and 25.3 ℃ respectively. The basic credibility of temperature factors is established as follows:

When a < 25.3 ℃, then m (4) = 0.9, m (1), m (2), m (3) are zero, m (Θ) = 0.1.

When 25.3 ℃ ≤ a ≤ 31.2 ℃, m (4) = [1-(a-25.3) / (31.2-25.3)]×0.9, m (2), m (3) are zero, m (1) = [(a-25.3) / (31.2-25.3)]×0.9, m (Θ) = 0.1.

When 31.2 ℃ ≤ a ≤ 35.3 ℃, m (3), m (4) are zero, m (2)= [(a-31.2) / (35.3-31 .2)]×0.9, m (1) = [1-(a-31.3) / (35.3 -31.3)]×0.9, m (Θ) = 0.1.

When 35.3 ℃ ≤ a ≤39.3 ℃, m (1), m (4) are zero, m (3) = [(a-35.3) / (39.3-35.3)]×0.9, m (2) = [1-(a-35.3) / (39.3 -35.3)]×0.9, m (Θ) = 0.1.

When 39.3 ℃ ≤ a, m = 0.9 (3), m (1), m (2), m (4) are zero, m (Θ) = 0.1.

The data collected at different times is A1={30.2℃，9.4clx，438 μL/L}, A2={33.8℃，12.4clx，358 μL/L}, A3={38.1℃，20.8clx，283 μL/L}, A4={23.0℃，8.5clx，371 μL/L}.Table III is shown as follows: Index a, b, and c represent temperature, illuminance, and carbon dioxide volume fraction respectively; A1, A2, A3, and A4 represent the four groups of experimental samples;m(1), m(2), m(3), m(4), and m(Θ) represent the support and uncertainty of opening the rolling curtain, opening the rolling shutter door to start the fan, starting the fan and wetting the curtain, respectively. Similarly, basic reliability calculations can be performed for both light intensity and CO_2 volume fraction.

In this case, the indexes a, b, and c represent temperature, light intensity, and CO_2 volume fraction respectively.

TABLE III
BASIC CREDIBILITY ALLOCATION BEFORE THE COMBINATION

Sample	Combine	m(1)	m(2)	m(3)	m(4)	m(Θ)
A1	a	0.747	0	0	0.153	0.1
A1	b	0.639	0	0	0.261	0.1
A1	c	0.552	0	0	0.348	0.1
A2	a	0.329	0.571	0	0	0.1
A2	b	0.579	0.321	0	0	0.1
A2	c	0	0.572	0	0.428	0.1
A3	a	0	0.270	0.630	0	0.1
A3	b	0	0.505	0.395	0	0.1
A3	c	0	0.179	0.721	0	0.1
A4	a	0	0	0	0.9	0.1
A4	b	0.384	0	0	0.516	0.1
A4	c	0	0.617	0	0.383	0.1

Finally, through the decision based on the allocation of basic credibility, we can determine the decision category and select the threshold value: $\varepsilon_1 = 0.2, \varepsilon_2 = 0.03$, Table IV is shown as follows, where L(1), L(2), L(3), and L(4) are the decision results, L(1) express opening rolling curtain, L(2) represents opening rolling curtain and starting the fan, L(3) corresponds to starting fan and wet curtain, and L(4) corresponds to no action[28].

TABLE IV
D-S EVIDENCE COMBINATION AND DECISION MAKING

Sample	Evidence Combination	m(1)	m(2)	m(3)	m(4)	m(Θ)	Decision Result
A1	a⊕b	0.89932	0	0	0.09124	0.00944	L(1)
A1	a⊕c	0.85113	0	0	0.13438	0.01449	L(1)
A1	a⊕b⊕c	0.91647	0	0	0.08327	0.00026	L(1)
A2	a⊕b	0.58793	0.38284	0	0	0.02923	L(1)
A2	a⊕c	0.08732	0.81573	0	0.06379	0.03316	L(2)
A2	a⊕b⊕c	0.16793	0.81674	0	0.01374	0.00159	L(2)
A3	a⊕b	0	0.42378	0.56825	0	0.00797	unknown
A3	a⊕c	0	0.15643	0.83797	0	0.00560	L(3)
A3	a⊕b⊕c	0	0.18479	0.81457	0	0.00064	L(4)
A4	a⊕b	0.05377	0	0	0.92976	0.01674	L(4)
A4	a⊕c	0	0.13893	0	0.84267	0.01840	L(4)
A4	a⊕b⊕c	0.01643	0.03766	0	0.94376	0.00215	L(4)

From Table IV, it can be observed that the fusion decision algorithm proposed using the D-S evidence theory has a significant influence on the judgment results, which are determined based on four samples. As in Table I, in the combination of evidence for {a, b} in sample A2, the difference between m (1) and m (2) is more than 0.2, m (2) is less than 0.03, and m (1) is much larger than m (2), so it is concluded that the combination of L (1), {a, c} is concluded. In contrast, the difference between m (2) and m (1) is more than 0.2, m (1) is less than 0.03, and m (2) is much larger than m (2), so the decision result is L (2), because the result of the two combined decisions is not the same, so the combination needs to be further integrated. On m(1) and m(2), the basic probability distribution values are 0.16793, and 0.81674, respectively, and the difference between m (2) and m (1) is greater than 0.2, m (1) is less than 0.03, and m (2) is much larger than m (2), so the decision result should be L (2). In addition, it can be seen from the change of m (Θ) in Table III that after the fusion of decision by D-S evidence theory, m (Θ) has decreased significantly, and after the combination of {a, b, c}, the uncertainty of the reduction of each set of attributes in the three sets of combined decision attributes will be reduced relative to the two sets of combined decision attribute sets. Three sets of combined decision attributes, each of which introduces less uncertainty than two sets of combined decision attributes. Table IV shows that the error value changes from 10^{-2} to 10^{-3}. Therefore, we believe that the D-S synthesis of multiple indicator sets can effectively reduce the uncertainty of decision-making and improve the accuracy of decision-making.

Fig.3. is a comparative diagram illustrating the basic reliability of key decision attributes, namely temperature, light intensity, and carbon dioxide volume fraction, when the decision outcome is L(1), as well as the basic reliability generated after combining evidence using D-S evidence theory.

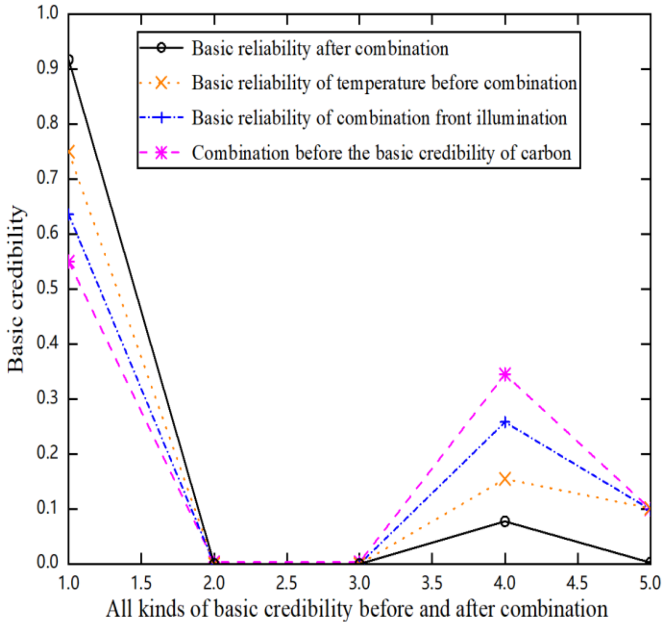

Fig.3. Basic reliability changes before and after the combination of M (1).

The findings from Fig.3. suggest that the basic reliability distribution following the D-S evidence combination exhibits a higher peak value, thereby bolstering the system's decision-categorization capacity. Furthermore, each influencing factor demonstrates an enhanced peak in basic reliability following the combination with the basic credibility at the initial point. This suggests a heightened decision-making precision prior to the fusion process. The D-S evidence fusion significantly augments decision-making accuracy and effectively mitigates issues of miscalculation or the inability to make accurate assessments.

B. Comparative Analysis With Svm Algorithm

In this study, we comparatively evaluate the SVM algorithm for small-scale prototype learning against the decision-making method grounded in rough set theory and D-S evidence theory. Firstly, the raw data from Table I are employed to train and test the support vector machine, with the samples presented in Tables V-VI. Subsequently, thesemodels are utilized to train and test the classifier. The optimal classification parameters are determined through the evaluation of the classifier's performance. The results suggest that the support vector machine is ineffective in learning and applying expert knowledge under sample conditions. By leveraging the rough set theory and the decision-making approach of D-S evidence theory, an experiment was conducted focusing on moisture, soil temperature, and soil moisture, excluding Table I. The achieved decision rate reached 100%. These findings demonstrate that this method can successfully eliminate unnecessary conditional attributes and significantly enhance the alignment between conditional attributes and decision attributes. On this basis, the rough set method, D-S evidence theory, support vector machine, and other algorithms are employed for classifying samples A1, A2, A3, and A4. As illustrated in Table VII, the average elapsed time is 0.002378 seconds and 0.017939 seconds, respectively. In comparison, the support vector machine approach proposed in this study, which is based on fusion methodology, exhibits lower computational requirements and is less complex than the latter[29].

TABLE V
TEST SET DATA IN SVM ALGORITHM

Test Set Date				
0.05377	0	0	0.92976	0.00674
0	0.13893	0	0.84267	0.01840
0.01643	0.03766	0	0.94376	0.00215

TABLE VI
THE TRAINING SET DATA IN THE SVM ALGORITHM

Training Set Date				
0.89932	0	0	0.09124	0.00944
0.85113	0	0	0.13438	0.01449
0.91647	0	0	0.08327	0.00026
0.58793	0.38284	0	0	0.02923
0.08732	0.81674	0	0.01374	0.00159
0.16793	0.81674	0	0.01374	0.00159
0	0.42378	0.56825	0	0.00797
0	0.15643	0.83797	0	0.00560
0	0.18479	0.81457	0	0.00064
0.05377	0	0	0.92976	0.00674
0	0.13893	0	0.84267	0.01840
0.01643	0.03766	0	0.94376	0.00022

TABLE VII
COMPARISON OF DECISION-MAKING FACTORS OF GREENHOUSE INFLUENCE

Methods	D-S evidence fusion	SVM algorithm
Accuracy	100%	90.34%
Decision Time	0.002378s	0.017939s

The 12 groups of greenhouse influencing factor data are processed and compared with expert knowledge. If the decision result obtained by the algorithm aligns with the expert knowledge, the recognition is considered accurate. Ultimately, both approaches can lead to the same correct decision result. The decision algorithm proposed in this study, based on rough set theory and D-S evidence theory, can allocate conflicting information with limited professional knowledge and make effective decisions in such cases to achieve accurate results. This method is feasible for controlling greenhouse-influencing factors. Furthermore, the decision-making outcomes of the D-S evidence theory adapt to the uncertainty of greenhouse decision-making factors. Employing D-S evidence combinations with multiple attribute sets can effectively reduce uncertainty in decision-making results, thereby enhancing judgment accuracy[30].

V. CONCLUSIONS

The present study proposes a novel approach to controlling greenhouse environments, grounded in rough set theory and evidence theory. Initially, it investigates data processing techniques for fuzzy c-means (FCM) clustering of continuous data and employs rough set theory to define properties and generate decision rules from the original dataset. Subsequently, the information entropy reduction method is applied to expert knowledge. Conclusively, the decision-making process employs Dempster-Shafer (D-S) evidence fusion to determine the optimal control method based on basic confidence distribution, decision category identification, and selection. To compare and verify the decision-making outcomes, the support vector machine (SVM) algorithm is utilized for processing the same dataset. The proposed decision-making method, based on rough set theory and D-S evidence, demonstrates significantly lower operational costs and computational complexity compared to the SVM algorithm while exhibiting better processing effectiveness.

1) The reasoning decision-making method proposed in this study enables efficient decision-making by reasonably configuring conflicting information under conditions of limited expert knowledge, demonstrating its feasibility for greenhouse environment control.

2) The attribute reduction method of information entropy proposed in this study minimizes unnecessary influencing factors in greenhouse environmental control decision-making, simplifies decision tables, effectively reduces the calculation requirements for evidence theory, and achieves a 100% correct decision rate through entropy property reduction, readjustment, and further testing.

3) The evidence theory derivation results are tailored to the uncertainty characteristics of greenhouse environment control decision-making. The hierarchical structure of the reduced attribute set is exploited for judgment, thereby significantly reducing complexity.

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