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Exploring Intelligent Decision Support Systems and Legal Suitability in Environmental Legal Issues

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Abstract With the complexity of environmental problems, the implementation of environmental laws faces many challenges. This paper proposes an intelligent decision support system based on radial basis function network and Takagi Sekino fuzzy model. The radial basis function network has a strong ability to predict the change trend and can efficiently learn and fit the complex data in the environmental law problems. Following the introduction of the T-S fuzzy model containing a large number of fuzzy rules, the inference module of the intelligent decision support system is constructed, which is responsible for simplifying the complex nonlinear problem into a linear correlation problem, in order to output a simpler and clearer discretionary result that meets the legal requirements. The research results show that radial basis function network and T-S fuzzy model achieve the most excellent performance compared with the comparison algorithm, and the classification accuracy of T-S fuzzy algorithm is improved by 0.176 compared with the simple fuzzy algorithm, and the output of the system is consistent with the realistic decision-making results on the four major influencing factors of the illegal circumstances, harmful consequences, economic conditions and mental quality, which are highly compatible with the existing legal structure. . The article concludes by adding strategies to improve the legal appropriateness of intelligent decision support systems, which contribute to the objectivity of decision-making on environmental legal issues.

Index Terms Radial Basis Function Network, Fuzzy Rules, T-S Fuzzy Model, Intelligent Decision Making

I. Introduction

In the era of artificial intelligence, algorithms are rapidly becoming embedded in the ecological and environmental domains as defined and limited steps to solve specific problems, and the automated collection and analysis of environmental big data with the help of computer models to assist in environmental decision-making, thus enhancing decision-making efficiency [1]-[4]. The scale of data and its accessibility and timeliness provided by digital technologies have created conditions for paradigm changes in environmental governance [5], [6]. On the one hand, the application of models for greenhouse gas emissions, resource utilization, and population density profiles in environmental planning and policymaking has become increasingly common [7], [8]. Algorithms can not only help decision makers monitor and predict environmental changes, but even directly design effective environmental strategies [9]. However, the greatest technological triumphs are almost juxtaposed with the greatest disasters, which are characterized by the fact that the productivity advances brought about by technology are not infrequently accompanied by the erosion of other people's or society's interests by the holders of the technology. Taking the full life cycle of algorithmic decision-making systems as a perspective, the intervention of algorithms also triggers systemic risks such as data risk, algorithmic risk, procedural risk, and accountability risk in the data preparation and computing phases of system design and development, and in the decision-making and relief phases of system application [10]-[13]. Applying intelligent decision-making systems to specific scenarios, on the basis of examining the positive effects of algorithm-enabled environmental decision-making, and proposing targeted legal regulation for the typological risks that may arise from this process, aims to place the operation of algorithmic environmental decision-making in the framework of rule of law [14]-[16].

Traditional decision-making methods rely more on the subjective judgment of experts, this paper develops an intelligent decision-making system that can efficiently deal with complex environmental legal problems. The radial basis function network, which can learn complex information efficiently, is used to extract the information characteristics of the violator and to judge the illegal circumstances. The T-S fuzzy model is applied to learn the information of environmental legal problems and deal with the uncertainties, so that the number of learned rules is the least and the most important, and the output results of the model are simplified. The adaptability of the existing laws and the system of this paper is explored from three aspects, namely, identification norms, integration system and dynamic protection system, and the system is supplemented with corresponding legal improvement strategies for the application of the system in reality, which provides theoretical support for the implementation of the intelligent decision support system in environmental legal issues.

II. Intelligent decision support systems in environmental law issues

II. A. Intelligent Decision Making Related Technologies

II. A. 1) Radial basis function networks

Radial Basis Function Network (RBF) [17] is a traditional and input and output-only neural network commonly used for solving black-box problems. RBF is formed by summing multiple RBFs with weights and is commonly used to fit rough and uneven landscapes. In addition, RBF has accuracy in constructing local models while determining the trend of different locations in the global model.

Suppose the known training set is $\{(x^i, y^i) \mid x^i \in \Omega, y^i = f(x^i), 1 \le i \le n\}$, where x^i is the input vector, y is the output value, and n is the current training set sample number. In this paper, the fitted outputs are all single target values, i.e., there is only one output of the RBF, and the generalized expression of the RBF used is shown below:

$$\hat{f}_R(x) = \lambda_0 + \sum_{i=1}^{n_c} \lambda_i \varphi(\| x - c^i \|) \tag{1}$$

The cubic function $\varphi(r) = r^3$, the Gaussian function $\varphi(r) = \exp(-r^2 / 2\sigma_R^2)$, and the multifaceted function $\varphi(r) = (r^2 + \sigma_R^2)^{1/2}$, inverse where λ_0 is a constant term, usually the mean or 0 of the output values. λ_i is the weight variable of the RBF. c^i is the center point of each RBF. n_c is the number of RBFs involved in the fit, i.e., the number of centroids. $\varphi(\cdot)$ is the function symbol of the RBF. According to the classification of functional properties, the common kernel function expressions for RBF are: linear function $\varphi(r) = r$ multifaceted function $\varphi(r) = (r^2 + \sigma_R^2)^{-1/2}$, etc. where the radial function, $r = \| x - c^i \|$, refers to the distance from the sample to the center point, and in this paper we use the Euclidean distance. The σ_R is a parameter greater than zero that determines the breadth of each RBF distribution.

In this paper, in order to fully utilize the information from the existing data on environmental legal issues, all sample points in the training set are used as centroids with $n_c = n$. In addition, to reduce the time complexity of the training process, the least squares method is used to determine the unknown weight parameters of the RBF $\lambda_1, ..., \lambda_n \in R^1$, which is solved by the following equation:

$$\Phi \lambda = y \tag{2}$$

$$\lambda = \Phi^{-1} y \tag{3}$$

where the radial basis function matrix $\Phi = (\Phi_i)_{n \times n}$, each element $\Phi_i i = \varphi(\| x^i - x^j \|)$, the weight vector $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]^T$, and the output vector $y = [y^1, y^2, \ldots, y^n]^T$. Since this paper's λ_0 uses the mean $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]^T$, and the output vectors $y = [y^1, y^2, \ldots, y^n]^T$. Since λ_0 in this paper uses the mean. Therefore $y - \lambda_0 1$ is the output vector after centering.

Another way to train is to use a backpropagation algorithm to obtain an unknown weight vector λ.

Suppose E_i represents the error of the i th training sample.

$$E_i = \frac{1}{2}(y^i - \hat{f}_R(x^i))^2 \tag{4}$$

Then, after taking the partial derivation of the weights for the errors, the amount of change in the weights can be obtained:

$$\Delta \lambda = -\eta \frac{\partial E_i}{\partial \lambda} \tag{5}$$

where η is the learning rate. In the backpropagation algorithm kind, it is also dynamically updated with the center and the error at the center point.

After the training is completed, the weight vector of the RBF is obtained with the known point x. Note that all the above RBFs have only one output.

II. A. 2) Principles of T-S fuzzy modeling

A typical T-S fuzzy model [18] is composed of different IF-THEN rules [19], where each rule is usually a special function on the input variables. The basic rule structure can be described as follows:

Rule i:

IF x_1 is A_i^l and... and x_{N_I} is $A_i^{N_I}$.

Then

$$y_i = c_i^0 + c_i^1 x_1 + \ldots + c_i^{N_I} x_{N_I} \quad i = 1, 2, \ldots, N_R \tag{6}$$

where N_R is the number of IF-THEN rules.

x_i is the i th input variable.

N_I is the number of input variables.

Typically, the posterior parameter c_i^j can be obtained by a linear least squares optimization method.

If the data of input variables are given, for any input variable of each fuzzy rule, there exists a special affiliation function corresponding to it. Suppose the rule strength of the i th rule is denoted by τ_i, which can be obtained according to the following equation:

$$\tau_i = A_l^1(x_1) \times A_m^2(x_2) \times \cdots \times A_n^{N_I}(x_{N_I}) = \prod_{j=1}^{N_I} \mu_{A_i^j}(x_j) \tag{7}$$

where the subscripts l, m, n denote the indexes of the corresponding affiliation functions in the i th fuzzy rule. The subscript $A_i^j(x_j)$ is the affiliation function of the antecedent variable x_j, also known as the antecedent parameter. $\times$ denotes a "fuzzy and" operation, where the result is the algebraic product of the operators. The $\mu_{A_i^j}$ denotes the weighting of the affiliation function of A_i^j, which can be characterized by a Gaussian function as:

$$\mu_{A_i^j} = \exp\left(-\frac{(x_j - w_i^j)^2}{\sigma_i^{j^2}} \right) \tag{8}$$

where w_i^j, σ_i^j are the center position and width of the affiliation function, respectively.

If the input variable vector is given as $x = [x_1 \ x_2 \ \cdots \ x_{N_I}]$, then the final output can be obtained by the weighted mean defuzzification method:

$$y = \frac{\sum_{i=1}^{N_R} \tau_i y_i}{\sum_{j=1}^{N_R} \tau_i} = \sum_{i=1}^{N_R} f_i (c_i^0 + c_i^1 x_1 + \cdots + c_i^{N_I} x_{N_I}) \tag{9}$$

where $f_i = \tau_i / \Sigma_{j=1}^{N_R} \tau_j$ is the normalized trigger strength for the i th rule. The equation itself is nonlinear with respect to all parameters. However, if the antecedent parameters of the affiliation function are fixed at the beginning of the model construction, then only the free parameters remain in the linear regression equation. Therefore, once the antecedent parameters of the affiliation function are fixed, its consequent parameters c_i^J can be computed by linear least squares optimization.

Suppose the following data pairs are defined:

$$z = [x \ \ y] \tag{10}$$

where $x = [x_1 \ \ x_2 \ \ \cdots \ \ x_{N_I}]$ is a vector of input variables. y is the output quantity.

If written in the form of a matrix, it can be obtained:

$$y=\begin{bmatrix} f_1c_1^0 & f_1c_1^1 & \cdots & f_1c_1^{N_I} \\ f_2c_2^0 & f_2c_2^1 & \cdots & f_2c_2^{N_I} \\ \vdots & \vdots & & \vdots \\ f_{N_R}c_{N_R}^0 & f_{N_R}c_{N_R}^1 & \cdots & f_{N_R}c_{N_R}^{N_I} \end{bmatrix}_{N_R\times(N_I+1)} \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_{N_I} \end{bmatrix}_{(N_I+1)\times 1} \tag{11}$$

The above equation can be rewritten in the following form by matrix manipulation:

$$Y=\overline{f}C_f \tag{12}$$

Among them:

$$\overline{f}=[f_1 f_1x_1\cdots f_1x_{N_I}\cdots f_{N_R}x_1\cdots f_{N_R}x_{N_I}]\in R^{1\times[N_R\times(N_I+1)]} \tag{13}$$

$$C_f=[c_{10}c_{11}\cdots c_{1N_I}\cdots c_{N_R0}c_{N_R1}\cdots c_{N_RN_I}]\in R^{[N_R\times(N_I+1)]\times 1} \tag{14}$$

The above equation describes the form in which only one parameter pair exists. Assuming that there exists N_T parameter pairs available, i.e., $Z=[z_1z_2\cdots z_{N_T}]$, then the matrix can be constructed:

$$F=[\overline{f}(1)\overline{f}(2)\cdots\overline{f}(N_T)]^T\in R^{N_T\times[N_R\times(N_I+1)]} \tag{15}$$

The numbers in parentheses indicate the ordinal numbers of the data pairs. The system can be viewed as a simple single-output structure. Then the required output matrix is $Y=[y(1)y(2)\cdots y(N_T)]\in R^{N_T\times 1}$. Then:

$$Y=FC_f \tag{16}$$

Therefore, the posterior parameter matrix can be obtained by generalizing the inverse matrix:

$$C_f=(F^TF)^{-1}F^TY \tag{17}$$

Once the prior parameters of a fuzzy model have been determined, the posterior parameters of the model can be obtained based on the above equation to determine the entire fuzzy model. An accurate fuzzy model needs to minimize the error between the fuzzy output and the desired output quantity. So, in order to evolve the model in a favorable direction, it is necessary to find a good evaluation function for this nonlinear system. In this paper, the root mean square error (MSE) between the predicted output of the fuzzy model and the target output is chosen as the evaluation function, which can be expressed as in the following equation:

$$J_{MSE}=\frac{1}{L}\sum_{k=1}^{L}(\hat{y}_k-y_k)^2 \tag{18}$$

where L is the data length. y_k is the predicted output. $\hat{y}_k$ is the target output.

II. B.Intelligent decision support system construction

Intelligent decision-making techniques in environmental legal issues rely on a penalty scheme corresponding to each state of violation and personal information, and are intelligently made by machines. This mapping relationship is the primary consideration of intelligent decision-making technology. This decision-making system should have the ability of self-learning and consist of a combination of software and hardware, which relies more on numerical computation than the traditional artificial intelligence approach. Therefore, a centralized management system can be used to run the whole system using the browser/server (B/S) model. The flow of this intelligent decision-making system is shown in Figure 1.

II. B. 1) Fuzzy neural network structure

The analytical reasoning module is the main intelligent decision-making module for environmental legal issues. This module utilizes the structure of dynamic neural network, and the processing process is to extract appropriate information features after collecting relevant information about the violator and importing them into the knowledge base. Combined with the neural network, the model training is continuously carried out until an appropriate penalty ruling is made and the results are output. The processing flow is shown in Figure 2.

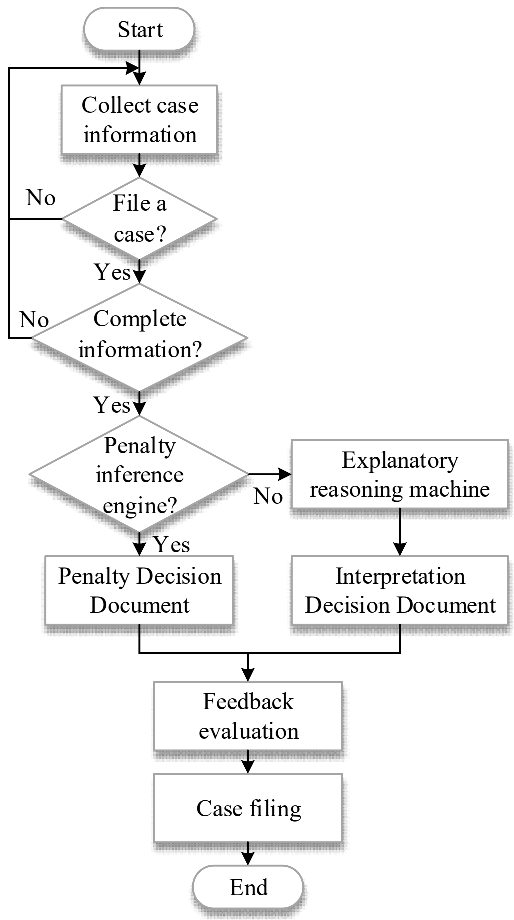

Figure 1: System flowchart

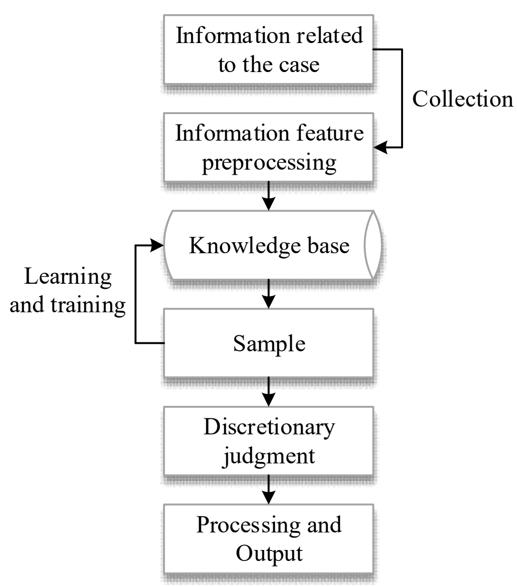

Figure 2: Schematic diagram of the processing flow

The inference module is based on the Takagi Sekino (T-S) fuzzy model. Its main idea is to simplify the complex nonlinear system problem into parts with similar line segments. In this design, the T-S fuzzy model is used to combine the inputs linearly into complex inputs and output the clarified loaded results so as to meet the requirements in the environmental legal problems. The fuzzy neural network structure is shown in Fig. 3.

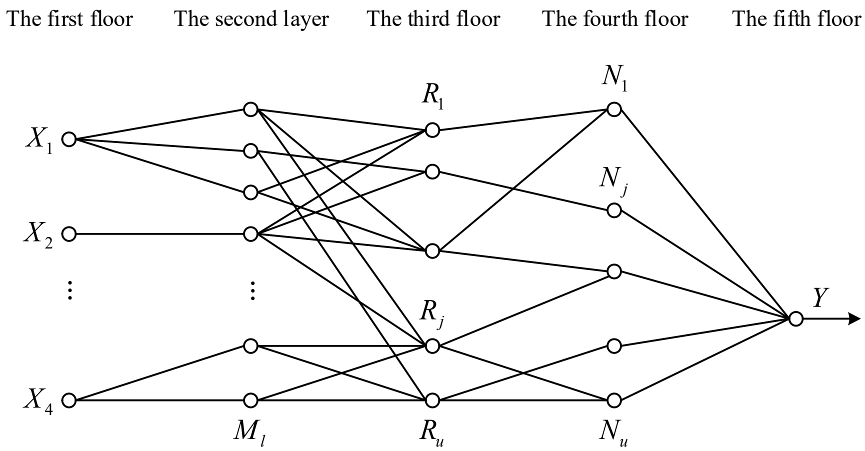

Figure 3: Structure diagram of the fuzzy neural network

The first layer is the information causality related to the cases of environmental protection problems. These inputs can be categorized into 4 major categories of item indicators, which are fed into the neural network structure. The second layer is the affiliation function. The third layer describes the number of fuzzy rules, which are learned by learning the samples in such a way that the number of learned rules is minimized and most important as much as possible. Where the j th rule outputs the formula, $c_j = (c_{ij}, c_{ij}, ..., c_{ij})$ is the center of the j th radial basis function (RBF) cell.

$$\mu_i(x_i) = \exp\left[\frac{(x_i - c_{ij})^2}{\sigma_j^2}\right], i = 1, 2, \ldots, r, j = 1, 2, \ldots, u \tag{19}$$

$$\varphi_j = \exp\left[-\frac{\sum_{i=1}^{r}(x_i - c_{ij})^2}{\sigma_j^2}\right] = \exp\left[-\frac{\| X - C_j \|^2}{\sigma_j^2}\right], j = 1, 2, \ldots, u \tag{20}$$

The RBF neural network is characterized by a higher activation level the closer the neuron is to the center, which is very much in line with the pattern of judging plot factors in environmental legal issues.

The fourth layer is the normalization layer. The nodes in this layer should be consistent with the fuzzy rule nodes. The fifth layer is the output layer. For the T-S fuzzy model, w_k is the connection of the k th rule, i.e., the sum of the products of the weights of the output variables.

$$\psi_j = \frac{\varphi_j}{\sum_{k=1}^{N}\varphi_k}, j = 1, 2, \ldots, u \tag{21}$$

$$y(x) = \frac{\sum_{i=1}^{n}\left[(a_{i0} + a_{i1}x_1 + \ldots + a_{1r}x_r)\exp\left(-\frac{\| x - c_i \|^2}{\sigma_i^2}\right)\right]}{\sum_{i=1}^{n}\exp(-\frac{\| x - c_i \|^2}{\sigma_i^2})} \tag{22}$$

$$y(x) = \sum_{k=1}^{\infty} w_k \times \psi_k \tag{23}$$

II. B. 2) Algorithm design

For the calculation of fuzzy neural network operator eigenvalues, the factors affecting the punishment of environmental legal issues are divided into four categories, namely, the circumstances of the violation of the law, the consequences of the harm, the economic conditions and the mental quality. Among them, the weight of the factors for the violation of the circumstances on the punishment result is divided into no violation, 1 violation, 2~3 violations, 4~5 violations and more than 5 violations. The circumstances of the offense are also divided into 4 subcategories, which are, in order, the record of the offense, the motive of the offense, the mental attitude, and the means of the offense. The weight of each factor of the consequences of harm on the penalty outcome is categorized as minor, minor, moderate, major and serious. Then, for economic conditions, they were considered in terms of residential level, living population, annual income/expenditure ratio, and loans, respectively. Finally, the factor that affects punishment is mental quality. The factors determining the mental quality are age, gender, marital status, education level and personality traits.

The above 4 major categories of characteristics are used as the eigenvalues of the operator for administrative offenses, which involves a total of 14 eigenfactors. The Intelligent Decision Support System will use these 4 types of eigenfactors as input values to the dynamic fuzzy neural network.

When considering the inputs to the neural network, four main types of information can be referred to, namely the circumstances of the offense, the consequences of the harm, the economic conditions, and the mental quality of the offender. The main design of the fuzzy neural network algorithm is to determine the optimal network structure and parameters, which are measured in terms of generalization ability, temporal complexity and spatial complexity. Based on the optimization of the error information, the generalization ability of the RBF neural network is improved, and the parameters of the network are adjusted by establishing a sliding window mechanism and generating hidden nodes online before merging and deleting them online in order to implement the algorithm. Set the input sample of the case as (x_n, t_n). Slide the case sample to the sliding window and the output of each hidden node is shown in the following equation:

$$\varphi_j = e^{-\left[\frac{\sum(\omega)}{\omega}\right]} \tag{24}$$

After calculating the error signal and the distance judgment from the sample to the data center, new hidden nodes are assigned and a predetermined number of training times is set. Then, check for redundant nodes each time. Finally, the redundant nodes are merged and deleted online to complete the whole operation.

The algorithm design flow is shown in Fig. 4.

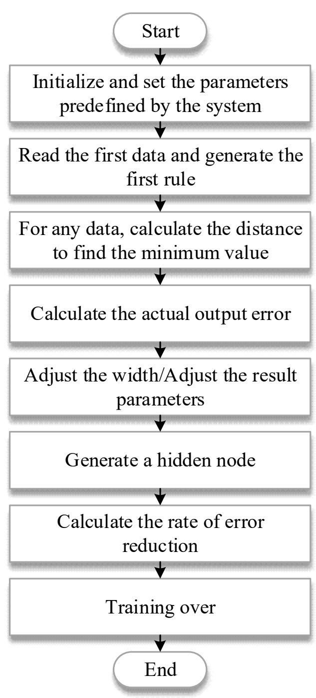

Figure 4: Flowchart of Algorithm Design

II. B. 3) Process modeling for system development

After analyzing the fuzzy neural network model, the more important case-based reasoning module for environmental legal issues in the system is elaborated. Case-based reasoning is a psychological model developed according to the theory of memory, which is a comprehensive expression of the three kinds of human thinking (intuition, logic, and creative thinking). When encountering a new thing, people not only see the specific problem, but also produce associations, and then categorize the thing, from which they find out the experience of having dealt with similar problems in the past, and go to solve the new thing after certain corrective treatment. For simple problems, case retrieval and matching is mainly a process of image thinking. For complex problems, it is often difficult to retrieve similar examples of environmental legal problems through simple matching. At this time, people will decompose the problem so that each sub-problem can be mapped to a similar case, or start from different angles to find similar problems in different aspects, and finally use logical and creative thinking to link the matched sub-cases together to form a new way to solve the current problem.

The process model of case-based reasoning is a process of memory and association, by analyzing the case information corresponding to the input message in the administration, analyzing the illegal situation at that time, and considering the situation of the violator and the relevant chain of evidence to form the basis of processing. The case reasoning process is shown in Figure 5.

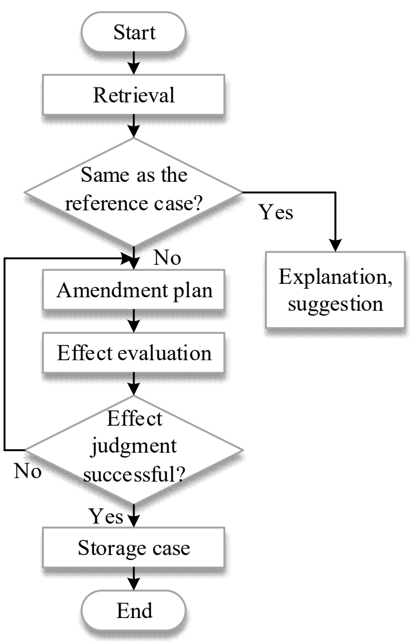

Figure 5: Flowchart of case-based reasoning

Searching for similar or identical cases is a fundamental, important step. It is the basis for subsequent judgment. The explanations and recommendations of the previous cases and the differences from the previous reference cases are then combined to arrive at a revised solution. After the offender in the environmental legal problem obtains the punishment, based on the offender's reaction to the punishment result, the case reasoning of the environmental legal problem is evaluated for its effectiveness, and the successful adjustment is also stored in the case library.

III. Experimental results on the performance of the algorithm

III. A. Analysis of Radial Basis Function Network Classification Results

Extracts text data from laws and regulations issued by government environmental protection departments, environmental policy documents and court judgments published in environmental resource cases. It includes provisions of environmental laws and regulations, descriptions of environmental enforcement cases, and factual findings and judgment results of environmental litigation cases. Accuracy, training time and other metrics are used to evaluate the performance of the model on the task of categorizing environmental legal issues.

The predicted accuracy, training accuracy and running time of the six MATLAB-based algorithms are shown in Table 1. As can be seen from the table, the lowest prediction accuracy of these six classification models is 88.54%, which indicates that all six methods have good classification learning ability for environmental legal case samples, among which the RBF algorithm has the highest accuracy and the shortest time, and the RBF algorithm is the best method for environmental legal problem classification. In the experiment, BP algorithm adopts gradient descent method, and the training process is a continuous iterative optimization process which consumes a lot of time, so their training time is relatively long, much higher than several other classification models.The training time of KELM and RBF is the least, and the training time of RBF is only 0.32s, and the prediction accuracy rate reaches 97.85%.

The time used by ELM is not much different from these two, but the stability of the classification accuracy of ELM is poor, which is due to the reason that ELM randomly selects the weights in the implicit layer, resulting in the algorithm's poor generalization performance, whereas RBF has a better generalization performance, and the classification performance is more stable.The initial weights of the BP algorithm are set randomly and the limitation of the learning rate also leads to the local optimum, so that the classification performance is not stable. The support vector machine model needs to adjust and define the analysis of many parameters, which makes the training time of this model a little more than RBF. From the comparison of the experimental results, it is concluded that the RBF model has a more stable classification performance, the highest prediction accuracy, the shortest training time, and can better meet the requirements of classification of environmental legal issues.

Table 1: Algorithm accuracy and time contrast

Algorithm	Bp neural network	Random forest	Support vector machine	ELM	KELM	RBF
Prediction accuracy/%	93.21	89.59	89.98	88.54	93.64	97.85
Time/s	4.85	0.97	0.89	0.65	0.45	0.32
Training accuracy/%	96.45	94.54	93.68	97.56	98.61	100

III. B. Validity test of T-S fuzzy modeling

In order to do further validation of the effectiveness of the algorithm, this section follows with further experimental comparisons of the T-S fuzzy algorithm using datasets. In order to compare the fuzzy algorithm with the T-S fuzzy model of this paper, experiments are conducted on four UCI datasets, namely, iris, glass, credit, and wine.The basic information of these datasets is shown in Table 2.

Table 2: Data set basic information

Data set	Attribute	Number	Classification number
Iris	150	4	3
Glass	150	8	4
Credit	700	10	6
Wine	200	10	3

All these datasets are commonly used to test the algorithm and the effectiveness and performance of the algorithm can be seen through experiments based on these datasets. Because these datasets are real-valued datasets, these datasets have to be fuzzified to make them into a fuzzy information system, and the fuzzy clustering algorithm can more accurately fuzzify these data to get a more desirable fuzzy information system. After the fuzzification process, these data should be randomly divided into two parts first, the first part is used as a training set and the other part as a test set. The training set is used to derive the final algorithm and the test set is used to test the accuracy of the algorithm. Tables 3 and 4 show the classification accuracy and the number of generated rules for the two algorithms in the four datasets, respectively.

In all four datasets, the T-S fuzzy algorithm accuracy is higher than the fuzzy algorithm, and in the Wine dataset, the classification accuracy of the T-S fuzzy algorithm improves by 0.176 compared to the fuzzy algorithm.Due to the important function of the T-S fuzzy algorithm in attribute parsimony, the number of fuzzy rules generated based on the T-S fuzzy algorithm is less while achieving the same or even higher classification accuracy, which can improve the efficiency of decision making in environmental legal problems in the future.

Table 3: The classification accuracy of two algorithms in data concentration

Data set	Fuzzy algorithm	T-S fuzzy algorithm
Iris	0.955	0.987
Glass	0.648	0.689
Credit	0.758	0.834
Wine	0.609	0.785

Table 4: Two algorithms are set in four kinds of rules

Data set	Fuzzy algorithm	T-S fuzzy algorithm
Iris	12	8
Glass	34	28
Credit	55	47
Wine	47	40

IV. Intelligent decision support system example test

IV. A. Sources of data sets

In order to test the validity of this method, without losing the generality, the sample data were collected from the number of cases of environmental problems in the last month, and the data were obtained from the environmental protection administrative enforcement unit - City Environmental Protection Administrative Law Enforcement Bureau of A City, which is better able to reflect the advantages of this system due to the fact that it handles more cases on a daily basis and has the characteristics of environmental protection cases in general. Nine sets of data were selected as samples.

IV. B. Assessment of the Effectiveness of Intelligent Decision Making on Environmental Legal Issues

In order to assess the effectiveness of the designed intelligent decision support system and to realize the role of penalty discretion for environmental problems, we first design a set of input data to test the effectiveness of the network. The data organizes the changes of each of the four parameters to see the changes of the output results. In order to examine the relationship between the circumstances of the offense and the penalty, the parameters are designed as shown in Table 5,After the network output, the relationship between the two graphs are shown in Figure 6. The change in the magnitude of the penalty is relatively large, from 0.588 to 0.680, which is in line with the positive relationship between the circumstances of the offense and the amount of penalty in the reality of environmental legal issues.

Table 5: A sample of the illegal plot changes

Sample size	1	2	3	4	5	6	7	8	9
Illegal plot	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Hazard	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Economic condition	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Mental quality	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4

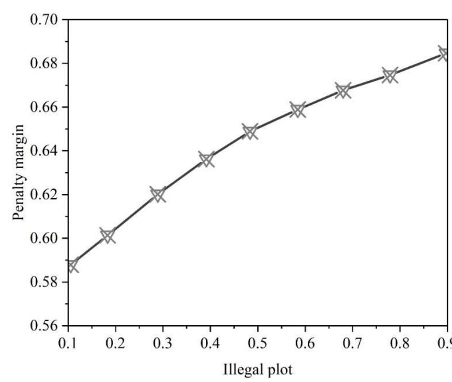

Figure 6: A sample of the illegal plot

In order to examine the relationship between harm consequences and penalties in environmental legal issues, the parameters are designed as shown in Table 6. After the output of the network, the relationship graph is shown in Figure 7, the consequences of harm affect the punishment to the greatest extent, when the parameter of the consequences of harm increases from 0.1 to 0.9, the range of punishment increases from 0.48 to 0.85, rising by 0.37. So it is in line with the principle that the punishment must be greater than the gain obtained in environmental law, and it is more in line with the reality as well.

Table 6: A sample table for the effecT-S of the consequences

Sample size	1	2	3	4	5	6	7	8	9
Illegal plot	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Hazard	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Economic condition	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Mental quality	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4

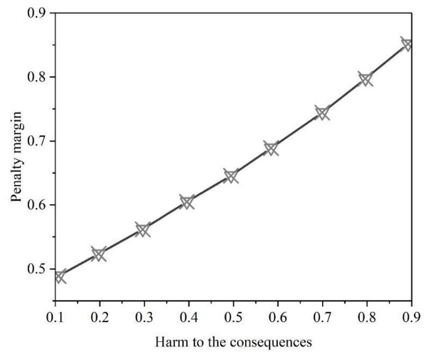

Figure 7: A sample of the effecT-S of the harm

In order to examine the relationship between mental quality and punishment, the parameters were designed as shown in Table 7. After the network output, the relationship graph is shown in Figure 8. Mental quality and punishment are not positively increasing, when the parameter of mental quality is 0.2-0.7, the magnitude of punishment is rising state, while when the parameter of mental quality is 0.7-0.9, the magnitude of punishment shows a decreasing trend. It shows that when the people who violate the law in environmental legal issues receive punishment, the weakest and the toughest people are not dealt with extreme punishment, and this point is in line with the reality of dealing with the model.

Table 7: Change of mental quality

Sample size	1	2	3	4	5	6	7	8	9
Illegal plot	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Hazard	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Economic condition	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Mental quality	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9

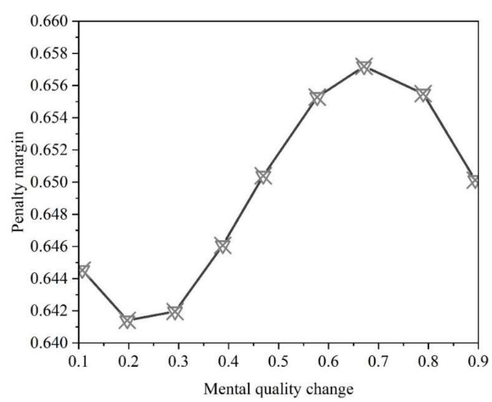

Figure 8: A sample of mental quality changes

In order to examine the relationship between economic conditions and penalties, the parameters were designed as shown in Table 8. After the network output, the relationship graph is shown in Figure 9. Offenders with good economic conditions are naturally proportional to the magnitude of the penalty. On the contrary, those with poor conditions should reduce the fines and increase the penalties in other aspects.

In summary, the intelligent decision support system for environmental legal problems designed in this paper is basically in line with the law of punishment in real environmental legal problems, and the synthesis of the four factors can give satisfactory decision-making results for environmental legal problems.

Table 8: Economic change

Sample size	1	2	3	4	5	6	7	8	9
Illegal plot	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Hazard	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Economic condition	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Mental quality	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9

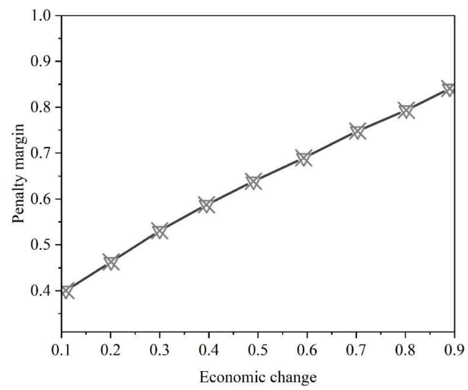

Figure 9: Economic change

V. Discussion of the legal suitability of intelligent decision support systems

The disclosure of sensitive personal information in the context of environmental legal issues dealt with by intelligent decision support systems can pose unforeseen risks or even particularly serious harm to individuals. Existing legislation has made great efforts to regulate the risk and institutional construction of the technology's “significant legal interests that may be jeopardized, technological uncertainty, precautionary measures, and proving mechanisms”, and China's existing normative system defines and protects personal information on a categorized basis, but the specificity of the protection of sensitive personal information in the context of intelligent decision support systems still poses specific requirements for the integration of values and the legal adaptation of the system. However, the specificity of the protection of sensitive personal information in intelligent decision support systems still puts forward specific requirements for the incorporation of values and the legal suitability of the system.

V. A. Recognition and standardization in handling information

While public administration subjects using automated intelligent decision support systems cannot rely on rule-making to solve all discrimination problems, the original intent of the algorithms should be to eliminate pre-existing innate inequalities or institutional inequalities rather than to circumvent the legal requirements and to seek defenses for discrimination in algorithmic outcomes due to deficiencies in algorithmic programming. Intelligent decision-support systems should carefully identify and screen sensitive personal information when making decisions in environmental legal issues, based on different legislative purposes, respectively.

V. B. Building an integrated legal system

The use of sensitive information in traditional decision-making methods may be subject to errors as well as possible fairness issues that may arise from the use of sensitive personal information among individuals for decision-making on environmental legal issues. While the accuracy of the collection of sensitive personal information is a problem that can be solved by intelligent decision support systems or technological developments, the risk of decision-making and the responsibility for decision-making, i.e., the rules for algorithmic handling of sensitive personal information, should be governed by publicly available and consistent rules for the protection of personal information, which must be left to the law. In traditional public governance legitimacy judgment, there is no way to fully separate these two obligations of decision transparency.

V. C. Building a dynamic system for the protection of fundamental rights

The protection of the fundamental rights of individuals based on the legal suitability of intelligent decision support systems should not only establish a set of standards and value systems to measure and regulate new problems, but more importantly, it can build bridges between algorithmic technical norms and established norms of subjects, behaviours, relationships, institutions and power that work well. When intelligent decision support systems deal with sensitive personal information, the quality of policy formulation, specific system design and decision-making using sensitive personal information should be assessed. This means that intelligent decision support systems should meet macro-level value and procedural requirements, linking policy decisions to the protection of sensitive personal information as a priority, and making empowerment, participation and redress feasible. In emphasizing the protection of fundamental rights in the processing of sensitive information by intelligent decision support systems, it is also important to prevent the downgrading of relevant evaluation criteria, such as algorithmic transparency requirements, algorithmic trustworthiness requirements, and algorithmic interpretability requirements, all of which should not be downgraded because they are based on the protection of fundamental rights, in order to achieve a healthy interaction between law and technology.

VI. Conclusion

In this paper, an intelligent decision support system for environmental legal issues based on radial basis function network and T-S fuzzy model is designed, and the system is utilized for administrative decision assistance.

The lowest prediction accuracy of radial basis function network and comparison algorithm in this paper is only 88.54%, in which the training time of radial basis function network algorithm is only 0.32s, which is 0.13s lower than the sub-optimal algorithm, but its prediction accuracy reaches 97.85%, which illustrates that the radial basis function network with high accuracy and high operation efficiency can get better performance in environmental legal problem classification.

In the Wine dataset, the classification accuracy of the T-S fuzzy algorithm is improved by 0.176 compared to the fuzzy algorithm, and the number of fuzzy rules generated is less. Besides that, the algorithm of this paper performs better than the fuzzy algorithm in the other three datasets. It shows that the T-S fuzzy algorithm has more excellent classification accuracy than the fuzzy algorithm and can improve the decision-making efficiency of the intelligent decision support system in environmental legal problems.

The results of the intelligent decision-making effect assessment of environmental legal problems identify that the hazardous consequence factor affects the punishment to the greatest extent, which is consistent with the actual decision-making results of environmental legal problems. The rationality of the system design is verified, and it meets the design requirements of the auxiliary decision-making task for environmental legal issues. It has the role of decision-making reference for the case processing in the process of administrative enforcement of environmental legal issues.

The article discusses the suitability of the system for administrative decision-making assistance and existing laws from three aspects: identification and standardization of information processing, construction of an integrated legal system, and construction of a dynamic protection system for fundamental rights, and provides corresponding strategies for further improvement of the suitability.

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