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Retraction

Retracted: An Intelligent Gray Prediction Model Based on Fuzzy Theory

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Wu, "An Intelligent Gray Prediction Model Based on Fuzzy Theory," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 8618586, 9 pages, 2022.

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Research Article

An Intelligent Gray Prediction Model Based on Fuzzy Theory

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In order to improve the forecasting effect of the gray prediction model, this paper combines the fuzzy theory to construct the gray prediction model and explores its forecasting accuracy. Moreover, this paper uses the entropy weight method to obtain the objective weight to correct the subjective weight, which makes the weight calculation more reasonable. In view of the uncertainty of the control signal of the research object, this paper introduces the gray system theory to conduct cluster analysis on the fire control computer and mainly introduces the general whitening weight function. Furthermore, this paper adopts the center point mixed with a triangular whitening weight function to carry out gray clustering according to the difficulty of defining the gray class boundary and gives the solution steps to obtain the intelligent gray prediction model. Finally, this paper verifies that the intelligent gray prediction model based on fuzzy theory has a good effect through experiments, which can effectively improve the prediction effect of the intelligent prediction model.

1. Introduction

The energy of the actual system will not change suddenly, and there are uncertain factors such as random interference, so it can be regarded as a gray system. According to the gray theory, the future output of the system can be predicted by modeling the historical data of the system. In the literature [1], the author carried out gray predictive control on the output of the univariate system and achieved a good control effect. In the literature [2], the author introduces the research results and application fields of gray control in recent years, but they are all limited to single-input–single-output systems. In the literature [3], the author conducted research on multivariable gray predictive control for the first time but did not consider the coupling effect between control loops. Because the input and output of the multiple-input–multiple-output system (MIM0) respond to each other, resulting in a cross-connection. However, the application of univariate control in the industry has developed quite maturely, so it is undoubtedly a good choice to decouple the multivariate system and utilize the control results of univariate. For decoupling, intelligent decoupling, robust decoupling, predictive decoupling, nonlinear decoupling, and adaptive and optimization decoupling that have appeared in recent years are all very popular research branches. In the literature [4], the author uses a genetic algorithm to optimize the weighting matrix of the controller so as to achieve the purpose of decoupling. In the literature [5], the author designs a linear robust adaptive decoupling control law and a neural network decoupling control law for a class of multivariable nonlinear systems, respectively. In the literature [6], the author designs an adaptive decoupling control system of an aero-engine combined with a neural network. In the literature [7], the author adopts the working mode of multiplexing to realize the decoupling and adaptive suppression of noise in the frequency band.

One of the main tasks of sensor data fusion is to use multisensor data to estimate the state of the target. A filter with a poor real-time processing ability is easy to lose track of when tracking a maneuvering target, but a filter with fast convergence can well solve the task of stabilizing the target and tracking the target. In addition, adaptive filtering has a certain ability to detect and track maneuvering targets, and its advantages are that the amount of computation is small and the real-time performance of target tracking is good. However, the filtering performance of adaptive filtering is poor; that is, the tracking accuracy is poor. The particle filter algorithm is a typical nonlinear tracking filtering method, which is an optimal regression Bayesian filtering algorithm based on Monte Carlo simulation. A state estimate can be computed [8]. Compared with other filtering algorithms, such as the extended Kalman filter (EKF) algorithm and the trajectory-free Kalman filter algorithm, the particle filter method is not limited by linearization error or Gaussian noise assumption and is suitable for any state or model in any environment. However, its filtering performance depends on the preassumed target state model. Over time, when the pre-established state model is no longer applicable to the real motion state of the target, serious particle degradation will occur [9].

When the state agenda and measurement equation of the target are preassumed mathematical models, when the target is tracked and filtered using a standard particle filter, the sampled particles are calculated according to the target state agenda. If the model can well represent the state and measurement of the target, then the standard particle filter algorithm may be able to achieve good results. However, in the case of target maneuvering, the real dynamic characteristics are difficult to represent by an accurate mathematical model. After several iteration cycles, most particle weights tend to approach zero, resulting in particle degradation, which means that those containing particles with little target state information will eventually degenerate [10].

Literature [11] proposes a method for constructing a decision support system for a decision support system based on a decision model based on the state of the world by applying a Bayesian network to consider causal random events in the environment; Literature [12] uses the Bayesian network inference to solve the problem in each scheme. Literature [13] considers the uncertain multiattribute decision-making problem when the probability distribution of some attribute values is an interval number and proposes an aggregation model based on two types of information: the Bayesian network and decision matrix. They determined the composite attribute value of the scheme. Bayesian networks have been widely and successfully applied in many fields such as medical diagnosis, life informatics, image and speech recognition, financial risk analysis, and software system testing, and are being integrated into artificial intelligence in the mainstream model of dealing with uncertainty in the field of data mining.

Before establishing the gray Bayesian network inference prediction model, it first involves the inference of the current development data of the system after the system shock. Generally speaking, according to the development trend of the system, the system shock can be divided into two forms. One is that the development of the system has been qualitatively improved and its development trend has been greatly strengthened; the other is that the original development trend of the system has been damaged. To add to the qualitative destruction, the system has experienced a serious recession. Each form of systemic shock can be divided into worst-case and best-case scenarios. In general, under the first and second shock forms, respectively, the worst and best scenarios of system development are that the system develops according to the original historical trend [14].

Literature [15] uses the nonhomogeneous gray index law of one-time accumulation to construct a dynamic sequence model. From the perspective of integral geometry, the idea of function approximation is used to improve the background value of the model combined with the complex trapezoidal formula; literature [16] proposes a combined optimization method that optimizes the background value and adjusts the initial system parameters, and simulates and predicts the sequence of unbiased exponential distribution by optimizing the background value in the gray differential equation; literature [17] proposes a method to find the minimum value of the average fitting error of the model. The particle swarm optimization algorithm is used to optimize the background value coefficient of the model, but the optimization is aimed at the traditional background value expression, and there is still a certain error in the construction of the background value expression. Aiming at the problem of model structure defects, there are mainly methods such as structure selection based on an intelligent algorithm and fusion optimization of parameters and structures. The literature [18] optimized the parameters of initial conditions, cumulative generation order, development coefficient, and background value distribution coefficient. The research results show that the optimization of the above parameters has a positive effect on improving the performance of multidimensional gray prediction models. These improved gray prediction models. There are still defects in structural compatibility; literature [19] proposed a gray prediction model based on the data algorithm white adaptive selection model structure, called the discrete gray polynomial model, which has the most common isomorphism and nonisomorphism model. The ability to construct a discrete gray model and generalize some other novel models, thus highlighting the relationship between the model and its structure; literature [20] adds adjacent variable lag terms, linear correction terms, and random disturbance terms to the model, which eliminates the multicollinearity problem between the explanatory variables and significantly improves the prediction performance of the model.

This paper combines the fuzzy theory to construct a gray prediction model, explores its prediction accuracy, and provides literature for the practical application of the subsequent algorithm.

2. Fuzzy Gray Prediction Algorithm

2.1. Entropy Weight Method. Information is a relatively abstract concept. It assumes that there are n independent results $S_1, S_2, \ldots, S_n$ of a random event, and the corresponding probability of each result is $P_1, P_2, \ldots P_n$, and the following conditions are satisfied:

$$\begin{gathered} 0 \leq P_i \leq 1, \\ \sum_{i=1}^{n} P_i = 1\,(i = 1, 2, \ldots n). \end{gathered} \tag{1}$$

For such a random event, the outcome of the event is uncertain. The probability distribution of the event determines the uncertainty of the event. C. E. Shannon proposed the following function in order to describe the uncertainty of events in a mathematical way.

$$H_n = H(P_1, P_2, \ldots P_n) = -k \sum_{i=1}^{n} P_i \ln P_i. \tag{2}$$

In the above formula, H_n is defined as information entropy, k is a nonnegative constant, and $0 \ln 0 = 0$ is specified in the formula.

In the research on the state evaluation method of fire control computer carried out in this section, the disorder of uncertain information in the system can be measured by entropy.

According to the relevant theory of information entropy. The specific process is shown in Figure 1, and the specific calculation process is shown in the following formulas:

$$X = (x_{ij})_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n1} & \cdots & x_{nm} \end{bmatrix}. \tag{3}$$

Among them, x_{ij} is the evaluation value of object i under index j.

Because of the difference between the different division and clustering levels, and the different magnitudes of the dimensions, it is usually necessary to perform dimensionless standard processing on the initial samples before the weighting of the evaluation indicators. That is, the polarization difference method of differentiated treatment is adopted, and each evaluation index is standardized in the interval [0, 1], so that the larger the index in the standardized interval, the better, and the subsequent calculation of the index weight is convenient.

Among them, the index positively correlated with the result adopt the following formula:

$$x_{ij}{}' = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}. \tag{4}$$

Among them, the index negatively correlated with the result adopts the following formula.

$$x_{ij}{}' = 1 - \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}. \tag{5}$$

In the above formula, $x_j^{\min}$ and $x_j^{\max}$ are the minimum and maximum values, respectively. x_{ij}' is the index norm value of the j-th index x_{ij} in the i-th sample to be evaluated.

2.1.1. Normalization of Evaluation Index Data. According to formula (6), the index value ratio p_{ij} of the i-th evaluation sample under the j-th index is calculated.

$$p_{ij} = \frac{r_{ij}}{\sum_{j=1}^{m} r_{ij}}. \tag{6}$$

2.1.2. Calculate Information Entropy E_j. After the data is normalized, the matrix p_{ij} can be obtained, and the information entropy E_j of any evaluation index can be calculated by the following formula:

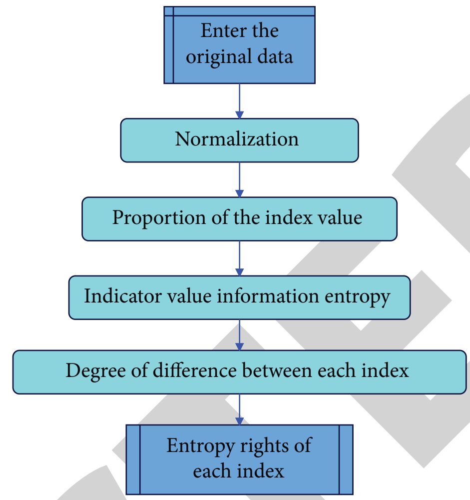

Figure 1: Entropy weight method process.

$$E_j = -k \sum_{i=1}^{n} (p_{ij} \ln p_{ij}) (i = 1, 2, \ldots n), k = \frac{1}{\ln n}. \tag{7}$$

2.1.3. Calculate the Index Entropy Weight ω_j. Through the following formula, the weight ω_j corresponding to the j-th evaluation index can be calculated as:

$$\omega_j = \frac{1 - E_j}{m - \sum_{j=1}^{m} E_j}. \tag{8}$$

In the above formula $\omega_j \in [0, 1]$, and $\omega_1 + \omega_2 + \cdots + \omega_m = 1$.

To sum up, the entropy weight ratio ω_j corresponding to each index in the state evaluation process of the fire control computer can be calculated according to the formula (8).

2.2. Analytic Hierarchy Process. An analytic hierarchy process (AHP) is a method that uses objective descriptions of people's thinking processes and subjective judgments to solve multi-objective decision-making problems. The AHP method is to analyze the influence of qualitative and quantitative indicators on the target in sufficient detail and then transform multi-objective decision-making into single-objective decision-making. Meanwhile, it builds a judgment matrix by comparing the relative importance of elements that are not at the same level. Then, the corresponding weight vector and weight matrix are calculated mathematically. Compared with traditional decision-making methods, AHP can simplify system analysis and improve computing efficiency, and can effectively solve the problem that qualitative information cannot be quantified.

The analytic hierarchy process (AHP) firstly stratifies decision-making problems and influencing factors and establishes a multilevel structure model. After that, after analyzing the model of each layer, it calculates the importance of each feature in the corresponding layer or the whole target, so as to obtain the weight of each feature in the decision problem to realize the decision. The specific process is as follows.

2.2.1. Build a Hierarchical Structure Model. It analyzes the decision-making problem and decomposes the influencing factors in the evaluation system into top-level goals, middle-level elements, and bottom-level elements. The specific structure diagram is shown in Figure 2. In general, there is only one top-level target, and there can be one or several middle-level elements, and the middle-level elements are further decomposed into several bottom-level elements.

According to the subjective evaluation of experts, the importance of each index is quantified through semantic variables, which is convenient for subsequent calculation.

The mathematical relationship between the two is

$$a_{ij} = \frac{1}{a_{ji}}. \tag{9}$$

In order to reasonably and effectively quantify the importance of each index of the evaluation object by experts, AHP uses the most extensive 1–9 scale method to construct an expert judgment matrix to compare the importance of element i and element j. If it is assumed that the weights of n parameter indicators need to be calculated, it is necessary to take $n(n-1)/2$ pairwise comparisons between each element to construct a judgment matrix A:

$$A = \left(a_{ij}\right) = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}. \tag{10}$$

In the above formula, when i and j are equal, it means that the scale value of the same index is 1. Other situations are shown in Table 1.

On the basis of the judgment matrix A, the size of the largest eigenvalue x and the corresponding eigenvector $\lambda_{\max}$ are obtained, and the calculation is as in the folllowing formula:

$$A_W = \lambda_{\max} \cdot w. \tag{11}$$

The feature vector w needs to be normalized to obtain the weight w' occupied by each feature in the overall evaluation.

2.2.2. Consistency Test. Consistency refers to the consistency of judging ideas. Specifically, in the process of judging the importance of indicators, experts need to coordinate the judgments to avoid conflicting conclusions. However, in the actual research process, the research objects themselves are complex and of different types, and people's judgments on the evaluation objects are also complex and have a certain sensibility. Therefore, it is difficult for experts to have consistency in the process of judging the evaluation object. Based on this, in order to obtain a more reasonable result:

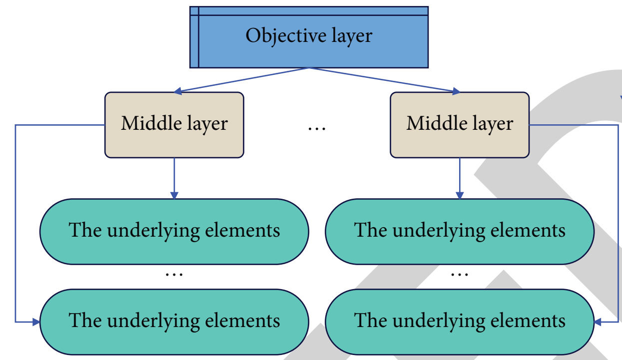

Figure 2: The general structure of AHP.

$$\begin{aligned} \mathrm{CR} &= \frac{\mathrm{CI}}{\mathrm{RI}} \\ \mathrm{CI} &= \frac{\left(\lambda_{\max} - n\right)}{(n-1)}. \end{aligned} \tag{12}$$

The calculated CR can determine whether the consistency requirements are met. When CR = 0, complete consistency is considered.

Although the AHP method has been widely used in index weighting, it has too many subjective components, and it is difficult to pass the one-time test at a time. Therefore, in view of this difficulty, this paper optimizes the calculation by improving the scaling method. The specific calculation process is shown in Figure 3.

The specific calculation steps of the improved method are as follows.

2.2.3. Constructing the Judgment Matrix According to the Three-Scale Method. The judgment matrix is established according to the three-scale method instead of the 1–9 scale method, which greatly reduces the misjudgment caused by the mutual comparison of matrix elements and improves the accuracy of the weight determination process. The three-scale method is introduced for each layer of evaluation indicators to compare the importance, and the matrix A is obtained as follows:

$$A = \left(a_{ij}\right) = \begin{bmatrix} \frac{a_1}{a_1} & \frac{a_1}{a_2} & \cdots & \frac{a_1}{a_n} \\ \frac{a_2}{a_1} & \frac{a_2}{a_2} & \cdots & \frac{a_2}{a_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_n}{a_1} & \frac{a_n}{a_2} & \cdots & \frac{a_n}{a_n} \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}. \tag{13}$$

According to the three-scale method, the element a_{ij} in formula (13) is quantitatively expressed, and the meaning is shown in Table 2.

Secondly, the sorting index is obtained as:

Table 1: Meaning of nine scales.

Scale a_{ij}	Meaning
1	i and j are equally important
3	i is slightly larger than j
5	i is significantly greater than j
7	i is strongly greater than j
9	i is extremely larger than j
2, 4, 6, 8	Represents the median value of the judgment between the above two element comparisons
Reciprocal	By swapping the comparison order of the above elements, we can get $a_{ji} = 1/a_{ij}$

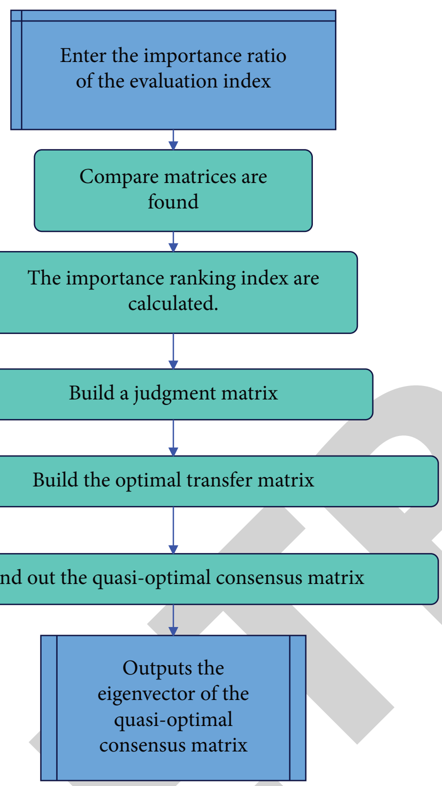

Figure 3: The flow of the improved AHP.

Table 2: The importance ratio and meaning of evaluation indicators.

Importance ratio $a_{ij} = a_i/a_j$	The specific meaning of the ratio
0	a_i is less important than a_j
1	a_i is as important as a_j
2	a_i is more important than a_j

$$r_i = \sum_{j=1}^{n} a_{ij}. \tag{14}$$

Finally, a judgment matrix B_{ij} is constructed according to the sorting index r_i, where b_{ij} is obtained by the following formula:

$$b_{ij} = \begin{cases} \dfrac{r_i - r_j}{r_{\max} - r_{\min}}\left(k_m - 1\right) + 1, & r_i \geq r_j, \\ \left(\dfrac{r_j - r_i}{r_{\max} - r_{\min}}\left(k_m - 1\right) + 1\right)^{-1}, & r_i < r_j. \end{cases} \tag{15}$$

2.2.4. Adjust the Judgment Matrix. Through the matrix B_{ij}, the algorithm finds the matrix element c_{ij}, and establishes the transfer matrix C_{ij}:

$$c_{ij} = \lg b_{ij}\,(i, j = 1, 2, \ldots, n). \tag{16}$$

Secondly, according to the above matrix, the algorithm obtains the matrix factor d_{ij} according to the following formula, and the optimal transfer matrix D_{ij} can be obtained.

$$d_{ij} = \frac{1}{n}\sum_{k=1}^{n}\left(c_{ik} - c_{jk}\right). \tag{17}$$

Finally, according to the above matrix, the matrix element b'_{ij} is obtained according to formula (18), and the quasi-optimal consistent matrix B'_{ij} is obtained.

$$b'_{ij} = 10^{d_{ij}}. \tag{18}$$

2.2.5. Confirm the Weight. According to the B'_{ij} matrix, according to formulas (19)–(21), the method of finding the square root is used to obtain the matrix eigenvector W.

The algorithm first finds the element-wise product of each row of B'_{ij} which is give as follows:

$$M_i = \prod_{j=1}^{n} b'_{ij}\,(i = 1, 2, \ldots n). \tag{19}$$

The algorithm then finds the square root as follows:

$$\overline{W}_i = \sqrt[n]{M_i}. \tag{20}$$

Finally, the algorithm normalizes the resulting vector $\overline{W} = (\overline{W}_1, \overline{W}_2, \ldots, \overline{W}_n)^T$ as follows:

$$W_i = \frac{\overline{W}_i}{\sum_{i=1}^{n}\overline{W}_i}. \tag{21}$$

Finally, the vector $W = (W_1, W_2, \ldots, W_n)$ is obtained, which is the evaluation index weight ratio vector of the improved AHP.

2.3. Grey System Theory. Aiming at the running state of the fire control computer, this paper adopts the evaluation method of gray clustering. This method divides evaluation indicators or samples into several defined categories and is widely used in various types of evaluation work. Among them, the evaluation indicators or samples belonging to a category constitute the same category. Through the gray whitening weight function clustering process of setting gray classes and determining the attribution of samples, the system state can be evaluated. This paper is consistent with the idea of gray clustering when evaluating the running state of a fire control computer, so gray whitening weight function clustering is used to realize state evaluation.

We assume that there are n experimental samples, m evaluation metrics, and s different categories. The specific process of this method is to divide the i-th sample into the $k(k \in 1, 2, \ldots, s)$-th sample through the $j(j = 1, 2, \ldots, m)$-th x_{ij} of the $i(i = 1, 2, \ldots, n)$-th experimental sample. The functional relationship of this process is called the whitening weight function, denoted as $f_j^k(\cdot)$. This article will introduce four forms of this function.

(1) As shown in Figure 4, the function expression is shown in the following formula:

$$f_j^k = \begin{cases} 0, & x \notin \left[x_j^k(1), x_j^k(4)\right], \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[x_j^k(1), x_j^k(2)\right], \\ 1, & x \in \left[x_j^k(2), x_j^k(3)\right], \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in \left[x_j^k(3), x_j^k(4)\right]. \end{cases} \tag{22}$$

(2) As shown in Figure 5, the function expression is shown in the following formula:

$$f_j^k = \begin{cases} 0, & x \notin \left[0, x_j^k(4)\right], \\ 1, & x \in \left[0, x_j^k(3)\right], \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in \left[x_j^k(3), x_j^k(4)\right]. \end{cases} \tag{23}$$

(3) We assume that when $x_j^k(2)$ of the whitening weight function $f_j^k(\cdot)$ coincides with $x_j^k(3)$, $f_j^k(\cdot)$, as shown in Figure 6, denoted as $f_j^k[x_j^k(1), x_j^k(2), -, x_j^k(4)]$, and the function expression is shown in the following formula:

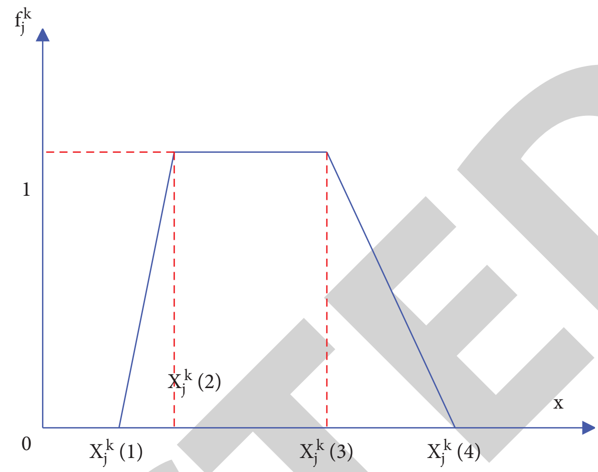

Figure 4: Typical schematic diagram.

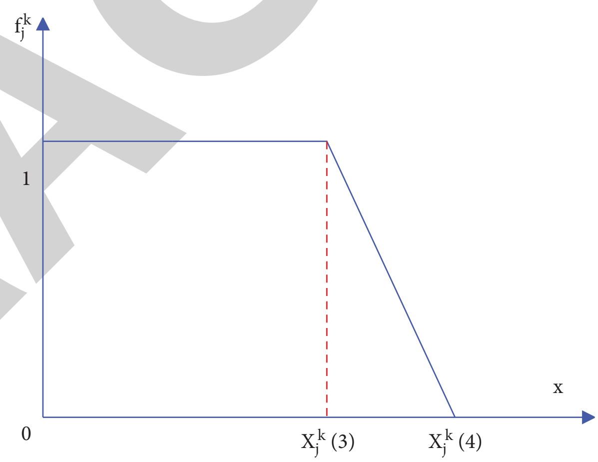

Figure 5: Schematic diagram of the lower limit measurement type.

$$f_j^k = \begin{cases} 0, & x \notin \left[x_j^k(1), x_j^k(4)\right], \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[x_j^k(1), x_j^k(2)\right], \\ \dfrac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in \left[x_j^k(2), x_j^k(4)\right]. \end{cases} \tag{24}$$

(4) We assume that when the whitening weight function $f_j^k(\cdot)$ has no turning point. $x_j^k(3), x_j^k(4)$, $f_j^k(\cdot)$ is the upper limit measurement whitening weight function, as shown in Figure 7, denoted as $f_j^k[x_j^k(1), x_j^k(2), -, -]$. The function expression is shown in the following formula:

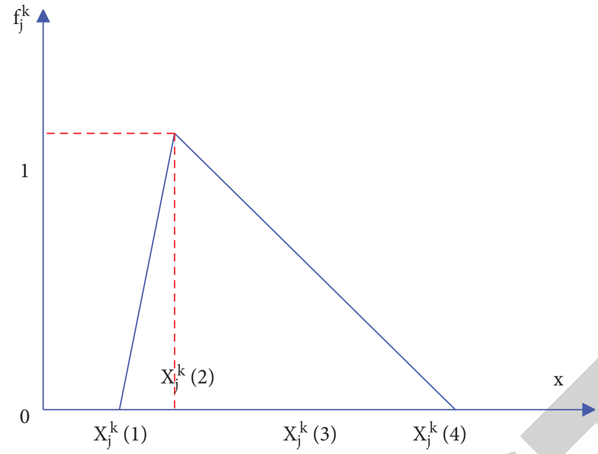

Figure 6: Schematic diagram of moderate measure type.

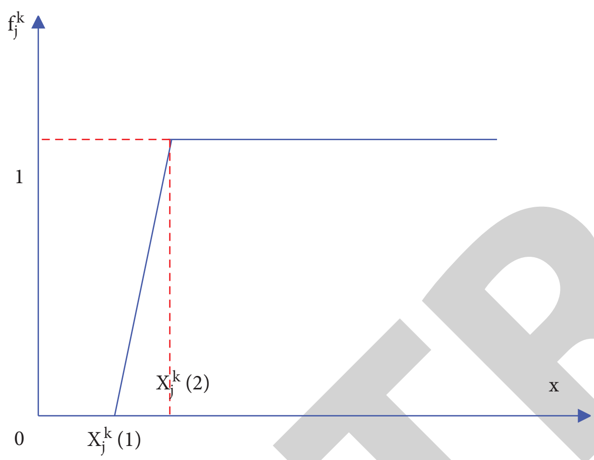

Figure 7: Schematic diagram of the upper limit measurement type.

$$f_j^k = \begin{cases} 0, & x < x_j^k(1), \\ \dfrac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in \left[x_j^k(1), x_j^k(2)\right], \\ 1, & x \geq x_j^k(2). \end{cases} \tag{25}$$

When the boundaries of gray classes are uncertain, a better clustering effect can be achieved by mixing the triangular whitening weight function at the center point. Among them, the maximum degree of belonging to a certain category is the cluster center point of the gray category. The steps are as follows:

(1) Regarding the index j, in the interval $[a_j, b_j]$ in Figure 8, the algorithm obtains the center point $\lambda_j^2, \lambda_j^3, \ldots, \lambda_j^{s-1}$ of the turning points λ_j^1 and $k(k \in \{2, 3, \ldots s-1\})$, respectively.

(2) The algorithm obtains the function $f_j^1[-, -, \lambda_j^1, \lambda_j^2]$ and the function $f_j^s[\lambda_j^{s-1}, \lambda_j^s, -, -]$ to obtain the membership degree.

(3) As shown in Figure 8, the turning point and the center point are connected, and the triangular whitening weight function $f_j^k(\cdot)$ of the index j with respect to k is obtained:

$$f_j^k\left[\lambda_j^{k-1}, \lambda_j^k, -, \lambda_j^{k+1}\right], j = 1, 2, \ldots, m; k = 2, 3, \ldots s-1. \tag{26}$$

The membership degree $f_j^k(x)$ of the index j with respect to $k(k \in \{2, 3, \ldots, s-1\})$ is obtained by formula (26).

(4) The algorithm determines the weight $\omega_j, j = 1, 2, \ldots m$ of each index.

(5) The algorithm calculates the clustering coefficient σ_i^k of the evaluation object index $i(i = 1, 2, \ldots, n)$ with respect to $k(k = 1, 2, \ldots, s)$.

$$\sigma_i^k = \sum_{j=1}^{m} f_j^k\left(x_{ij}\right)\omega_j. \tag{27}$$

(6) The algorithm obtains $\sigma_i^{k^*} = \max_{1 \leq k \leq s}\{\sigma_i^k\}$, and the maximum gray clustering coefficient is called the evaluation object i belongs to the gray class k^*.

3. Effect Verification of Intelligent Gray Prediction Model Based on Fuzzy Theory

The method in this paper is the composite control method of adaptive gray predictive control (CAGPC). The input signal has a process of increasing acceleration-smoothing-decreasing deceleration. The system tracking curves of the three methods are shown in Figure 9.

The above-mentioned method verifies that the intelligent gray prediction model based on fuzzy theory has a good effect and can effectively improve the prediction effect of the intelligent prediction model.

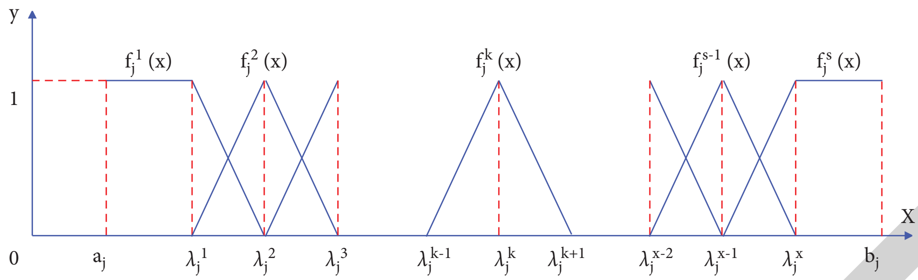

FIGURE 8: Schematic diagram of center point hybrid type.

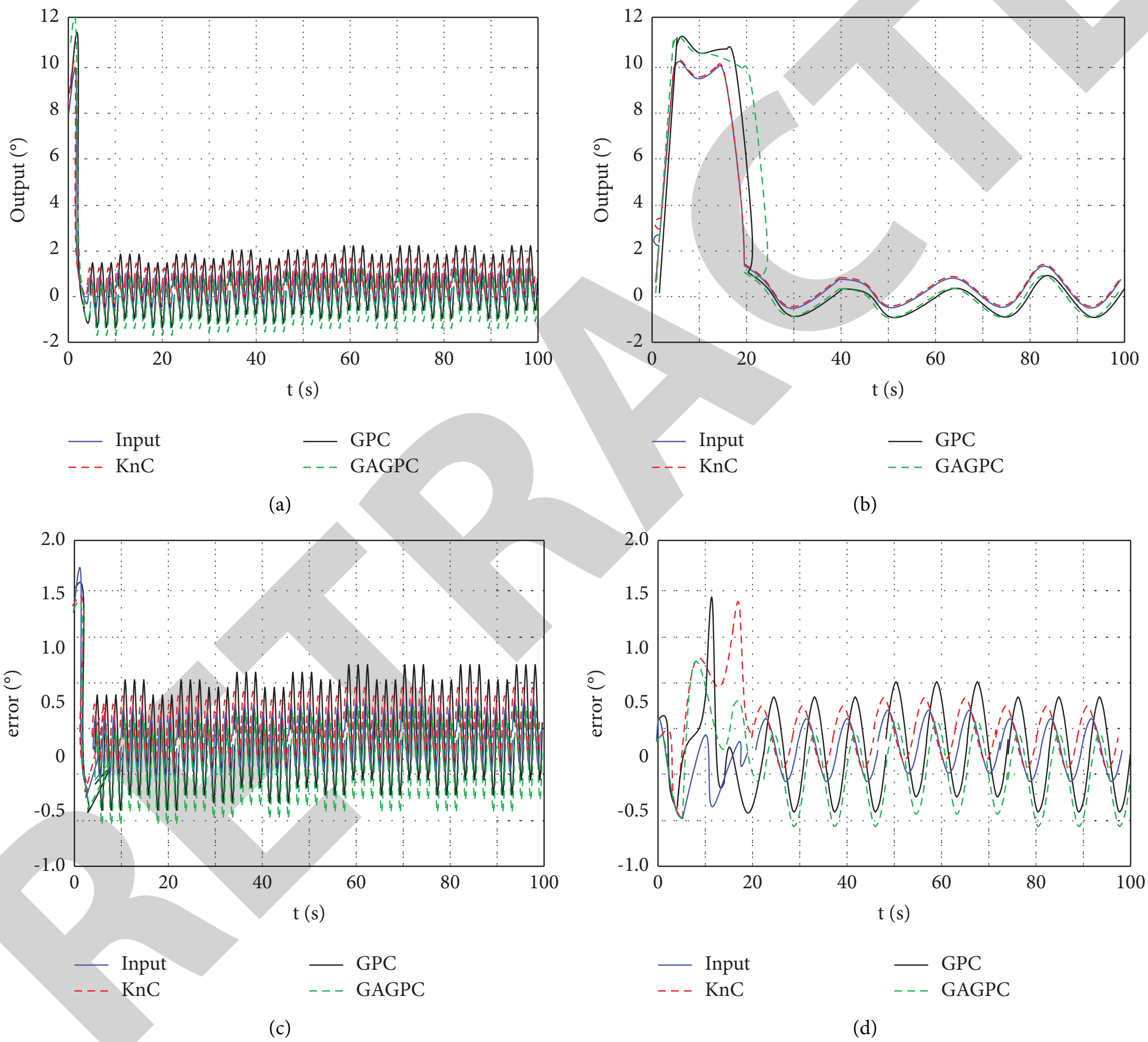

FIGURE 9: Tracking and error curves of stable platform under disturbance conditions. (a) Tracking curve. (b) Local magnification curve. (c) Deviation curve. (d) Local magnification curve.

4. Conclusion

The fixed-step gray predictive controller can reduce or even eliminate the overshoot of the system response, but at the same time, the response time of the system will be significantly longer. The overshoot is smaller, and any prediction model has prediction errors. Moreover, the prediction error will be transmitted to the system output through the stabilized platform control loop, thus affecting the tracking accuracy of the stabilized platform. Therefore, it is necessary to deal with the prediction error to some extent. The measured value reduces and increases its role in the control loop according to the size of the prediction error, thereby reducing the influence of the prediction error on the servo control system of the stable platform. This paper combines the fuzzy theory to construct a gray prediction model to explore its forecasting accuracy. The experimental results verify that the intelligent gray prediction model based on fuzzy theory has good effects, which can effectively improve the prediction effect of the intelligent prediction model.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of Interest.

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