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A Comprehensive Decision Analysis Method Based on Analytic Hierarchy Process and Grey Prediction Model

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Abstract: This paper proposes an integrated decision analysis framework combining the Analytic Hierarchy Process (AHP) with a grey prediction model, focusing on a unified modeling approach for matching different entities and forecasting trends under multi-objective constraints. First, a multi-level structural model based on AHP is constructed. Starting from weight allocation and consistency testing, it quantitatively evaluates the comprehensive performance of different entities under multi-dimensional indicators, enabling systematic identification of optimal matching targets. Second, a grey prediction model is introduced to model and forecast the trend changes of key indicators under limited sample conditions. The model's reliability and applicability are validated through accuracy testing and residual analysis, thereby delineating the system's future evolutionary direction. Finally, combining linear regression and time series analysis methods, the model quantitatively evaluates the effects of implemented intervention measures, forming a complete analytical process from prediction to decision-making to effect verification. This model features a clear structure, stable computation, and low sample size requirements. It enables effective prediction and decision support under conditions of incomplete information, demonstrating strong universality and promotional value. It provides a feasible and efficient modeling approach for the comprehensive analysis of similar complex systems.

Keywords: Analytic Hierarchy Process, Grey Prediction Model, Comprehensive Decision Analysis.

1. Introduction

This paper focuses on the challenge of simultaneously capturing multi-objective decision-making and trend evolution within complex systems, aiming to construct a unified analytical framework that integrates subject matching, trend forecasting, and strategy evaluation. As demands for resource allocation, risk control, and long-term governance continue to grow, related research often faces common challenges such as limited data samples, strong subjectivity in indicator weighting, and difficulties in translating predictive outcomes into actionable decision-making [1]. Existing approaches typically rely on single algorithmic models, struggling to achieve seamless integration from analysis to decision-making under uncertain information environments. To address this, this paper introduces the Analytic Hierarchy Process (AHP) at the system modeling level. This method structurally decomposes and calculates weights for multidimensional evaluation indicators, thereby reducing uncertainty stemming from subjective judgments and enabling quantitative comparisons among different decision-making entities [2][3]. Subsequently, integrating a grey prediction model, the evolution trends of time-series data are modeled to leverage its predictive strengths under conditions of small samples and weak information, thereby characterizing the future direction of key indicators [4]. Building upon this foundation, regression analysis and time-series methods are further introduced to quantitatively assess the impact of strategic interventions before and after implementation, forming a complete model loop [5][6]. Centered on algorithmic modeling, this approach organically integrates multi-objective evaluation, trend forecasting, and strategy optimization. It validates the model's feasibility and stability in practical scenarios. Experimental results demonstrate that this comprehensive model performs well in prediction accuracy, decision consistency, and application adaptability, providing effective analysis and decision support for similar complex systems problems.

2. Multi-Stakeholder Optimal Matching Model Based on Analytic Hierarchy Process

2.1. Data description

Different attributes enable governments, non-profit organizations and the general public to provide heterogeneous contributions to the achievement of relevant indicators. Each goal presents differentiated requirements for the three factors, which means that differentiated weights should be assigned to the three factors for each project. Corresponding scores are assigned to the three customer groups based on power, resources and interests, and the analytic hierarchy process is further adopted to identify the optimal customer group corresponding to each individual goal.

Evaluations of each customer group are conducted from three dimensions including power, resources and interests, with corresponding scores assigned to form the following numerical matrix, as shown in the Table 1 (on a scale of 1 to 10).

Power: the capacity for formulating and enforcing laws, and the capacity for coordinating transnational cooperation.

Resources: financial funds, scientific research and technical tools, and professional personnel.

Interests: long-term commitment to environmental protection and biodiversity conservation.

Table 1. Client evaluation form

	power	resources	interests
the government	10	9	4
non-profit organizations	7	8	10
the public	4	4	6

2.2. Application of analytic hierarchy process for matching optimal customers to each goal

The analytic hierarchy process (AHP) model is adopted in this section, which is divided into four core steps as follows:

1. Establish a hierarchical structure model
2. Construct judgment matrices for each level
3. Conduct consistency test
4. Conduct weight evaluation

Four independent hierarchical structure models need to be established for the four respective goals (indicators). Raising awareness is set as the target layer, three indicators are set as the criterion layer, and three customer groups are set as the scheme layer.

Each goal presents differentiated requirements for the three factors, which means that differentiated weights should be assigned to the three factors for each project. A judgment matrix is constructed on this basis: pairwise comparisons are implemented for the importance of the three indicators (power, resources and interests), so as to realize scientific weight calculation. The Table 2 below presents the judgment matrix constructed for the first indicator (where the row coordinate of each element is denoted as i and column coordinate is denoted as j, representing the importance degree of the i-th indicator relative to the j-th indicator).

Table 2. Judgment matrix

	power	resources	interests
power	1	0.333	0.2
resources	3	1	1
interests	5	1	1

From the Table 2, a value of 3 indicates that one element is slightly more important than another element, a value of 5 indicates that one element is significantly more important than another element, and a value of 1 indicates that the two elements hold equal importance.

A consistency test is then performed on the constructed judgment matrix, which verifies whether excessive deviation exists between the constructed matrix and a consistent matrix. The steps for consistency checking are as follows:

1. Calculate the consistency indicator CI.
2. Determine the corresponding average random consistency index RI.
3. Calculate the consistency ratio CR: the judgment matrix is confirmed to have satisfactory consistency if CR < 0.1.

In the formula, n denotes the dimension of the matrix with a value of 3 in this case, and λ_{max} represents the maximum eigenvalue.

$$CI = \frac{\lambda_{max} - n}{n-1}, \quad CR = \frac{CI}{RI} \tag{1}$$

Calculations via MATLAB yield a CR value of 0.028, which is less than 0.1, confirming that the consistency test is passed.

Subsequent calculations with the root method in MATLAB generate the following weight results:

Power accounts for 11.496%, resources account for 40.548%, and interests account for 47.956%.

The weight of each factor corresponding to the target is obtained through the above process. The weight vector is multiplied by the attribute row vector of each customer to derive the score of each customer, and the customer with the highest score is selected as the optimal match for the corresponding goal.

2.3. Presentation of model solution results

Table 3. The results of model

	NO.1	NO.2	NO.3	NO.4
the government	6.71716	9.10264	9.00009	7.80375
Non-profit org.	8.84416	7.57905	7.72735	8.41492
the public	6.58104	4.21236	4.18186	4.52104

As shown in the Table 3, the results demonstrate that non-profit organizations serve as the optimal customers for Goal NO.1; the government is identified as the optimal customer for Goal NO.2 and Goal NO.3, while non-profit organizations are confirmed as the optimal customers for Goal NO.4.

3. Trend Analysis and Decision Support Based on Grey Prediction Model

3.1. Application of grey prediction model for Earth vitality index prediction

3.1.1. Establishment process of grey prediction model

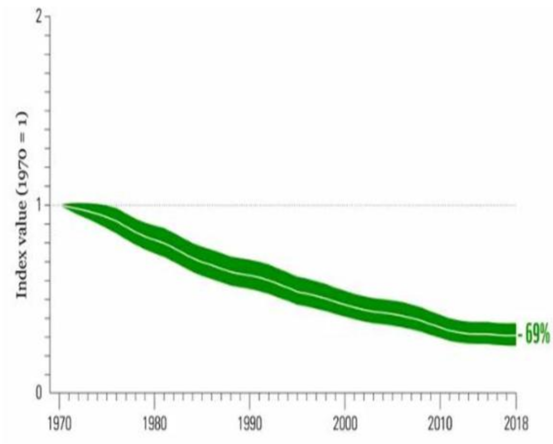

Figure 1. Data image presentation

Figure 1 displays the multi-year Earth vitality index.

Grey system theory is first introduced. A grey system uses the depth of color to reflect the volume of information. A system between a black system and a white system, i.e., a system with incomplete information, is defined as a grey system. The independent variable selected is year, and the dependent variable is the Earth vitality index. System factors of this system are not fully clarified, the correlation between factors is not fully defined, the system structure is not fully understood and the system mechanism is not fully clear, which confirms the system as a grey system.

System data are non-negative values measured on an annual basis, which satisfy the exponential law test with a short time span of data periods. Grey prediction is thus applicable to forecast the future variation of the dependent variable.

Grey prediction is implemented through the following steps:

1. Prior to establishing the grey prediction model GM(1,1), a grade ratio test is conducted on the time series. A qualified grade ratio test result indicates the sequence is suitable for grey model construction; an unqualified result requires a

translation transformation to the sequence for the grade ratio to meet the test criteria, thus making the new sequence eligible for the grade ratio test. After translation transformation, all grade ratios of the data fall within the interval $\left(e^{-2/(n+1)}, e^{2/(n+1)}\right)$, namely $(0.9, 1.111)$, so the grade ratio test is passed.

2. The development coefficient, grey action quantity and posterior error ratio are derived.

A grey prediction model can be constructed based on the development coefficient and grey action quantity.

The development coefficient characterizes the development law and trend of the sequence, and the grey action quantity reflects the variation correlation of the sequence.

The posterior error ratio is used to verify the prediction accuracy of the grey model, with a smaller posterior error ratio corresponding to higher prediction accuracy.

General accuracy criteria for the posterior error ratio C: the model has high accuracy when C<0.35; qualified accuracy when $0.35 \le C < 0.5$; basically, qualified accuracy when $0.5 \le C < 0.65$; and unqualified accuracy when $C \ge 0.65$.

For the data in this study, the posterior error ratio is 0.03 (less than 0.35), indicating high model accuracy; the development coefficient is 0.026 and the grey action quantity is 1.98.

3. The fitting degree of the model to the original data is verified via the residual test method. A relative error less than 20% means the model fitting to the original data meets general requirements. The average relative error of the model is 6.242%, representing a good fitting effect.

4. Future variation values of the dependent variable are predicted according to the prediction step length.

3.1.2. Solution results of the grey prediction model

Forecast results show the predicted Earth vitality index values for the next five years are 0.232, 0.201, 0.171, 0.141 and 0.112, respectively. The results indicate a continuous downward trend of the Earth vitality index in the future. The Living Planet Index is an indicator for measuring global biodiversity, and a decline in the Living Planet Index implies a significant reduction in species diversity.

3.2. Application of grey prediction model for forecasting illegal wildlife trade cases in Guangdong Province, China

3.2.1. Data collection

Illegal wildlife trade cases are divided into four categories:

A: Illegal purchase, transportation and sale of rare and endangered wild animals and their products

B: Smuggling of precious animals and precious animal products

C: Illegal hunting and killing of rare and endangered wild animals

D: Illegal hunting cases

The original data values refer to the annual total number of cases across the four categories, as shown in the Table 4 below:

Table 4. Total number of cases from 2014 to 2018

Year	2014	2015	2016	2017	2018
Number	87	79	84	79	116

3.2.2. Construction of grey model and presentation of results

Model prediction results show a gradual increase in the number of illegal wildlife trade cases in the region over the next five years, with predicted values of 118, 131, 144, 158 and 173 respectively.

This result demonstrates a rising trend of case numbers in the region under current conditions. Existing literature confirms that illegal wildlife trade not only causes irreversible damage to global biodiversity, but also triggers the transmission of zoonotic viruses from a human health perspective. The SARS virus outbreak in 2003 was linked to the consumption of wild bats in this region. Meanwhile, the project aligns with the Sustainable Development Goals proposed by the United Nations. The above facts confirm the necessity of curbing illegal wildlife trade, and stakeholders can make contributions to global sustainable development by investing in this project.

3.3. Application of data analysis for optimal strategy selection and project formulation

$$\text{maximize} \quad F\left(x_1, x_2, \ldots, x_n\right) = \sum_j w_j \tag{2}$$

$$\text{s.t.}\begin{cases} f_j\left(x_1, x_2, \ldots, x_n\right) \\ C_k\left(x_1, x_2, \ldots, x_n\right) \le R_k, \forall k \\ x_i \ge 0, \forall i \end{cases} \tag{3}$$

A set of alternative policies is available for policy selection. x_i denotes the implementation intensity of the i -th strategy (e.g., capital investment, human resource allocation). The implementation effect of each individual strategy on goal achievement is assumed to be independent. $f_j(x_1, x_2, \ldots, x_n)$ represents the j -th objective function (four objective functions are involved in this study corresponding to four goals), reflecting the achievement degree of the j -th goal; F represents the overall achievement degree of the project.

$C_k(x_1, x_2, \ldots, x_n) \le R_k$ defines the constraint condition of the k -th resource, where R_k is the available quantity of the k -th resource. Equal weights are assigned to all objective functions in this model.

The core objective is to determine the implementation intensity of each strategy when F reaches the maximum value, followed by ranking all strategies in ascending order of their implementation intensity. The top-ranked strategies feature low investment input and rapid effect realization, and such strategies are prioritized for selection and implementation, thus forming the comprehensive strategy set for project execution.

The distribution of implementation intensity corresponding to each goal is shown in the Figure 2:

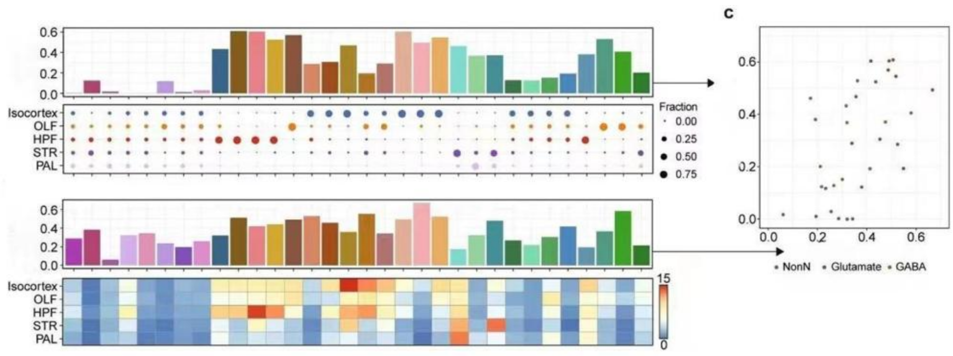

Figure 2. Implementation intensity bar chart

4. Prediction of measurable impacts after project implementation via linear regression method

Linear regression combined with historical data on illegal wildlife trade volumes enables the construction of a time series model, which is further applied to predict the future trend of illegal wildlife trade volumes.

The time series model is represented by the following autoregressive moving average (ARIMA) model:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ... \quad (4)$$

Definitions of relevant parameters are listed below:

Y_t : trade volume at time point t ;

$\phi_1, \phi_2, \ldots, \phi_p$: autoregressive parameters;

$\theta_1, \theta_2, \ldots, \theta_q$: moving average parameters;

ϵ_t : white noise term.

The implementation steps of the intervention analysis based on the time series model are as follows:

a. A univariate time series model is established using pre-intervention historical data, and extrapolation predictions are conducted with this model. The predicted values are regarded as the trade volume values without intervention effects. The concrete impact magnitude of the intervention is derived by subtracting the actual observed values from the predicted values, which provides a basis for estimating the parameters of the intervention model.

b. Parameters of the intervention model are estimated.

c. A univariate time series model is re-identified and estimated using the full dataset with the intervention impact excluded.

d. The integrated intervention analysis model is constructed.

The core variable of the intervention analysis model is the intervention variable, with two common types of intervention variables applied in practice: the first type is the continuous intervention variable. Continuous intervention refers to a scenario where the intervention generates a persistent impact after the time point T, which can be mathematically expressed by a step function. This type of intervention features a gradual onset of impact with long-term persistence. In some cases, an intervention may occur suddenly, and its impact is not fully realized immediately but is gradually manifested over time.

4.1. Variable determination and data presentation

Four independent variables are identified as follows:

B: Public awareness of wildlife protection

C: Intensity of crackdown on illegal wildlife trade

D: Efforts to crack down on illegal wildlife trade networks

E: Quality of wildlife reserves

The value range of all independent variables is specified as [-10,10]. The dependent variable (A) is defined as the number of illegal wildlife trade cases in Guangdong Province, China.

Field investigation results of the actual situation yield the following dataset, as shown in Table 5.

Table 5. Actual situation form

A	B	C	D	E
87	-5	1	0	-3
79	-5	3	3	-2
84	-4	2	0	-1
79	-5	3	2	0
116	-4	-1	-2	0
80	-5	3	3	1

4.2. Model construction and solution

A linear regression model is adopted: the column vector of the first column in the table is set as the dependent variable, and the matrix composed of the second to fifth columns is set as the independent variable matrix, forming the linear expression $Y = \beta x$, where β represents the regression coefficient to be estimated.

Calculations are conducted using the `regress` function in MATLAB, and the estimated regression coefficients for each independent variable are obtained as shown in the Table 6 below:

Table 6. Feature importance

Feature	B	C	D	E
Value	-0.192	-1.218	-1.59	-0.793

In the coefficient results, a negative sign indicates a negative correlation (negative influence) between the independent variable and the dependent variable, while a positive sign indicates a positive correlation (positive influence).

4.3. Result interpretation

All independent variables exhibit a negative correlation with the number of illegal wildlife trade cases (A).

After project implementation, improvements are expected in all indicators: public awareness of wildlife protection (B) will be enhanced, the intensity of crackdown on illegal wildlife trade (C) will be increased, efforts to combat illegal wildlife trade networks (D) will be strengthened, and the quality of wildlife reserves (E) will be improved. Based on the negative correlation between these indicators and the number of cases, it can be inferred that project implementation will reduce the occurrence of illegal wildlife trade cases.

5. Conclusions

This paper proposes an integrated analytical framework combining the Analytic Hierarchy Process (AHP) with a grey prediction model to support decision-making and trend assessment under multi-objective conditions. First, by constructing a multi-level evaluation structure and conducting consistency tests, quantitative comparisons among different entities under multidimensional indicators are achieved, enhancing the systematicity and reliability of the decision-making process. Second, the grey prediction model is introduced to forecast trends for key indicators, maintaining high accuracy even under small sample conditions. With a posterior error ratio of 0.03 and an average relative error of 6.242%, the model's stability and applicability are validated. Finally, by integrating linear regression analysis, the model quantitatively assessed post-implementation changes. Results revealed significant negative correlations between intervention factors and target indicators, providing data-driven support for strategy optimization. Overall, this model offers clear structure, computational feasibility, and strong generalizability, effectively supporting analysis and decision-making within complex systems. Future research may further expand its application across diverse scenarios and dynamic conditions.

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