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Empirical Study on Employment Trend Prediction for Engineering Management Undergraduates in Local Universities

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Abstract

This study develops a Hausdorff Fractional Grey Model (HFGM(1,1)) to address traditional models' limitations in predicting engineering management undergraduates' employment trends. Integrating Hausdorff fractional accumulation and particle swarm optimization, the model dynamically adapts to nonlinear dynamics under the "new information priority" principle. Empirical validation using Tianjin university data demonstrates superior accuracy (1.84% MAPE) over conventional models. It quantifies coupled impacts of construction cycles, curriculum design, and practical training, providing actionable insights for academic reforms and tiered career guidance. The framework aids policymakers in optimizing enrollment strategies and industry-academia collaboration. Future research should expand regional validation and hybrid modeling approaches for enhanced predictive precision in higher education management.

Keywords

Undergraduate employment in engineering management; Hausdorff fractional-order grey model; data-driven; employment trend prediction; local higher education institutions.

1. Introduction

As a critical nexus for transforming higher education outcomes, graduate employment not only impacts household well-being but also sustains national developmental momentum and social stability. Within the context of supply-side structural reforms and industrial upgrading, forecasting employment trends in Engineering Management—a discipline at the intersection of technology and administration—holds particular significance for optimizing academic program development and talent cultivation strategies at local universities[1]. Existing studies predominantly focus on macro-level employment rate predictions, overlooking the regional specificity of local university graduates, disciplinary heterogeneity, and the evolving dynamics of labor market information, thereby limiting their practical utility[2-3].

In methodological domains, early expert systems relied excessively on subjective experience, suffering from informational lag amid rapid technological shifts[4]. Econometric approaches, constrained by linear assumptions, prove inadequate in addressing "black swan" events. While machine learning models enhance prediction accuracy, their demand for continuous high-volume data and poor adaptability to geographically localized employment patterns inherent to regional institutions remain critical limitations[5]. The classical GM(1,1) model in grey system theory has emerged as an alternative for small-sample forecasting scenarios[6]. Its strength lies in requiring minimal historical data while accommodating inherent uncertainties through accumulated generating operations[7]. However, two fundamental constraints undermine its applicability in engineering management employment prediction: First, the fixed-weight mechanism fails to adaptively prioritize emerging critical factors—such as

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differential impacts from industrial digitization policies versus traditional infrastructure cycles[8]. Second, the model's inherent preference for monotonic trends conflicts with the punctuated equilibrium characteristics of regional labor markets, where disruptive technologies or regulatory changes frequently induce non-linear phase transitions in employment trajectories[9].

To address these challenges, which include model inflexibility, delayed response to dynamic information, and insufficient disciplinary relevance, this study introduces a data-driven Hausdorff fractional-order accumulated grey prediction model (HFGM(1,1)) with an adaptive dynamic weighting mechanism grounded in the "new information priority" principle[10]. By dynamically adjusting fractional orders through entropy-weighted optimization, the model achieves precise forecasting of employment trends for Engineering Management graduates at local universities, ultimately providing scientific evidence for curriculum optimization and talent cultivation strategies.

2. Model Formulation

Definition. Let $X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(m)\right\}$ be a non-negative original sequence, and $X^{(r)}$ be the r-order accumulated generating sequence of $X^{(0)}$. The operator

$$x^{(r)}(k) = \sum_{j=1}^{k} x^{(0)}(j)\left[j^r - (j-1)^r\right], (j = 1,2,\cdots, m) \tag{1}$$

is called the Hausdorff fractional-order accumulated generating operator[11]. Let H^r be the r-order fractional-order accumulation matrix satisfying the above equation for any $x^{(r)}(k)$, then $X^{(r)} = X^{(0)}H^r$, where

$$H = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 0 & 2^r - 1 & \cdots & 2^r - 1 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & (m-1)^r - (m-2)^r \\ 0 & 0 & \cdots & m^r - (m-1)^r \end{bmatrix}$$

is the generalized combination number.

In general, the original sequence $X^{(r)}$ can be restored by r-order accumulation subtraction, i.e., $X^{(0)} = X^{(r)}H^{-r}$, where $X^{(0)}$ is the r-order accumulation subtraction operator.

The Hausdorff fractional-order accumulated grey model, which introduces Hausdorff fractional-order accumulation into the traditional univariate first-order grey model (GM(1,1)), is abbreviated as HFGM(1,1). Given a non-negative sequence $X^{(0)} = \{x^{(0)}(1),\ x^{(0)}(2),\ \cdots, x^{(0)}(n)\}$, the modeling process of HFGM(1,1) is as follows:

Step 1: Obtain the r-order accumulated sequence $X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \cdots, x^{(r)}(n)\}, x^{(r)}(1) = x^{(0)}(1)$ through the Hausdorff fractional-order accumulation operator:

$$x^{(r)}(k) = \sum_{j=1}^{k} x^{(0)}(j)\left[j^r - (j-1)^r\right], (i = 1,2,\cdots,n)$$

Step 2: For the r-order accumulated sequence $X^{(r)}$, the HFGM(1,1) model is expressed as:

$$\frac{dx^{(r)}}{dt} + ax^{(r)} = b \tag{2}$$

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where a is the development coefficient and b is the grey action quantity.

The solution to Equation (2) is $x^{(r)}(t+1)=(x^{(0)}(1)-\frac{b}{a})e^{-at}+\frac{b}{a}$. Using least squares estimation to minimize the sum of squared residuals, the parameter vector $\hat{a}$、$\hat{b}$ is solved by:

$$\begin{bmatrix}\hat{a}\\ \hat{b}\end{bmatrix}=\left(B^T B\right)^{-1}B^T Y$$

where

$$B=\begin{bmatrix} -\frac{x_1^{(r)}(1)+x_1^{(r)}(2)}{2} & \frac{x_2^{(r)}(1)+x_2^{(r)}(2)}{2} & \cdots & \frac{x_n^{(r)}(1)+x_n^{(r)}(2)}{2} & 1 \\ -\frac{x_1^{(r)}(2)+x_1^{(r)}(3)}{2} & \frac{x_2^{(r)}(2)+x_2^{(r)}(3)}{2} & \cdots & \frac{x_n^{(r)}(2)+x_n^{(r)}(3)}{2} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -\frac{x_1^{(r)}(m-1)+x_1^{(r)}(m)}{2} & \frac{x_2^{(r)}(m-1)+x_2^{(r)}(m)}{2} & \cdots & \frac{x_n^{(r)}(m-1)+x_n^{(r)}(m)}{2} & 1 \end{bmatrix},$$

$$Y=\begin{bmatrix} x_1^{(r)}(2)-x_1^{(r)}(1) \\ x_1^{(r)}(3)-x_1^{(r)}(2) \\ \vdots \\ x_1^{(r)}(m)-x_1^{(r)}(m-1) \end{bmatrix}。$$

Step 3: Substitute $\hat{a}$、$\hat{b}$ into the time response function to obtain the fitted value at time $k+1$:

$$\hat{x}^{(r)}(k+1)=(x^{(0)}(1)-\frac{\hat{b}}{\hat{a}})e^{-\hat{a}k}+\frac{\hat{b}}{\hat{a}}$$

Step 4: For $X^{(r)}=\{\hat{x}^{(r)}(1),\hat{x}^{(r)}(2),\cdots,\hat{x}^{(r)}(n),\cdots\}$, the prediction sequence is:

$$\hat{X}^{(0)}=\{\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),\cdots,\hat{x}^{(0)}(n),\hat{x}^{(0)}(n+1),\cdots\}$$

and the restored prediction value of the original sequence is $\hat{x}^{(0)}(k)=\frac{\hat{x}^{(r)}(k)-\hat{x}^{(r)}(k-1)}{k^r-(k-1)^r}$.

Step 5: The Mean Absolute Percentage Error (MAPE) is used as the standard to evaluate model performance:

$$\text{MAPE}=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}^{(0)}(k)-x^{(0)}(k)}{x^{(0)}(k)}\right|\times 100\%$$

3. Employment Rate Prediction for College Graduates Based on HFGM(1,1)

3.1. Data Processing and Model Construction

3.1.1 Data Transformation and Initialization

For the filtered raw employment rate data, normalization or standardization methods are applied to map the data to a specific interval, eliminating the influence of varying dimensions and enhancing comparability and stability. Subsequently, the processed data undergoes initialization according to the requirements of the HFGM(1,1) model to construct the initial data sequence.

3.1.2 HFGM(1,1) Model Construction

Based on the initialized data sequence, the grey prediction model is established following the principles of HFGM(1,1). This involves determining relevant parameters within the model and constructing a mathematical structure that reflects the inherent patterns of the employment rate data, thereby forming the core tool for subsequent predictive analysis.

3.1.3 Dynamic Adjustment of Accumulation Operator Order

In the HFGM(1,1) model, the order of the accumulation operator plays a critical role in model fitting and prediction performance. The Particle Swarm Optimization (PSO) algorithm is employed to dynamically optimize the order. By comparing model predictions with historical data under different order values, the accumulation operator order is iteratively adjusted until the model achieves optimal fitting and predictive accuracy.

3.1.4 Result Validation and Output

The optimized HFGM(1,1) model is utilized to predict future employment rates for engineering management undergraduates at target universities. The reliability of predictions is rigorously validated through error analysis and statistical testing. This process provides robust data support for universities to formulate employment guidance policies and adjust disciplinary training programs.

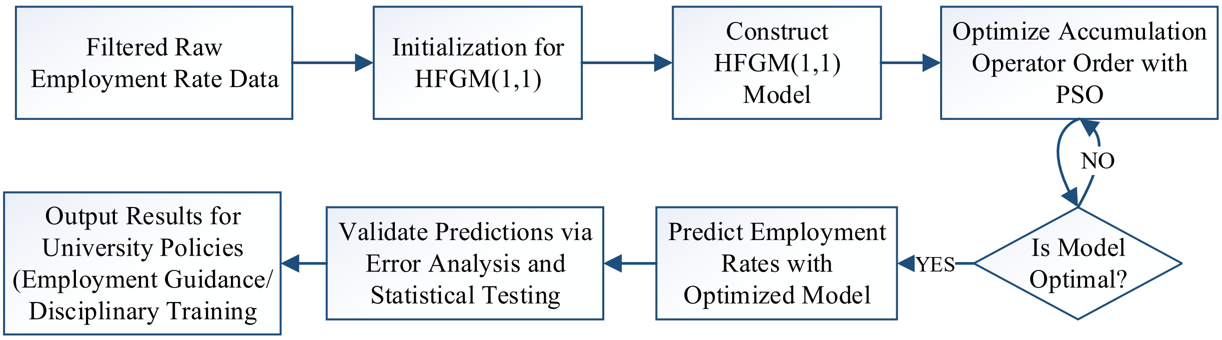

Figure 1. HFGM(1,1) prediction process for graduate employment rates

3.2. Predictive Analysis of the Employment Rates of College Students

3.2.1 Prediction Results

The original sequence of the employment rates of undergraduate graduates majoring in Engineering Management at a certain university in Tianjin is

$$x^{(0)} = \{0.9524, 0.8000, 0.7708, 0.8515, 0.8786, 0.9259, 0.9314\}$$

The predicted value of the FHGM(1, 1) model is expressed as

$$\hat{x}^{(0)}(k+1) = \frac{(1-e^{\hat{a}})(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}})e^{-\hat{a}k}}{(k+1)^r - k^r}, (k = 1, 2, \dots, n)$$

The simulated data $\hat{x}^{(0)}(k+1)$generated by the FHGM(1, 1) model does not always conform to an exponential model. Consequently, the convexity and monotonicity of the simulated values obtained from the FHGM(1, 1) model are indeterminate and data - driven.

A comparison between the model - fitting results and the actual values is presented in Figer 1. When r=0.86, the MAPE of the FHGM(1,1) model is 1.84%, which is less than 10%. This suggests that the model can effectively predict the employment rates of undergraduate graduates majoring in Engineering Management at the aforementioned university in Tianjin.

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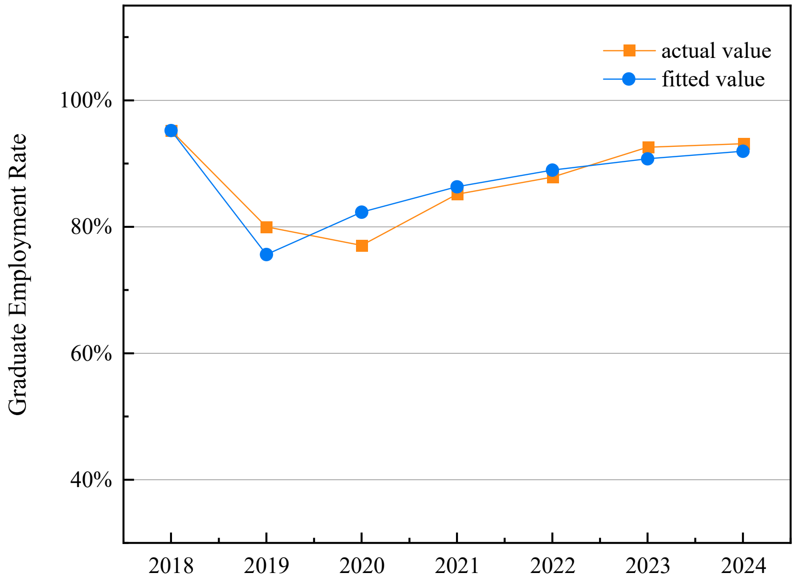

Figure 2. HFGM(1,1) true versus fitted values

To validate the superiority of the HFGM(1,1) model, comparative experiments were conducted by selecting GM(1,1), the grey Verhulst model, exponential smoothing, and linear regression methods. These models were applied to predict the employment rate of engineering management undergraduate graduates at the target university for the period 2025–2028. The predictive performance was evaluated using the MAPE, with detailed numerical results presented in Table 1.

Table 1. Predicted values and MAPE for different models

Year	HFGM(1,1)	GM(1,1)	Verhulst	Exponential Smoothing Model	Linear Regression Model
2025	93.48%	98.05%	88.17%	93.14%	91.53%
2026	94.74%	101.88%	87.66%	93.14%	92.59%
2027	95.82%	105.84%	87.20%	93.14%	93.65%
2028	96.76%	109.97%	86.79%	93.14%	94.71%
MAPE	1.84%	2.09%	8.23%	13.94%	40.16%

3.2.2 Applicability Analysis of Models

(1) HFGM(1,1) Model

The HFGM(1,1) model demonstrates exceptional predictive performance, achieving the lowest MAPE value among all models. This indicates its superior capability to accurately forecast employment rates for engineering management undergraduates. Its advantages likely stem from its ability to deeply explore inherent data patterns and systematically model complex influencing factors, such as curriculum adjustments, industry demand fluctuations, and student competency improvements. In practical applications, this model provides highly reliable references for institutional decision-making—for instance, enabling timely curriculum optimization and enhanced practical training to boost graduate employability.

(2) GM(1,1) Model

The GM(1,1) model ranks second in MAPE, showing relatively high accuracy. It performs well in capturing general trends in time-series data but falls short in resolving detailed variations

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and adapting to complex factors compared to HFGM(1,1). Suitable for preliminary trend analysis, it offers macro-level insights into employment patterns. However, its limitations necessitate supplementary models when formulating specific pedagogical reforms.

(3) Verhulst Model

With higher MAPE values, the Verhulst model exhibits larger prediction errors. Designed for saturated growth scenarios, it struggles to adapt to dynamic employment market uncertainties in engineering management. While potentially useful when employment rates approach stability, it cannot serve as a primary forecasting tool.

(4) Exponential Smoothing Model

The exponential smoothing model shows further increased MAPE and reduced accuracy. Relying on weighted historical averages, it responds sensitively to short-term fluctuations but fails to capture long-term trends or complex interactions. Given the volatile nature of employment ecosystems, this method is limited to short-term estimations.

(5) Linear Regression Model

The linear regression model yields the highest MAPE, reflecting significant prediction errors. Its assumption of linear relationships contradicts the multidimensional nonlinear interactions governing employment rates. Consequently, it provides unreliable support for educational policy decisions.

Comprehensive analysis of MAPE values and model applicability confirms the HFGM(1,1) model's outstanding performance in forecasting employment rates for engineering management undergraduates at a Tianjin-based university. Its low prediction errors deliver accurate, actionable insights for pedagogical reforms—enabling curriculum adjustments, teaching strategy optimization, and ultimately enhanced graduate employability. Future research and practice should prioritize HFGM(1,1) for employment forecasting while integrating complementary models to ensure scientifically robust decision-making.

4. Conclusion

The escalating transformation of higher education and increasingly competitive job market necessitate precise employment rate prediction as a cornerstone of evidence-based decision-making for universities and policymakers. This study addresses this imperative through the innovative HFGM(1,1) model, which leverages localized graduate data and a new information priority mechanism to significantly enhance forecasting accuracy in engineering management—a discipline shaped by construction industry cycles, curriculum design, and practical training quality.

For academic institutions, the model's predictive insights enable targeted curriculum reforms. Integrating BIM and smart construction courses aligns programs with industry digitization, while project simulations in contract management and risk assessment courses bridge theoretical-practical gaps. A stratified career guidance system—combining discipline-specific orientation for early undergraduates with job-search workshops and internships for seniors—further strengthens graduate employability.

Education authorities can utilize these predictions to dynamically adjust enrollment quotas and optimize resource allocation. Establishing industry-academia training bases with construction firms enhances practical skill development, while policy incentives for modernized teaching facilities foster interdisciplinary talent cultivation.

By harmonizing theoretical innovation with governance needs, the HFGM(1,1) framework facilitates proactive alignment between higher education outputs and labor market demands. Future research should validate the model's efficacy across regions and explore hybrid methodologies to advance predictive analytics in educational management.

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