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Express Delivery Quantity Prediction Based On The Grey GM(1,1) Model

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Abstract: To accurately forecast express delivery demand within a specific region and enhance the efficiency of its logistics management system, this study utilizes express delivery volume data from 2018 to 2024 to construct a grey GM(1,1) prediction model. The ratio-of-adjacency test and smoothness ratio test are first applied to verify that the original dataset meets the requirements for grey modeling. Subsequently, the model undergoes a validity test, accuracy test, posterior variance ratio test, and small error probability test, confirming that its fitting performance reaches the first-level accuracy standard. Based on the established model, the express delivery volume from 2025 to 2029 is predicted. The results indicate a sustained upward trend, with the volume estimated to reach 1.5358 million pieces in 2025 and further increase to 4.03 million pieces by 2029. These findings provide a scientific foundation for the rational allocation of regional logistics resources, the optimization of express delivery station layout, and the development of service strategies for express delivery enterprises.

Keywords: grey GM (1,1) model; express delivery volume forecasting; medium-to-long-term forecasting; model accuracy test

1. Introduction

Against the backdrop of the deep integration of the digital economy and e-commerce, the logistics industry, as a crucial link between production and consumption, has experienced rapid growth in demand. Regional express delivery volume, as a core indicator of logistics demand, plays a vital role in optimizing resource allocation and enhancing supply chain efficiency. Whether in urban communities, industrial parks, or specific functional areas, the continuous increase in express delivery volume not only provides opportunities for logistics service upgrading but also introduces challenges in station layout, workforce allocation, and inventory management. Without scientific forecasting, fluctuations in express delivery volume can easily lead to either resource waste or insufficient service capacity, thereby reducing the operational efficiency of regional logistics systems and affecting user experience. Consequently, identifying efficient and reliable methods to forecast express delivery volume has become a pressing issue in logistics management research.

The prediction of express delivery volumes has become a significant research focus in the logistics field. At the international level, early studies mainly relied on traditional statistical models, such as the ARIMA (Autoregressive Integrated Moving Average) model and its variants. These models capture linear patterns in time series data and perform well when the dataset is large and stable. For example, ARIMA models based on monthly urban express delivery data successfully reflected short-term periodic fluctuations. With the development of machine learning, algorithms such as Support Vector Machines (SVM), Random Forests, and Long Short-Term Memory (LSTM) networks have increasingly been applied. These methods excel at handling nonlinear,

Published: 02 December 2025

high-dimensional data, making them suitable for predicting express delivery volumes affected by multiple factors, including holidays, promotional campaigns, and economic conditions. Some studies combined e-commerce transaction data with meteorological information to construct multi-input LSTM prediction frameworks, reducing forecasting errors by 15-20% compared to traditional approaches. Ensemble learning has further enhanced prediction robustness in complex scenarios. However, these models are highly data-dependent, requiring extensive historical datasets and complex preprocessing, which limits their applicability in scenarios with limited or incomplete information.

Domestic research on logistics demand forecasting often emphasizes characteristics of local contexts, with grey system theory, particularly the GM(1,1) model, being widely used. The GM(1,1) model is known for its high prediction accuracy under conditions of "limited data and incomplete information" and has been applied in areas such as regional logistics, traffic flow, and energy demand forecasting. Studies have used GM(1,1) to predict provincial logistics demand trends over five years, with posterior tests confirming first-level accuracy. Other research focused on specific scenarios, including port and rural logistics, analyzing correlations between logistics demand and economic development to support infrastructure planning. Further improvements to the GM(1,1) model-such as residual correction, integration with Markov chains, or hybridization with neural networks-have reduced prediction errors. For instance, integrating residual sequences with SVM models lowered average relative errors from 3.2% to 1.8%. Nevertheless, existing studies have limitations: most focus on macro-regions or major logistics nodes, with relatively few examining small- to medium-scale functional areas, where factors such as population structure, consumption habits, and regional functions produce distinct demand patterns. Additionally, some research relies on a single accuracy metric, lacking multi-dimensional verification, which may affect prediction reliability.

The grey GM(1,1) model has been widely adopted due to its robustness under small-data conditions. For example, the model has been used to predict logistics demand at major coastal ports in Shandong Province, demonstrating steady growth over five years [1]. It has also been applied to Qingdao Port, showing reliable predictions and supporting the formulation of development strategies [2]. Similar applications include forecasting freight turnover in Inner Mongolia Autonomous Region, where residual and posterior tests confirmed that predicted values fluctuated within a controllable range [3]. The model has also been employed for Neijiang City, the Nanjing Metropolitan Area, Chengdu's logistics system, rural logistics in Anhui Province, and regional freight forecasting in Northeast China, with results confirming its practical effectiveness [4].

In light of this, the present study examines express delivery volume data from a large functional area from 2018 to 2024, constructing a GM(1,1) model for predictive research to provide a scientific basis for logistics management in such areas. The methodology incorporates several considerations to enhance rigor and practical relevance. First, data preprocessing includes dual applicability tests: the ratio-of-adjacency test to determine if data meet GM(1,1) modeling requirements, and the smoothness ratio test to assess sequence stationarity, mitigating accuracy loss from high fluctuations. Second, model validation employs a multi-dimensional system: residual and relative error analysis, validity verification (based on the development coefficient), posterior variance ratio assessment, and small error probability evaluation [5]. This comprehensive verification ensures the model not only predicts but predicts accurately. Third, scenario-specific characteristics are accounted for, as large functional areas exhibit high volumes with significant seasonal and event-driven fluctuations. Data collection focuses on capturing annual trends and variations, while iterative parameter estimation (for the development coefficient a and grey input b) aligns the model with observed patterns, avoiding mismatches caused by direct application of macro-regional models [6].

Based on these considerations, this study constructs a GM(1,1)-based prediction method tailored to express delivery volumes in large functional areas. This approach enriches logistics demand forecasting research, provides theoretical and practical guidance for resource allocation, station layout optimization, and service strategy formulation, and ultimately supports enhanced operational efficiency and service quality within regional express logistics systems [7].

2. Data Collection

Based on the data statistics of Cainiao Station of Chengdu Polytechnic College, the express delivery volume from 2018 to 2024 was recorded as the sample data of logistics demand as Table 1, the trend is shown in Figure 1, and a grey GM (1,1) model was constructed to predict the express delivery volume of Chengdu Polytechnic College from 2025 to 2029, aiming to provide theoretical support for the further development of the college's express logistics system [8].

Table 1. Express Delivery Volume from 2018 to 2024.

Year	Express delivery volume (ten thousand pieces)
2018	36.25
2019	45.25
2020	56.10
2021	68.48
2022	87.59
2023	105.09
2024	126.04

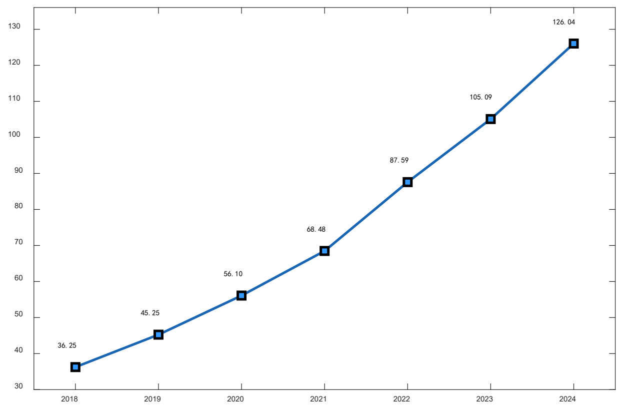

Figure 1. number of express deliveries from 2018 to 2024.

Specifically, the data collection work covered the express delivery receiving and dispatching records of the school's Cainiao Post Station over the past seven years. Through systematic organization and in-depth analysis of these data, the annual changing trend and seasonal fluctuation characteristics of the campus express delivery quantity can be clearly revealed, laying a solid data foundation for the subsequent construction of the grey GM (1,1) model.

3. Construct the Grey Prediction Model GM(1,1)

3.1. Generate the Original Data Time Series

Based on the number of express deliveries from 2018 to 2024 in Table 1, construct the original data of the quantity $X^{(0)}$:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}, \text{ Among them n=7} \quad (1)$$

namely $X^{(0)} = \{362475,452538,561025,684780,875916,1050895,1260402\}$

To ensure the feasibility of this modeling scheme, it is necessary to process the original sequence in terms of rank ratio and smooth ratio. The formula for calculating the order ratio of the original sequence $\lambda(k)$ is as follows:

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, k = 2,3,\dots,n \tag{2}$$

$$\lambda(k) \in \left\{exp\left[\frac{(-2)}{n+1}\right], exp\left[\frac{2}{n+1}\right]\right\} \tag{3}$$

Year n=7. Through calculation, $\lambda(k) \in \{0.779,1.284\}$ can be obtained. The calculation results are shown in Table 2. It is not difficult to see that the proportion of each level in the original sequence of campus express delivery quantity demand is within the required $\lambda(k)$ interval. The level ratio test is passed, indicating that the original sequence is suitable for the prediction of the gray GM(1,1) model.

Table 2. Original sequence level ratios from 2018 to 2024.

Year	Grade ratio
2018	/
2019	0.801
2020	0.807
2021	0.819
2022	0.782
2023	0.833
2024	0.834

Conduct a smoothness ratio $\rho(k)$ test: $\rho(k) = \frac{x(k)}{\sum_{i=1}^{k-1} x(i)}$, where, $x(k)$ is the total volume of express deliveries in the KTH year, and $\sum_{i=1}^{k-1} x(i)$ is the sum of the express deliveries in the k-1 year.

The calculation results are shown in Table 3, and the trend is shown in Figure 2. Except for the smooth ratios of 2018 and 2019 which are greater than 0.5, the other years are all less than or equal to 0.5, indicating that the conditions for constructing the grey GM(1,1) model of the original sequence are valid.

Table 3. Smooth Ratios of the original Series from 2018 to 2024.

Year	Grade ratio
2018	/
2019	1.25
2020	0.69
2021	0.50
2022	0.43
2023	0.36
2024	0.32

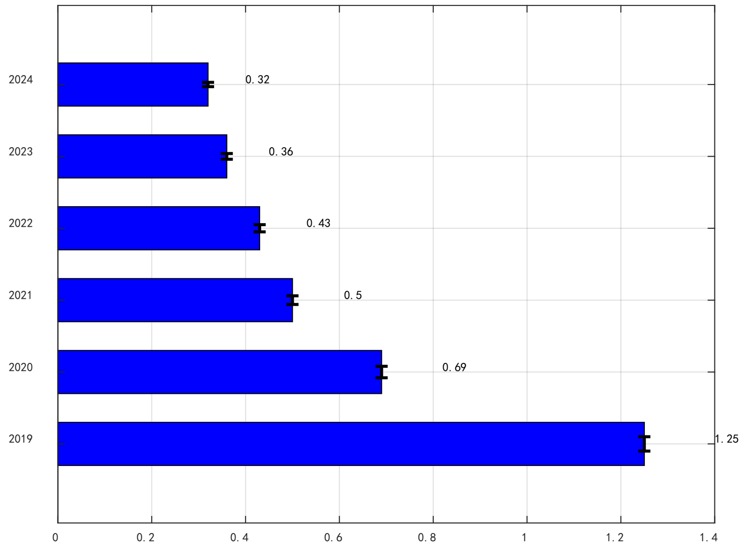

Figure 2. smoothness ratio of the original sequence from 2018 to 2024.

3.2. Generate A 1-AGO Sequence

Accumulate the original sequence $X^{(0)}$ once to generate a 1-AGO sequence $X^{(1)}$:

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(k-1), x^{(1)}(k)\} \tag{4}$$

Among them, $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, $k = 1,2,\ldots,n$

Get $X^{(1)} = \{362475,815013,1376038,2060818,2936734,3987629,5248031\}$

Establish the grey GM(1,1) model:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{5}$$

Here, a represents the development coefficient of the model, reflecting the changing trends of the accumulated generated sequence $X^{(1)}$ and the original sequence $X^{(0)}$. b represents the grey action of the model, indicating the variation relationship of the data.

For $X^{(1)}$, generate it right next to the mean, let:

$$z^{(1)}(k) = \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k-1)\right], k = 2,3,\ldots,n \tag{6}$$

Get:

$$Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n-1), z^{(1)}(n)\} \tag{7}$$

Namely $Z^{(1)} = \{588744,1095525.5,1718428,2498776,3462181.5,4617830\}$

Its whitening equation is $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$, where $\frac{dx^{(1)}}{dt}$ represents the function of the annual cumulative data of output with respect to the time (number of years) t. Let the parameters $\hat{A} = [a, b]^T$ (T represent the matrix transpose), the development coefficient a and the grey action b satisfy the matrix equation $Y = BA$, and the least squares estimation of the grey GM(1,1) model satisfies:

$$\hat{A} = (B^T B)^{-1} B^T Y \tag{8}$$

Among them, $Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix}$, $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \\ -z^{(1)}(n) & 1 \end{bmatrix}$

Substituting the data yields:

$$Y = \begin{bmatrix} 452538 \\ 561025 \\ 684780 \\ 875916 \\ 1050895 \\ 1260402 \end{bmatrix}, B = \begin{bmatrix} -588744 & 1 \\ -1095525.5 & 1 \\ -1718428 & 1 \\ -2498776 & 1 \\ -3462181.5 & 1 \\ -4617830 & 1 \end{bmatrix}$$

Obtained a ≈ -0.202, b ≈ 342916.

The time response sequence $\hat{x}^{(1)}(k+1)$ and predicted value model $\hat{x}^{(0)}(k+1)$ of the grey GM(1,1) model are determined as follows:

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] exp(-ak) + \frac{b}{a}, k = 1,2,\ldots,n-1 \tag{9}$$

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), k = 1,2,\ldots,n-1 \tag{10}$$

4. Model Checking

To ensure the reliability and applicability of the constructed grey GM (1,1) model in the prediction of express delivery quantity, systematic tests should be carried out from four dimensions: data adaptability, model validity, fitting accuracy and result stability. Through cross-validation of multiple indicators, the risk of model bias should be eliminated to provide support for the scientific nature of subsequent prediction results.

4.1. Validity Test

The development coefficient a is the core parameter of the grey GM (1,1) model. It not only reflects the growth trend of the original sequence but also determines the applicable prediction period of the model. By developing the value of coefficient a, the validity of the model and its applicable scenarios can be judged. The calculation formula was obtained by fitting the least square method. After calculation, the development coefficient a=-0.202 [9].

Referring to the corresponding standards of the development coefficient in the grey system theory and the applicable scenarios of the model (as shown in Table 4): when -A ≤0.3, the model is suitable for medium and long-term predictions; When 0.3<−a≤0.5, it is only applicable to short-term predictions. When -A >0.5, the model accuracy drops significantly [10]. In this study, −a=0.202<0.3, indicating that the model's ability to capture the growth trend of express delivery volume is stable without significant attenuation. It can be used for the prediction of express delivery volume in 2025-2029 and beyond, providing effective model support for subsequent medium and long-term logistics planning.

Table 4. Scope of Application of Grey GM(1,1) Models with Different development Coefficients.

Development coefficient (a)	Application scenarios of the grey GM(1,1) model
-a≤0.3	It can be used for medium and long-term predictions
0.3<-a≤0.5	It can be used for short-term prediction, but should be used with caution for medium and long-term prediction
0.5<-a≤0.8	Great caution should be exercised when it comes to short-term predictions
0.8<-a≤1	The residual correction grey model should be adopted
-a>1	It is not advisable to adopt the grey model

4.2. Precision Inspection

The fitting accuracy directly determines the reliability of the model. By calculating the residuals, relative errors and average relative errors, the degree of deviation between the simulated values of the model and the actual express delivery volume can be quantified.

Residual calculation formula:

$$\varepsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \tag{11}$$

Among them, $x^{(0)}(k)$ represents the actual express delivery volume and $\hat{x}^{(0)}(k)$ represents the simulated value of the model, reflecting the absolute deviation of a single simulation. Through calculation, it is known that the residuals from 2018 to 2024 are 0, -9191, -4398, -7620, 26,916, 10,895, and -9598 respectively. Except for 2022, which was slightly higher due to short-term consumption stimulus within the region, the absolute values of the residuals in the other years are all less than 10,000 pieces, and the overall deviation is controllable.

Relative error calculation formula

$$\Delta_k = \frac{|\varepsilon(k)|}{x^{(0)}(k)} \quad (12)$$

Through calculation, the relative errors for 2018 to 2024 are 0, 2.03%, -0.78%, -1.11%, 3.07%, 1.04%, and -0.76% respectively. The relative errors for all years are less than 4%, which is far lower than the standard of the first-level accuracy of the grey model (relative error ≤5%).

The formula for calculating the average relative error

$$\Delta = \frac{1}{n}\sum_{k=2}^{n} \Delta_k \quad (13)$$

The overall accuracy of the comprehensive assessment model in this study is 1.47%, which is far below the first-level accuracy requirement (≤1% is the super-level accuracy, and ≤5% is the first-level accuracy), indicating that the model has an excellent fitting effect on historical express delivery volumes and high reliability.

The calculation results of the actual values, simulated values, residuals and relative errors of the express delivery volume of Chengdu Polytechnic College of Industry from 2018 to 2024 are shown in Table 5, and Figure 3 provides a more intuitive comparison between the actual and simulated express delivery volumes. The analysis results show that the absolute value of the relative error for each year from 2018 to 2024 did not exceed 4%, and the average relative error was only 1.47%. This indicates that the grey prediction model has excellent prediction accuracy and better fitting effect.

Table 5. Accuracy Test of Express Volume Prediction Model of Chengdu Polytechnic College of Industry.

Year	Actual express delivery volume (ten thousand pieces)	Simulated express delivery volume (pieces)	Residual (piece)	Relative error (%)
2018	36.25	36.25	0	0
2019	45.26	46.17	-9191	2.03
2020	56.10	56.54	-4398	-0.78
2021	68.48	69.24	-7620	-1.11
2022	87.60	84.90	26916	3.07
2023	105.09	104.00	10895	1.04
2024	126.04	127.00	-9598	-0.76

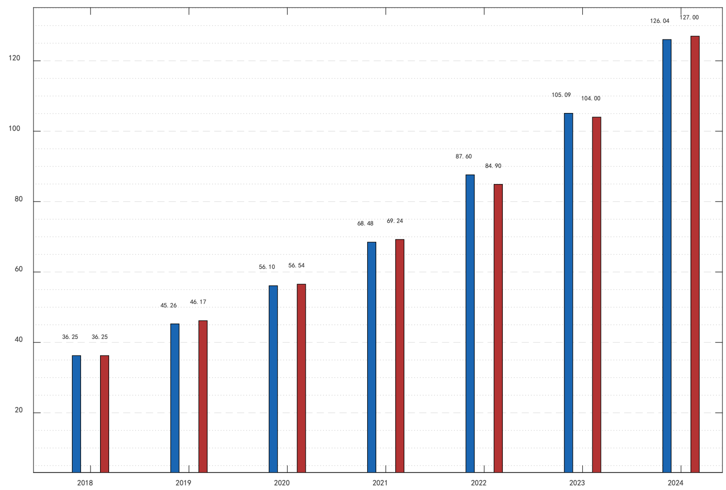

Figure 3. Accuracy test of express volume prediction model of Chengdu Polytechnic College of industry.

4.3. Posterior Difference Ratio And Small Error ProbabilityTest

The posterior difference ratio (C) and the probability of small error (P) are key indicators for testing the stability of the model's prediction results. By analyzing the degree of dispersion and distribution characteristics of the residual sequence, it can be determined whether the model has systematic bias.

The calculation formulas for the posterior difference ratio (C) and the small error probability (P) are as follows:

Posterior difference ratio (C) calculation formula:

$$C = \frac{S_2}{S_1} \tag{14}$$

Among them, $S_1^2 = \frac{1}{n}\left[x^{(0)}(k) - \overline{x}^{(0)}\right]^2$, $S_1^2 = \frac{1}{n}\sum_{k=1}^{n}[\varepsilon(k) - \overline{\varepsilon}]^2$, $\overline{x}^{(0)}$ is the mean of the original sequence. $\overline{\varepsilon}$ is the mean of the residual. The smaller C is, the smaller the degree of residual dispersion is and the stronger the stability of the model is.

After calculation, S1≈ 326,700 pieces, S2≈ 12,700 pieces, and C≈0.0388. Referring to the prediction accuracy grades of the grey GM(1,1) model (as shown in Table 6), C<0.35 is the first-level accuracy. In this model, C=0.0388 is much lower than this threshold, indicating that the residual distribution is concentrated and the model has no systematic bias.

The calculation formula for the small error probability (P):

$$P = P\{|\varepsilon(k) - \overline{\varepsilon}| < 0.6475 \times S_1\} \tag{15}$$

Table 6. Prediction Accuracy Grades of the Grey GM(1,1) Model.

Grade	Precision	C	P
Level 1	Great	≤0.35	≥0.95
Level 2	Qualified	0.35<C≤0.5	0.8≤P<0.95
Level 3	Reluctantly	0.5<C≤0.65	0.7≤P<0.8
Level 4	Unqualified	>0.65	<0.7

The probability of small error (P) reflects the probability that the residuals fall within the "small error" of piece retrieval. After calculation, it is approximately 328 pieces, and 0.6475S1 is approximately 219,400 pieces. All residuals satisfy $|\varepsilon(k) - \bar{\varepsilon}|$ <219, 400 pieces, so P = 1. According to the accuracy grade standard, P≥0.95 is classified as the first-level accuracy. In this model, P = 1, further confirming that the prediction results of the model are stable and reliable, with no risk of extreme deviation.

5. Forecast of Express Delivery Volume

5.1. Five Groups of Express Delivery Quantity Predictions

Based on the above model and formula, five sets of forecast data for 2025-2029, 2026-2030, 2027-2031, 2028-2032, and 2029-2033 were generated, covering annual express delivery volume, growth volume, and growth rate (the growth rate reflects the trend of data changes). Consistent with the historical data growth range of 21.9%-28.3%, as shown in Table 7 below:

Table 7. Forecast of Express Delivery Volume of Chengdu Polytechnic College from 2025 to 2029.

Predicted group	Predicted year	Express delivery volume (ten thousand pieces)	Annual growth rate (ten thousand pieces)	Annual growth rate (%)
Group One	2025	153.58	27.54	21.9
	2026	191.22	37.64	24.5
	2027	245.10	53.88	28.2
	2028	314.00	68.90	28.1
	2029	403.00	89.00	28.3

Group Two	2026	191.22	37.64	24.5
	2027	245.10	53.88	28.2
	2028	314.00	68.90	28.1
	2029	403.00	89.00	28.3
	2030	515.60	112.60	27.9
Group Three	2027	245.10	53.88	28.2
	2028	314.00	68.90	28.1
	2029	403.00	89.00	28.3
	2030	515.60	112.60	27.9
	2031	661.80	146.20	28.3
Group Four	2028	314.00	68.90	28.1
	2029	403.00	89.00	28.3
	2030	515.60	112.60	27.9
	2031	661.80	146.20	28.3
	2032	849.10	187.30	28.3
Group Five	2029	403.00	89.00	28.3
	2030	515.60	112.60	27.9
	2031	661.80	146.20	28.3
	2032	849.10	187.30	28.3
	2033	1089.40	240.30	28.3

5.2. Optimal Data Group Selection

5.2.1. Select Indicators And Weights

Five sets of data were evaluated from three core indicators: "timeliness", "trend stability", and "application adaptability". The weights and meanings of each indicator are as follows:

(1) Timeliness (weight 40%): Prioritize the prediction period that is closest to historical data (2024), as the data has a higher correlation with current actual demand and a lower risk of error.

(2) Trend stability (weight 35%): It is necessary to meet the requirement that the annual growth rate is within the historical growth range (21.9%-28.3%), and the growth volume is continuously increasing (in line with the objective law that the volume of campus express delivery increases with the consumption demands of teachers and students).

(3) Application adaptability (weight 25%): The data should match the common cycle of campus logistics planning (such as 3-5 years planning) and can be directly used for actual decisions such as the layout of express delivery stations and human resource allocation.

5.2.2. Scores of Each Group of Indicators And Comprehensive Assessment

Based on the above indicators, five groups of data were scored (out of 100 points), and the results are shown in Table 8 below:

Table 8. Scores of Indicators in Each Group and Comprehensive Evaluation.

Predicted group	**Timeliness (40 points)**	**Trend stability (35 points)**	**Application adaptability (25 points)**	**Comprehensive score**
Group One (2025 -2029)	40 (Closest to 2024, with the	35 (The growth rate is 21.9%-28.3%, exactly matching	25 (The five-year cycle is in line with the medium	100

	strongest timeliness)	the historical range, with the growth volume increasing continuously.)	and long-term planning requirements of campus logistics.)	
Group Two (2026-2030)	32 (Lagging behind the first group by one year, with weakened timeliness)	35 (The growth rate and growth volume trends are stable.)	25 (5-year planning cycle adaptation)	92
Group Three (2027-2031)	24 (Lagging by 2 years, with further decline in timeliness)	35 (Stable trend)	25 (Cycle adaptation)	84
Group Four (2028-2032)	16 (Lagging by 3 years, with poor timeliness)	35 (Stable trend)	25 (Cycle adaptation)	76
Group Five (2029-2033)	8 (Lagging by 4 years, with the poorest timeliness)	35 (Stable trend)	25 (Cycle adaptation)	68

5.2.3. The Optimal Data Set Has Been Determined

The first group (2025-2029) has a comprehensive score of 100 points. In terms of timeliness, it is the closest to historical data and can minimize the uncertainty of long-term predictions to the greatest extent. The trend stability is completely in line with the historical growth law, with no abnormal fluctuations. In terms of application adaptability, the five-year cycle is highly compatible with the actual planning requirements of campus logistics resource allocation and site optimization, and thus is determined as the optimal prediction data set.

6. Conclusion

This paper takes the number of express deliveries of Chengdu Polytechnic College from 2018 to 2024 as sample data and constructs a grey GM(1,1) model for predicting the demand of express deliveries on campus. The applicability of the data was verified through grade ratio test and smoothness ratio test. Further validity test, accuracy test, posterior difference ratio test and small error probability test confirmed that this model has a high fitting accuracy, and its development coefficient $-a<0.3$, which is suitable for medium and long-term prediction.

The prediction results of the campus express delivery volume from 2025 to 2029 using this model show that the express delivery volume will continue to grow in the next five years. It is expected to reach 1.5358 million pieces in 2025 and increase to 4.03 million pieces in 2029, with a significant average annual growth trend. This result provides a scientific basis for the relevant departments of the school to optimize the layout of express delivery stations, rationally allocate logistics resources, and for express delivery enterprises to formulate service improvement strategies. It helps to enhance the operational efficiency of the campus express delivery logistics system and better meet the growing express delivery service demands of teachers and students.

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