

Research on China's Power Generation Forecasting Based on a Dual-Perspective Grey Forecasting Model

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Abstract: Power generation is a critical indicator for measuring a nation's energy supply capacity, power supply-demand balance, and economic operational level. Accurate forecasting of power generation holds significant practical importance for power grid dispatching, energy infrastructure planning, and strategic management. Based on grey forecasting models, this study investigates China's power generation from the dual perspectives of total volume trend forecasting and fluctuation interval forecasting. First, the damping discrete GM(1,1) model is employed to conduct medium- and short-term trend forecasting for China's total annual power generation, aiming to enhance the model's utilization of new information and improve forecasting precision. Second, addressing the intra-year fluctuation characteristics of power generation, an interval grey number sequence is constructed using the annual maximum and minimum monthly power generation data. By integrating the geometric feature sequence transformation method with the damping discrete GM(1,1) model, an annual interval grey number forecasting model is established to characterize the future fluctuation range of power generation. The results indicate that China's power generation will maintain an overall growth trend in the future, with the annual power generation fluctuation intervals continuously expanding. This suggests that while the scale of power generation continues to rise, the intra-year fluctuation characteristics will further intensify. This research serves as a foundational framework for energy supply-demand analysis, grid reliability studies, and strategic foresight in the energy domain.

Keywords: Power Generation Forecasting; Grey Forecasting Model; Interval Grey

Number; Particle Swarm Optimization

1. Introduction

In recent years, with China's continuous economic and social development and the ongoing evolution of its energy consumption structure, power demand has generally exhibited a persistent upward trend. Consequently, ensuring the safe and stable operation of power systems and the development of next-generation power grids are facing novel challenges. Facing the developmental needs of energy structure optimization and the large-scale integration of renewable energy, improving the scientific, forward-looking, and precise nature of power supply-demand forecasting and system dispatch has become a vital foundation for ensuring operational reliability and promoting the high-quality evolution of the energy sector. In this context, scientifically forecasting the future evolutionary trends of China's power generation is not only an essential prerequisite for maintaining the balance of power supply and demand and mitigating supply risks, but also a crucial quantitative basis for strategic energy planning, optimizing the layout of the power industry, and facilitating sustainable development goals. Therefore, this research holds significant theoretical value and practical implications for the modern energy landscape. The variation in power generation is closely related to economic growth, industrial structure adjustments, and long-term energy development strategies. Accurate forecasting of power generation is a vital link in supporting the high-quality evolution of the power industry and macro-energy management. Currently, forecasting methods for power generation are relatively abundant, primarily including multiple linear regression [1], time series analysis [2], support vector machines [3], and neural networks [4]. Compared to traditional statistical models and certain intelligent

algorithms, the grey prediction model imposes lower requirements on sample size and does not rely on strict statistical assumptions regarding data distribution. It is particularly suitable for sequence forecasting under conditions of small samples and incomplete information, thus demonstrating strong applicability in short- and medium-term power generation forecasting. In existing relevant studies, grey prediction models have been widely applied to various types of power generation forecasting problems. For instance, Zhou et al. coupled the metabolic GM(1,1) model with a damping trend model to construct a grey-ARIMA combined model, applying it to short-term power generation forecasting [5]. Ye et al. proposed a hybrid decomposition-reconstruction framework to achieve effective forecasting of photovoltaic power generation by identifying different characteristic trend components in the raw data [6]. Zhang et al. established a probabilistic non-homogeneous grey prediction model and optimized the probability accumulation operator using the whale optimization algorithm to enhance the model's information extraction capability [7]. Addressing the seasonal characteristics of wind power generation, Lv et al. proposed a seasonal multivariate grey prediction model, achieving unbiased forecasting of short-term wind power [8]. The aforementioned research indicates that grey prediction methods possess a solid application foundation and substantial expansion potential in the field of power generation forecasting. Despite this, there remains room for further expansion in existing grey prediction research concerning power generation. First, previous studies typically employ traditional grey models to depict sequence variation patterns but insufficiently consider the dynamic evolution characteristics of power generation driven by the joint effects of the economic environment, environmental factors, and seasonal variations. In particular, the priority of new information is not adequately reflected, making it difficult to effectively weaken the interference of historical data on forecasting results, which in turn affects the model's capability to characterize future trends. Second, existing research predominantly utilizes single numerical values as forecasting results. While this approach can indicate the overall directional change in power generation, it struggles to further reveal the uncertainty range corresponding to intra-year power

generation fluctuations. Consequently, it fails to effectively depict the interval characteristics formed under the influence of seasonal variations, load fluctuations, and differences in unit operations. Such single-perspective forecasting results still exhibit certain limitations when serving power dispatch, system reliability assessment, and risk management. Based on these considerations, this paper focuses on the short- and medium-term forecasting of power generation and constructs a dual-perspective forecasting framework based on grey prediction models. Initially, targeting the total power generation sequence and considering that new information provides a stronger indication for future trend evolution, a damped discrete grey prediction model is introduced. By optimizing the information accumulation mechanism with a damping coefficient, the role of new information in the modeling process is enhanced, and the interference of old information is weakened, thereby realizing the trend prediction of total future power generation. Subsequently, to address the shortcoming that single-point forecasting struggles to reflect fluctuation intervals, this paper approaches the problem from the perspective of interval grey numbers. An interval grey number sequence is constructed using the maximum and minimum monthly values within the annual power generation. Combined with the geometric sequence transformation method and the damped discrete grey prediction model, an interval grey number power generation prediction model is established to depict the fluctuation range and boundary variation characteristics of future power generation. By integrating total trend forecasting with interval fluctuation forecasting, this paper strives to more comprehensively reflect future development dynamics, providing more targeted reference bases for energy management departments and relevant institutions in the power industry to conduct short- and medium-term resource planning, supply-demand dispatch, and strategic decision-making.

2. Methodology

Given that the core forecasting process of the interval grey number prediction model remains reliant on the foundational grey prediction model, this section first introduces the damping discrete GM(1,1) model to establish the basis

for subsequent model extensions. Subsequently, by integrating the geometric characteristic sequence transformation method for interval grey numbers with the DAGM(1,1) model, an interval grey number forecasting model is constructed. This framework is designed to characterize the interval fluctuation ranges of future power generation.

2.1 Damping Discrete GM(1,1) Model

Accumulated generating operation (AGO) is a critical preprocessing step in grey prediction modeling, serving to weaken the random fluctuations of the raw sequence and extract the underlying developmental laws of the data. The traditional GM(1,1) model typically employs a first-order AGO to process raw data; however, this approach offers relatively limited utilization of new information and fails to fully embody the "principle of new information priority." The Damping Discrete Grey Prediction Model (DADGM(1,1)) represents an improved iteration of the traditional GM(1,1) model. On one hand, by introducing a damping accumulation operator, the model assigns differential weights to information from different stages. This reinforces the role of recent information in model construction while mitigating the interference of outdated information on forecasting results. On the other hand, both the parameter estimation and the derivation of the time response function in the DADGM(1,1) model are conducted within a discrete framework. This effectively avoids the "jump error" caused by the inconsistency between the continuous whitening equation and discrete parameter estimation, thereby enhancing the model's fitting performance and forecasting accuracy.

Definition 1[9]. Given a damping parameter $\delta \in (0, 1]$ and the original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, the

$$X^{(\delta)} = (x^{(\delta)}(1), x^{(\delta)}(2), \dots, x^{(\delta)}(n)) \quad (1)$$

is referred to as the δ -AGO damping accumulated generating sequence,

where, $x^{(\delta)}(k) = \sum_{i=1}^k \frac{x^{(0)}(i)}{\delta^{i-1}}, k = 1, 2, \dots, n.$ and

$x^{(\delta)}(k)$ represents the k -th element of $X^{(\delta)}$, then,

$$x^{(\delta)}(k+1) = \beta_1 x^{(\delta)}(k) + \beta_2 \quad (2)$$

is defined as the DADGM(1,1) model.

Theorem 1[9]. The parameters $[\beta_1, \beta_2]$ can be estimated using the least squares method, which is expressed as:

$$[\beta_1, \beta_2]^T = (B^T B)^{-1} B^T Y \quad (3)$$

Where,

$$Y = \begin{bmatrix} x^{(\delta)}(2) \\ x^{(\delta)}(3) \\ \vdots \\ x^{(\delta)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} x^{(\delta)}(1) & 1 \\ x^{(\delta)}(2) & 1 \\ \vdots & \vdots \\ x^{(\delta)}(n-1) & 1 \end{bmatrix}$$

By setting the initial value as $x^{(\delta)}(t)|_{t=1} = x^{(\delta)}(1) = x^{(0)}(1)$, the time response function of the model is obtained as:

$$\hat{x}^{(\delta)}(k+1) = \beta_1^k x^{(0)}(1) + \frac{1-\beta_1^k}{1-\beta_1} \beta_2 \quad (4)$$

The inverse accumulated generating operation formula is given by:

$$\hat{x}^{(0)}(k+1) = \begin{cases} x^{(0)}(1), & k=0; \\ [(x^{(\delta)}(k+1) - x^{(\delta)}(k))\delta^k, & k=1, 2, \dots \end{cases} \quad (5)$$

2.2 Interval Grey Number Prediction Model

2.2.1 Geometric sequence transformation method

The sequence transformation of interval grey number is a fundamental step in building an interval grey number prediction model. Its primary purpose is to circumvent potential issues such as interval boundary crossing and information distortion that may arise during direct grey algebraic operations. To achieve effective forecasting of interval grey number, this paper employs the classic geometric characteristic method to transform the original interval sequences. The core concept of this method involves whitening the interval grey number into two-dimensional geometric characteristic sequences. Specifically, each interval grey number is treated as a geometric object on the grey number layer. By extracting area information and position features that reflect the overall characteristics of the interval, the original interval sequence is transformed into several point-value sequences suitable for subsequent modeling. Compared to the approach of modeling the upper and lower bounds of the interval separately, the geometric characteristic method can, to a certain extent, simultaneously characterize both the range and

distribution features of interval grey number, thereby avoiding the one-sidedness of information representation caused by relying solely on individual boundary information.

Definition 2[10]. A grey number characterized by both a lower bound a_k and an upper bound b_k is termed an interval grey number, denoted by $\otimes(t_k) \in [a_k, b_k]$, where $a_k \leq b_k$, when $a_k = b_k$, the interval grey number $\otimes(t_k)$ degenerates into a real number a_k .

Let $X(\otimes) = (\otimes(t_1), \otimes(t_2), \dots, \otimes(t_n))$ be an interval grey number sequence, where, $\otimes(t_k) \in (a_k, b_k), \Delta t_k = t_k - t_{k-1} = 1$.

Assuming $\otimes(t_k), k=1,2,\dots,n$ and $X(\otimes)$ are as described above, projecting the interval grey number sequence onto a two-dimensional Cartesian coordinate system and sequentially connecting the upper and lower bound points yields a geometric figure, which is termed the grey number band of the interval grey number sequence. Within the grey number band, the region between $\otimes(t_k)$ and $\otimes(t_{k+1})$ is defined as the grey number layer $S(i)$, and the midpoint of the median line in the grey number layer is marked as $M(i)$ [10]. The grey number band and grey number layers are illustrated in Figure 1.

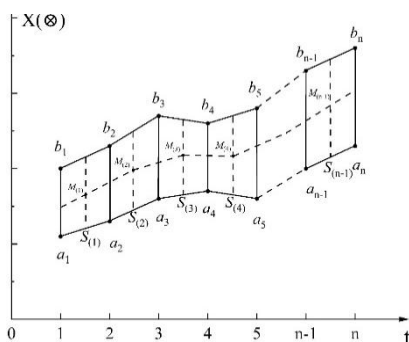


Figure 1. Grey Number Band and Grey Number Layer

Definition 3[10]. Let the interval grey number sequence be $X(\otimes) = (\otimes(t_1), \otimes(t_2), \dots, \otimes(t_n))$, where $\otimes(t_k) \in [a_k, b_k], k=1,2,\dots,n$ is as defined in Definition 1. The area sequence of the grey number layers is denoted as $L = (l(1), l(2), \dots, l(n))$, which is given by:

$$l(i) = \frac{(b_i - a_i) + (b_{i+1} - a_{i+1})}{2}, i = 1, 2, \dots, n-1. (6)$$

Definition 4[10]. Let the interval grey number sequence be $X(\otimes) = (\otimes(t_1), \otimes(t_2), \dots, \otimes(t_n))$,

where $\otimes(t_k) \in [a_k, b_k], k=1,2,\dots,n$ is as defined in Definition 1. The coordinate sequence of the midpoints of the median lines in the grey number layers is denoted as $M = (m(1), m(2), \dots, m(n))$, which is given by:

$$m(i) = \frac{(b_i + a_i) + (b_{i+1} + a_{i+1})}{4}, i = 1, 2, \dots, n-1. (7)$$

2.2.2 Construction of the interval grey number prediction model

Building upon the previously introduced DADGM(1,1) model and the geometric sequence transformation method, this section further integrates these components and applies them to the problem of interval grey number forecasting. Specifically, the original interval grey number sequence is first transformed into point-value sequences suitable for modeling using the geometric characteristic method. Subsequently, the DADGM(1,1) model is applied to perform the forecasting. Finally, an inverse transformation is conducted to restore the predicted point values into the final interval grey numbers.

Based on Eq. (6) the area sequence generation operation is performed on all grey number layers within the grey number band, denoted as $L = (l(1), l(2), \dots, l(n-1))$. According to Eq. (7), the midpoint length generation operation is performed on all grey number layers to obtain the sequence $M = (m(1), m(2), \dots, m(n-1))$. Following Definition 1, the DADGM(1,1) models are established for sequences L and M respectively. Consequently, the damping parameters δ_1, δ_2 and the estimated parameter vectors $\beta_l = [\beta_{l1}, \beta_{l2}]^T, \gamma_m = [\gamma_{m1}, \gamma_{m2}]^T$ are obtained. The time response functions for the area sequence and the midpoint sequence are respectively expressed as:

$$\hat{l}^{(\delta)}(k+1) = \beta_1^k l^{(0)}(1) + \frac{1 - \beta_1^k}{1 - \beta_1} \beta_2, (8)$$

$$\hat{m}^{(\delta)}(k+1) = \gamma_1^k m^{(0)}(1) + \frac{1 - \gamma_1^k}{1 - \gamma_1} \gamma_2, (9)$$

The restored values obtained through the inverse accumulated generating operation are respectively expressed as:

$$\hat{l}^{(0)}(k+1) = \begin{cases} l^{(0)}(1), k=0 \\ (\beta_1^{k-1}(\beta_1 l^{(0)}(1) - l^{(0)}(1) + \beta_2)) \delta_1^k, k=1,2,\dots \end{cases} \quad (10)$$

$$\hat{m}^{(0)}(k+1) = \begin{cases} m^{(0)}(1), k=0 \\ (\gamma_1^{k-1}(\gamma_1 m^{(0)}(1) - m^{(0)}(1) + \gamma_2)) \delta_2^k, k=1,2,\dots \end{cases} \quad (11)$$

Definition 5. Given that the restored values of the transformed sequences L and M exhibit distinct developmental patterns, a recursive method is employed to solve for the boundary restoration. The final boundary restoration formulas for the interval grey numbers are expressed as:

$$\begin{cases} \hat{a}_n = \frac{D_1 + D_2 - C_1 - C_2}{2} \\ \hat{b}_n = \frac{C_1 + C_2 + D_1 + D_2}{2} \end{cases} \quad (12)$$

Where,

$$\begin{cases} C_1 = \frac{2\delta^{n-2}\beta_1^{n-3}(\beta_1 l^{(0)}(1) - l^{(0)}(1) + \beta_2)[1 - (-\delta^{-1}\beta_1^{-1})^{(n-2)}]}{(1 + \delta^{-1}\beta_1^{-1})} \\ C_2 = (-1)^n(b_2 - a_2) \\ D_1 = \frac{4\delta^{n-2}\gamma_1^{n-3}(\gamma_1 m^{(0)}(1) - m^{(0)}(1) + \gamma_2)[1 - (-\delta^{-1}\gamma_1^{-1})^{(n-2)}]}{(1 + \delta^{-1}\gamma_1^{-1})} \\ D_2 = (-1)^n(b_2 + a_2) \end{cases} \quad (13)$$

Proof: By rearranging the terms in Eq. (6), we can obtain:

$$b_{i+1} - a_{i+1} = 2l(i) - (b_i - a_i)$$

When $i=1$,

$$\hat{b}_2 - \hat{a}_2 = 2\hat{l}^{(0)}(1) - (b_1 - a_1)$$

When $i=2$,

$$\hat{b}_3 - \hat{a}_3 = 2\hat{l}^{(0)}(2) - (b_2 - a_2)$$

⋮

When $i = n - 1$,

$$\hat{b}_n - \hat{a}_n = 2\hat{l}^{(0)}(n-1) - 2\hat{l}^{(0)}(n-2) + 2\hat{l}^{(0)}(n-3) - \dots + (-1)^{n-2}2(b_2 - a_2) \quad (14)$$

Combined with Eq. (10), it can be observed that the first $n - 2$ terms of Eq. (14) form a geometric progression with a common ratio of $q_1 = -\beta_1^{-1}$. According to the summation formula for geometric progressions, we can obtain:

$$\hat{b}_n - \hat{a}_n = \frac{2\delta_1^{n-2}\beta_1^{n-3}(\beta_1 l^{(0)}(1) - l^{(0)}(1) + \beta_2)[1 - (-\delta_1^{-1}\beta_1^{-1})^{(n-2)}]}{(1 + \delta_1^{-1}\beta_1^{-1})} + (-1)^n(b_2 - a_2) \quad (15)$$

Similarly, by rearranging the terms in Eq. (7), it follows that:

$$b_{i+1} + a_{i+1} = 4m(i) - (b_i + a_i)$$

When $i=1$,

$$\hat{b}_2 + \hat{a}_2 = 4\hat{m}^{(0)}(1) - (b_1 + a_1)$$

When $i=2$,

$$\hat{b}_3 + \hat{a}_3 = 4\hat{m}^{(0)}(2) - (b_2 + a_2)$$

⋮

When $i = n - 1$,

$$\hat{b}_n + \hat{a}_n = 4\hat{m}^{(0)}(n-1) - 4\hat{m}^{(0)}(n-2) + 4\hat{m}^{(0)}(n-3) - \dots + (-1)^{n-2}4(b_2 + a_2) \quad (16)$$

Combined with Eq. (11), it can be seen that the first $n - 2$ terms of Eq. (16) form a geometric progression with a common ratio of $q_2 = -\delta^{-1}\gamma_1^{-1}$. According to the summation formula for geometric progressions, it follows that:

$$\hat{b}_n + \hat{a}_n = \frac{4\delta^{n-2}\gamma_1^{n-3}(\gamma_1 m^{(0)}(1) - m^{(0)}(1) + \gamma_2)[1 - (-\delta^{-1}\gamma_1^{-1})^{(n-2)}]}{(1 + \delta^{-1}\gamma_1^{-1})} + (-1)^n(b_2 + a_2) \quad (17)$$

By setting

$$\begin{cases} C_1 = \frac{2\delta^{n-2}\beta_1^{n-3}(\beta_1 l^{(0)}(1) - l^{(0)}(1) + \beta_2)[1 - (-\delta^{-1}\beta_1^{-1})^{(n-2)}]}{(1 + \delta^{-1}\beta_1^{-1})} \\ C_2 = (-1)^n(b_2 - a_2) \\ D_1 = \frac{4\delta^{n-2}\gamma_1^{n-3}(\gamma_1 m^{(0)}(1) - m^{(0)}(1) + \gamma_2)[1 - (-\delta^{-1}\gamma_1^{-1})^{(n-2)}]}{(1 + \delta^{-1}\gamma_1^{-1})} \\ D_2 = (-1)^n(b_2 + a_2) \end{cases}$$

By solving Eq. (15) and Eq. (17) simultaneously, the final restored values for the upper and lower boundaries of the interval grey numbers can be obtained as:

$$\begin{cases} \hat{a}_n = \frac{D_1 + D_2 - C_1 - C_2}{2} \\ \hat{b}_n = \frac{C_1 + C_2 + D_1 + D_2}{2} \end{cases}$$

From the perspective of the boundary sequence restoration process described above, the geometric information transformation method—which incorporates dynamic weights—fully preserves the information contained within the interval grey number sequences. This indicates that the sequence transformation technique proposed in this study satisfies the requirements of both information equivalence and data integrity for interval grey numbers [10].

2.3 Parameter Optimization

Particle Swarm Optimization (PSO) is a swarm intelligence optimization algorithm inspired by

natural collective behaviors, such as bird flocking and fish schooling. The algorithm simulates a collaborative search process within the solution space, where the search direction is jointly guided by the individual best positions of the particles and the global best position of the entire swarm to iteratively solve complex optimization problems [11]. Compared to traditional optimization algorithms, PSO is characterized by fewer parameter settings, simple implementation, rapid convergence, and high parallelism, making it well-suited for high-dimensional and nonlinear parameter optimization problems [12]. Since the damping operator effectively capitalizes on new information priority and serves as a core parameter for the prediction of transformed sequences, this study employs PSO to determine the optimal values for the damping accumulated operator parameters. The fitness function and constraints for the PSO are defined as follows:

$$\min_{(\delta_i)} f(r) = \frac{1}{(n-1)} \sum_{k=2}^n \frac{|\hat{x}^{(0)}(k) - x^{(0)}(k)|}{x^{(0)}(k)} \times 100\% \quad (18)$$

$$s.t. \begin{cases} [\beta_1, \beta_2]^T = (B_a^T B_a)^{-1} B_a^T Y_a \\ \hat{x}^{(\delta)}(k+1) = \beta_1^k x^{(0)}(1) + \frac{1-\beta_1^k}{1-\beta_1} \beta_2 \\ \hat{x}^{(0)}(k+1) = (x^{(\delta)}(k+1) - x^{(\delta)}(k)) \delta^k \\ x^{(1)}(1) = x^{(0)}(1) \\ 0 < \delta_i \leq 1, \\ i = 1, 2. \quad k = 2, 3, \dots, n. \end{cases}$$

2.4 Error-Value metrics

The selection of model evaluation metrics is crucial for accurately assessing the performance of a forecasting model. Building upon the existing literature, this study selects two widely used statistical metrics to evaluate the proposed model. Their calculation formulas are as follows:

$$APE = \frac{|\hat{x}^{(0)}(k) - x^{(0)}(k)|}{x^{(0)}(k)} \times 100\%, k = 2, 3, \dots, n. \quad (19)$$

$$MAPE = \frac{1}{(n-1)} \sum_{k=2}^n \frac{|\hat{x}^{(0)}(k) - x^{(0)}(k)|}{x^{(0)}(k)} \times 100\% \quad (20)$$

Where, $\hat{x}^{(0)}(k)$ and $x^{(0)}(k)$ represent the fitted value and the actual value at time k respectively.

3. Case Study

As a key indicator for measuring power supply capacity and energy development levels, power generation is directly linked to industrial operations, residential life, and national energy security. It also serves as a vital basis for long-term energy planning, power supply-demand dispatching, and strategic management. Currently, the power sector is in a critical stage of synergistic advancement between energy structure transition and high-quality development. Against the background of the ongoing evolution of the energy development layout, the growth trends and fluctuation characteristics of power generation have become increasingly prominent in supporting power system operations and strategic decision-making. Therefore, it is essential to analyze and forecast the future trends of China's power generation based on empirical data.

To this end, this section selects official statistical data as research samples to conduct an empirical study on power generation from the dual perspectives of total volume forecasting and fluctuation interval forecasting. This analysis aims to verify the applicability and effectiveness of the proposed model constructed in the previous sections.

Table 1. Two Categories of Power Generation Data (10⁸ kwh)

Year	Annual power generation	Annual interval grey number power generation
2016	61331.6	[4444.5, 5617.2]
2017	66044.5	[4767.2, 6047.4]
2018	71661.3	[5107.8, 6404.9]
2019	75034.3	[5440.2, 6682.4]
2020	77790.6	[5525.1, 7238.3]
2021	85342.5	[6230.1, 7586.2]
2022	88487.1	[6085.7, 8248.0]
2023	94564.4	[6583.5, 8461.7]
2024	100868.8	[6900.8, 9074.2]
2025	105752.5	[7111.1, 9362.7]

The power generation data used in this study are sourced from the official website of the National Bureau of Statistics. According to the research objectives, two categories of power generation data were collected: one consists of annual power generation data, which is used for total trend forecasting; the other consists of monthly power generation data. Based on the latter, the maximum monthly power generation within a year is set as the upper boundary, and the minimum as the lower boundary. This allows for the construction of an interval grey

number sequence of annual power generation, which is utilized for the interval forecasting study. Specifically, the annual power generation data adopts the officially published annual statistics, while the annual interval grey number sequences are compiled from the monthly power generation data of each respective year. The results of the data collection are presented in Table 1.

3.1 Modeling Steps for Annual Power Generation Forecasting

In this section, the DADGM(1,1) model constructed in Section 2.1 is employed to conduct trend forecasting for China’s total annual power generation. Data from 2016 to 2024 are selected as the training set, while data from 2025 serve as the testing set. The specific modeling process is as follows:

- (1) The damping accumulated generating operation is applied to the original sequence, and the optimal damping accumulated operator is determined through optimization using the Particle Swarm Optimization (PSO) algorithm;
- (2) Under the optimal damping parameters, the least squares method is utilized to estimate the structural parameters of the model;
- (3) The fitted and forecasted values of the sequence are calculated according to the time response function of the model, and the simulated results of the original sequence are obtained through the inverse accumulated generating operation (IAGO);
- (4) The accuracy of the model is verified in conjunction with the evaluation metrics.

The structural parameters of the model and the optimal damping accumulated operator are listed in Table 2, and the fitting and forecasting results of the model on the training and testing sets are presented in Table 3.

Table 2. Calculated Values of Model Parameters

Parameter	δ_1	β_{11}	β_{12}
Value	0.80	1.32	62490.49

Table 4. Forecasting Results for 2026–2030 (10⁸ kwh)

Year	2026	2027	2028	2029	2030
Annual power generation	113161.9	120139.2	127546.8	135411.0	143760.2

3.2 Modeling Steps for Annual Interval Power Generation Forecasting

In this section, the interval grey number forecasting model constructed in Section 2.2 is employed to predict the fluctuation intervals of

As illustrated in Table 3, the DADGM(1,1) model demonstrates superior performance in both fitting and forecasting the sequence of China’s annual power generation. The Mean Absolute Percentage Error (MAPE) for the training set is 0.92%, and for the testing set is 0.79%. Both values remain at a low level, indicating that the model possesses high precision in both in-sample fitting and out-of-sample forecasting.

From the results of individual years, the calculated values of the model are highly consistent with the original data, effectively capturing the continuous growth trend of China’s annual power generation. This suggests that the model has a robust capability to identify the developmental direction of the sequence. Furthermore, it demonstrates that by incorporating the damping accumulated mechanism, the model can more effectively utilize new information, thereby enhancing its modeling performance for annual power generation data. Given the favorable predictive performance of the model on both the training and testing sets, this study further employs it to conduct extrapolated forecasting for China’s annual power generation from 2026 to 2030, with the results presented in Table 4.

Table 3. Modeling Results of China’s Annual Power Generation (10⁸ kwh)

Year	Actual data	Fitting and forecasting results	APE (%)
2016	61331.6	61331.6	
2017	66044.5	66044.7	3.15
2018	71661.3	70116.9	2.13
2019	75034.3	74440.2	0.75
2020	77790.6	79030.0	1.66
2021	85342.5	83902.8	1.60
2022	88487.1	89076.1	0.78
2023	94564.4	94568.4	0.14
2024	100868.8	100399.3	0.31
MAPE(%)		0.92	
2025	105752.5	106589.7	0.79
MAPE(%)		0.79	

China’s annual power generation. Data from 2016 to 2024 are selected as the training set, while data from 2025 serve as the testing set. The specific modeling process is as follows:

- (1) The original interval grey number sequence undergoes geometric feature transformation to

obtain the area transformation sequence and the midpoint transformation sequence;
 (2) For each of the two transformation sequences, the Particle Swarm Optimization (PSO) algorithm is utilized to determine the optimal damping accumulated operator, based on which the structural parameters are estimated using the DADGM(1,1) model;
 (3) The fitted and forecasted values for both transformation sequences are calculated according to the time response functions of the

models, and the simulated results of the interval grey number sequence are obtained through inverse transformation;
 (4) The accuracy of the model is verified in conjunction with the evaluation metrics.
 The structural parameters of the model and the optimal damping accumulated operators are listed in Table 5, and the modeling results for the training and testing sets are presented in Table 6.

Table 5. Calculated Values of Model Parameters

Parameter	δ_1	δ_2	β_{11}	β_{12}	γ_{21}	γ_{21}
Value	0.70	0.99	1.54	1232.99	1.05	5306.24

Table 6. Modeling Results of Annual Interval Power Generation (10⁸ kwh)

Year	Actual data	Fitting and forecasting results	APE(%)
2016	[4444.5, 5617.2]	[4444.5, 5617.2]	[0.00, 0.00]
2017	[4767.2, 6047.4]	[4955.0, 6073.5]	[0.00, 0.00]
2018	[5107.8, 6404.9]	[5100.0, 6487.5]	[0.15, 1.29]
2019	[5440.2, 6682.4]	[5287.1, 6790.9]	[2.81, 1.62]
2020	[5525.1, 7238.3]	[5646.2, 7275.0]	[2.19, 0.52]
2021	[6230.1, 7586.2]	[5860.8, 7627.2]	[5.93, 0.54]
2022	[6085.7, 8248]	[6248.6, 8163.0]	[2.68, 1.03]
2023	[6583.5, 8461.7]	[6493.2, 8568.1]	[1.37, 1.26]
2024	[6900.8, 9074.2]	[6912.5, 9161.3]	[0.17, 0.96]
MAPE(%)		[2.19, 1.03]	
2025	[7111.1, 9362.7]	[7190.0, 9627.3]	[1.11, 3.47]
MAPE(%)		[1.11, 3.47]	

As demonstrated in Table 6, the interval grey number forecasting model exhibits strong applicability in predicting the interval fluctuation of China’s annual power generation. The Mean Absolute Percentage Error (MAPE) values for the upper and lower boundaries of the intervals are 2.19% and 1.03%, respectively, indicating a robust capability to characterize the fluctuation intervals of annual power generation. Furthermore, combined with the fitting results for each year, it can be observed that the predicted intervals maintain high overall consistency with the original intervals, effectively reflecting the fluctuation range and its developmental trend.

This suggest that the interval grey number modeling approach, which is based on geometric feature sequence transformation, can simultaneously account for both the range features and location features of interval data. Meanwhile, the damping discrete GM(1,1) model enhances the utilization of new information within the transformation sequences. The combination of these two elements improves the overall forecasting performance of the model. Given its favorable modeling performance, this study further employs the model to forecast the annual power generation fluctuation intervals, with the results presented in Table 7.

Table 7. Forecasting Results for 2026–2030 (10⁸ kwh).

Year	2026	2027	2028	2029	2030
Annual Interval Value	[7643.6, 10285.1]	[7956.9, 10819.9]	[8447.9, 11550.8]	[8800.3, 12163.3]	[9332.0, 12976.8]

From the perspective of the total power generation forecast for 2026–2030, annual total power generation is expected to maintain a sustained growth trend. This indicates that against the background of the in-depth promotion of energy transition and the accelerated construction of next-generation power systems during the upcoming planning

cycle, the power demand driven by economic and social development will retain strong resilience. According to the calculations in Table 4, the annual total power generation will grow from 113,161.9*10⁸kWh in 2026 to 143,760.2*10⁸kWh in 2030, showing a steady upward trajectory overall. This suggests that the power supply scale needs to expand further in

the coming years to meet the incremental demand arising from economic growth, industrial upgrading, and the improvement of residential living standards. Meanwhile, the sustained growth in total volume implies that pressures regarding supply security, resource allocation, and low-carbon transition will further intensify.

Regarding the forecast results of the annual power generation fluctuation intervals, both the upper and lower boundaries from 2026 to 2030 show a year-on-year upward trend, with the interval width continuously expanding. Specifically, the lower boundary of the interval rises from $7,643.6 \times 10^8 \text{kWh}$ to $9,332.0 \times 10^8 \text{kWh}$, while the upper boundary increases from $10,285.1 \times 10^8 \text{kWh}$ to $12,976.8 \times 10^8 \text{kWh}$. This indicates that while power generation is growing overall, the intra-year fluctuation characteristics will also become more pronounced. The continuous elevation of the upper boundary signifies increasing power demand during peak months, which will further heighten the pressure on grid stability during high-load periods such as summer and winter, placing higher requirements on peak-shaving capacity and system regulation capabilities. The simultaneous growth of the lower boundary indicates a steady increase in the baseload, reflecting the expanding fundamental demand for electricity in socio-economic operations. Furthermore, the expansion of the interval width implies a widening peak-to-valley difference, suggesting that future power system operations will face stronger seasonal fluctuations and load imbalances. This poses greater challenges for renewable energy integration, energy storage configuration, and the system's flexible regulation capacity.

3.3 Management Implications

Based on the aforementioned forecasting results, it can be observed that the total annual power generation will maintain a sustained growth trend in future 5 years, accompanied by a continuous expansion of fluctuation intervals. This suggests that future power system management will face a dual challenge: ensuring supply capacity to meet total volume growth and managing the stability risks posed by enhanced intra-year fluctuations. Therefore, from the perspective of strategic resource planning, management entities should transition from a single focus on scale expansion to a

dual-track management approach that incorporates both trend growth and interval variations into their operational frameworks. This will significantly improve the scientific precision and robustness of supply-demand matching.

Furthermore, the forecasting results emphasize that the future power grid will require higher levels of system flexibility and optimized resource allocation. As the upper and lower boundaries of power generation lift simultaneously, the complexity of load regulation and peak-load management will increase. Consequently, in the process of energy infrastructure management, priority should be given to enhancing flexible regulation capacities and improving operational resilience. By integrating forecasted fluctuation characteristics with regional supply-demand dynamics, managers can further refine dispatching schemes and storage configurations. This provides a quantitative technical basis for maintaining the stable and efficient operation of the power system.

4. Conclusion

Focusing on the forecasting of power generation, this study constructs a dual-perspective analysis framework that combines total volume trend forecasting with fluctuation interval forecasting based on the grey forecasting model. First, at the total volume forecasting level, the DADGM(1,1) model is employed to model and predict total annual power generation. The results demonstrate that the model possesses superior fitting and forecasting performance, accurately capturing the sustained growth trend in this sector. Second, at the interval forecasting level, an annual interval grey number forecasting model is developed by integrating the geometric feature sequence transformation method with the DADGM(1,1) model. The forecasting results indicate that both the upper and lower boundaries of annual power generation intervals will show a year-on-year upward trend, with the interval width continuously expanding. This suggests that while power generation is growing overall, the intra-year fluctuation characteristics will also further intensify.

The research in this paper demonstrates that conducting power generation forecasting from the dual levels of total volume and intervals can more comprehensively reflect future

evolutionary trends. These conclusions provide a strategic reference for the assessment of power supply and demand, the optimization of resource allocation, and the operational arrangements of the power system in future. Furthermore, this study offers new empirical support for the application of grey forecasting models in the complex energy management landscape.

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