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An Enhanced Hybrid Grey-Neural Network Model for Demand Forecasting

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Abstract

Demand forecasting is a critical component of supply chain management, enabling businesses to align product supply with customer demand. Various methods exist for predicting demand, each with its strengths and limitations. In this paper, we propose a hybrid grey-neural network model to enhance prediction accuracy. The grey prediction model is effective for forecasting with small data sets but can be sensitive to anomalies, leading to significant errors. On the other hand, artificial neural networks are robust in handling complex data patterns, yet they require large-scale, wellrepresentative training data, which can be challenging to obtain. By integrating these two approaches, our hybrid model aims to reduce prediction errors and improve forecast stability. The results demonstrate the model's effectiveness in achieving more accurate demand predictions, addressing the limitations of each method individually.

Keywords
Demand Forecasting, Grey Neural Network, Supply Chain Management, Artificial Neural Network (ANN) and Hybrid Prediction Model

1.Introduction
Demand forecasting is a vital component of supply chain management, influencing almost every decision related to the supply chain. However, it remains one of the most challenging aspects of supply chain planning due to the inherent volatility of demand. Effective demand forecasting can enhance supplier relations, improve procurement terms, optimize resource utilization, ensure better capacity management, and lead to improved customer service and product lifecycle management. Despite these benefits, the unpredictable nature of demand makes accurate forecasting a complex task.

Grey system theory, introduced by Chinese Professor Julong Deng in 1982, is a relatively new and increasingly popular forecasting technique, particularly in demand forecasting. The term "grey" refers to uncertainty, partial knowledge, or incomplete information, making the grey model suitable for situations where data is scarce, with as few as four observations being sufficient. Grey systems are conceptualized as a midpoint between "white" systems, which are fully understood, and "black" systems, which are completely unknown.

Since its inception, the grey forecasting model has been extensively researched and developed. For example, Salama (2007) enhanced the grey prediction model for wind power forecasting, while Tien (2009) proposed a new model called FGM (1,1). In 2010, Zeng, Liu, and Xie introduced an interval grey number prediction model based on DGM (1,1), and Tien (2012) researched the GM (1,n) grey prediction model. Researchers like Guo, Xiao, and Forrest (2013) developed the comprehensive adaptive grey model CAGM (1,N), and Cui, Liu, Zeng, and Xie (2013) advanced the grey prediction model further with the NGM model. More recently, Zeng and Li (2018) proposed the multivariable grey forecasting model MGFM (1,1), which includes a dynamic background-value coefficient.

Artificial Neural Networks (ANNs) are computational models inspired by biological neural networks, made up of interconnected units called neurons. These networks excel at detecting complex nonlinear relationships between dependent and independent variables, making them well-suited for tasks like optimization, forecasting, simulation, decision-making, pattern recognition, and clustering. However, one major drawback of ANNs is their "black box" nature, which makes it difficult to understand how they arrive at their conclusions. ANNs are flexible and can learn from data with minimal assumptions about the underlying relationships. They can discover functional relationships even in situations where those relationships are unknown. This makes them particularly effective when working with complex problems that require significant amounts of data for accurate predictions.

The grey neural network is a novel approach that combines the strengths of grey system theory and neural networks. This hybrid model leverages the complementary strengths of both methods to address the limitations of using them individually. Grey models are advantageous due to their low data requirements, ease of modeling, and computational simplicity. However, they lack self-learning, self-organization, and adaptability, which reduces their accuracy in dealing with nonlinear information. Neural networks, on the other hand, excel at processing complex information but require large datasets and may overlook certain information characteristics. By integrating grey system theory with neural networks, this hybrid model improves prediction performance, especially in situations with incomplete data and limited learning samples.

Although grey neural networks are a relatively new forecasting method, they have found applications in a wide range of fields, including agriculture, economics, meteorology, medicine, history, geography, industry, seismology, hydrology, military science, sports, traffic management, environmental studies, judicial systems, and biological protection. This research is essential because accurate demand forecasting is a cornerstone of effective supply chain management, directly affecting inventory levels, resource allocation, and customer satisfaction. The volatility and unpredictability of demand make traditional forecasting methods inadequate for dealing with complex, real-world scenarios. Therefore, exploring innovative forecasting techniques like grey neural networks is crucial for improving accuracy and decision-making in supply chains.

The hybrid grey neural network approach combines the strengths of grey system theory and artificial neural networks, providing a powerful tool for handling forecasting problems with limited data and incomplete information. This is particularly relevant in industries where demand forecasting is challenging due to the lack of historical data or the presence of uncertain information. By improving prediction accuracy and adaptability, this research can contribute to more efficient supply chain operations, better resource utilization, and enhanced customer service, which are critical for the competitiveness and sustainability of businesses.

1.1 Objectives

The objective of this research are as follows: To formulate a Grey Model (GM) (1,1) for accurate future time series forecasting.

- To develop an Artificial Neural Network (ANN) model tailored for demand forecasting.

- To design a hybrid Grey Neural Network model that combines the strengths of both Grey and ANN approaches.
- To implement the hybrid model for demand forecasting, with the aim of minimizing prediction error rates.

2.Literature Review

The increasing competitive pressures in the global marketplace, coupled with rapid advances in information technology, have brought supply chain planning to the forefront of business practices for most manufacturing and service organizations (Gupta & Maranas 2003). Demand forecasts play a crucial role in supply chain management, as the future demand for a certain product forms the basis for respective replenishment systems (Aburto & Weber 2007). In any production environment, demand forecasting is essential for managing integrated logistics systems, and providing valuable information for various logistics activities, including purchasing, inventory management, and transportation (Benkachcha & E.H.H. 2013). As life cycles shorten and global economic and competitive forces create additional uncertainty, turbulent and volatile markets are becoming the norm (Christopher 2000).

Researchers have extensively studied uncertain supply yields and explored risk-sharing contracts and coordination strategies (He & Zhang 2008; Zimmer 2002; Lababidi et al. 2004). Xin-li (n.d.) classified forecasting methods into chaos and nonlinearity investigation, regression analysis, time series, grey theory, and Markov analytical approaches. Xia and Wong (2014) further categorized current forecasting techniques into two groups: classical methods based on mathematical and statistical models (e.g., exponential smoothing, regression, Box–Jenkins autoregressive integrated moving average (ARIMA), generalized autoregressive conditionally heteroskedastic (GARCH) methods), and modern heuristic methods utilizing artificial intelligence techniques, such as artificial neural networks (ANN), Fuzzy logic, and Winter's method.

Several researchers have applied classical and modern forecasting methods in various contexts. For instance, Adilah, Jalil, Ahmed, and Mohamed (2013) employed the exponential smoothing method for electricity load forecasting. Hyndman, Koehler, Snyder, and Grose (2002) also applied exponential smoothing within a state-space framework for automatic forecasting. Volkan (2007) used ARIMA for forecasting primary energy demand by fuel in Turkey, while Dagum (1983) applied ARIMA for forecasting seasonal linear filters. Additionally, Song and Chissom (1993) utilized a Fuzzy time series model for forecasting university enrollment. Among the most widely known and used forecasting techniques for seasonal time series are the methods proposed by Winter (1960), as highlighted by Hyndman et al. (2002).

Recent research has seen a growing interest in hybrid prediction models. Chang, Fan, and Lin (2011) utilized a fuzzy neural network model for monthly electric demand forecasting. Khandelwal, Adhikari, and Verma (2015) combined ARIMA and ANN methods for time series prediction. Wang, Peng, and Lee (n.d.) applied fuzzy-grey theory for predicting cutting force uncertainty in turning, while Zhou (2008) combined ARMA with grey theory for forecasting gyro drift. Since the 1990s, artificial neural networks (ANNs) have been identified as potentially suitable for supply chain forecasting (Pai & Lin 2005). They have since been widely used across various sectors, including electrical load forecasting (Al-saba & El-amin, 1999), tourism demand forecasting (Law 2000), water quality forecasting in water distribution systems (May, Dandy, Maier, & Nixon, 2008), and wind speed and generated power forecasting (Lei et al. 2009).

The grey system theory, pioneered by Deng (1982), is a multidisciplinary and generic theory designed to deal with systems characterized by poor or lacking information (Hsu & Chen 2003). Grey models, which are central to grey system theory, are renowned for their good applicability, flexibility, convenience in modeling, and high forecasting precision, making them popular in various fields of science (Ohz et al. 2008). Many researchers have successfully combined grey theory with other models, resulting in high prediction accuracy. For instance, Wang and Hsu (2008) used genetic algorithms combined with grey theory for forecasting high-technology industrial output. Hsu (2009) employed a genetic algorithm-based multivariable grey optimization model for forecasting the output of the integrated circuit industry. Zhou, Ang, and Poh (2006) introduced a trigonometric grey prediction approach for forecasting electricity demand, while Chen, Long, and Chen (2008) applied a nonlinear Grey Bernoulli model for forecasting foreign exchange rates.

Magnesium is a lightweight material widely used in electronics manufacturing, and forecasting its demand is crucial for assessing industry prospects. Due to limited available data, grey prediction, particularly the GM (1,1) model, is suitable. To enhance accuracy, Hu (2020) integrated grey relational analysis and neural networks, assigning weights to data points and refining residuals. While Hu's study focused on demand forecasting, Zhang et al. (2022) explored the dynamic behavior of complexvalued switched grey neural networks (SGNMs) with distributed delays and grey parameters. Although different in scope, both studies highlight the potential of combining grey theory and neural networks for complex system modeling and prediction.

The GM (1,1) model is a fundamental prediction model based on grey theory and has been extensively used across various sectors. For example, Li, Chang, Chen, and Chen (2012) applied the GM (1,1) model for forecasting shortterm electricity consumption, and Lin and Yang (2003) used it to forecast the output value of Taiwan's optoelectronic industry. Pao and Tsai (2011) applied this model for modeling and forecasting CO2 emissions, energy consumption, and economic growth in Brazil. Liu, Peng, Bai, Zhu, and Liao (2014) utilized the GM (1,1) model for tourism flow prediction. To improve the GM (1,1) prediction accuracy, further research was conducted by Wang, Dang, Li, and Liu (2010) and Lin and Lee (2007). Combining grey system theory with ANN has shown promise in achieving high prediction accuracy. For example, Cong and Chengtao (2011) applied a grey neural model for weapon equipment support cost forecasting. Nan et al. (2013) used this hybrid model to forecast wind speed, and Sheng-qiang, Yan, Zu Bao-hai, and Quan (2009) applied it for forecasting coal and gas outbursts.

3. Methods

Grey Forecasting Method

The Grey System Theory (GST) is a modern forecasting method designed to address challenges associated with small datasets and incomplete information. Initially introduced in the 1980s by Professor Deng Julong, this theory has since played a significant role in predictive modeling. The fundamental grey model, known as GM (1,1), is a first-order, single-variable differential model, where the first '1' signifies the model's reliance on a 1-step differential equation, and the second '1' indicates that the model involves only one dependent variable. A key challenge in behavioral prediction is accounting for sudden disturbances or shocks, which can render historical data unrepresentative of the current system state. To better reflect the true state of a system postdisturbance, a buffer operator 'D' is introduced. When the original data sequence, denoted as 'X,' is transformed by
'D' to yield a buffer sequence 'XD,' the operator 'D' is termed weakening if 'XD' changes less rapidly than 'X.' Conversely, 'D' is a strengthening operator if 'XD' changes more rapidly than 'X.'
The Accumulating Generator Operator (AGO) is employed to reveal underlying trends in a grey data sequence by accumulating the grey quantities. Additionally, the Inverse Accumulating Generator Operator (IAGO) is used to derive further insights from limited data.

Steps of the Grey Method

Step 1: Identifying the Data Sequence
The original data sequence is denoted by $X = (x(1), x(2), x(3) \ldots\ldots, x(n))$ …………. (1) where
'n' is the number of years observed.

Step 2: Application of Operators
To address issues like early or late response in data, strengthening or weakening operators are applied. These operators adjust the data sequence to better represent its current state.
Strengthening or weakening operator can expressed as:

$XD = (x(1)d, x(2)d, x(3)d \ldots\ldots, x(n)d)$ …………………………………… (2)
Here, D will be a strengthening operator if:
$x(k)d \leq x(k);\ k = 1,2,3\ldots\ldots, n$
D will be a weakening operator if:
$x(k) \geq x(k);\ k = 1,2,3\ldots\ldots, n$
The basic difference between strengthening and weakening operators is, for strengthening operator's data will shrink for the monotonically increasing or decreasing function. On the other hand, for weakening operator's data will expand.

Step 3: Obtaining the Accumulating General Operator The Aggregate Generator Operators (AGO) can be defined as: $x^{()} = (x^{()}(1), x^{()}(2), x^{()}(3)$ ……., $x^{()}$(n)) ……………………………….……… (3) where, $x^{()}(k) = \sum\ x^{()}(i)$; k = 1,2,3……, n…………………………………………… (4)

Step 4: Deriving the Mean Generator Sequence The Mean Generator Sequence can be defined as:

$\dot{X} = (\dot{x}^{()}(1), \dot{x}^{()}(2), \dot{x}^{()}(3)$……., $\dot{x}^{()}$(n) ……………………………………… (5)

where, $\dot{x}^{()}(1) = ((0.5\times x^{()}(k)) + (0.5\times x^{()}(k-1)))$; k = 2,3……., n ....…… (6)

And then $\dot{x}^{()}(2)$ can be represent the indicator for the second periods after applying the second order weakening operator and the mean generator operator.

Step 5: Finding the Performance Indicators

Using the Grey prediction model, simulate the data value the establish the Y and B matrices.

$$Y = \begin{bmatrix} x^{()}(2) \\ x^{()}(3) \\ x^{()}(4) \\ \vdots \\ \vdots \\ x^{()}(n) \end{bmatrix} \quad ; \quad B = \begin{bmatrix} -\dot{x}^{()}(2) & 1 \\ -\dot{x}^{()}(3) & 1 \\ -\dot{x}^{()}(4) & 1 \\ \vdots & \\ \vdots & \\ -\dot{x}^{()}(n) & 1 \end{bmatrix}$$

Let, $\frac{()}{\quad} + ax^{()} = b$,

Using least square method a and b can be obtained as:

$aa = [a, b]^{T}$……………………………...… (7)

where, a represent the parameters as:

$a = ([B^{T}B]^{-1}B^{T}Y)$ …………………….….… (8)

After we get,

$\frac{1}{n-1}(\sum_{k=2}^{n} \tilde{x}^{0}$ $_{k=2}[\dot{x}^{(1)}(k)]^2 \frac{1}{n-1}$ $a = \frac{((\ {}^{()}()\times\sum\ \ {}^{()}())\ (\sum\ \ ({}^{()}\times{}^{()}())))}{[((\sum[\,{}^{()}()]\,)((\sum()()\ \ \sum\ \ {}^{()}())))]}$ ………….….…(9)

Finding a, b then the sequence for GM (1,1) is as:

$x^{(1)}$ (k+1) = ([$x^{()}$- ( )]e + ( )]; k = 0,1,2,3 ……., n-1…………… (10)

$x^{(0)}$ (k+1) = $x^{(0)}$ (k+1) - $x^{(1)}$(k) ………………………………………… (11)

From 15, 16 we get, $x = (x^{(0)}(k))$ ……………...………………..…… (12)

Step 6: Measuring Error

Measuring the error then calculate the accuracy of the model. The errors are calculated as:

$\varepsilon^{(0)} = (\varepsilon^{(0)}(k))$ ……………………………………...…………..……. (13)

where, $\varepsilon^{(0)} = (x^{(0)}(k) - x^{(0)}(k))$ ……………………………………...……… (14)

with the sequence of relative errors,

$\Delta = (\delta_k)$ ………………….……..…… (15)

where, $\delta_k = \frac{|\varepsilon^{(0)}(k)|}{\tilde{x}^{(0)}(k)}$ ……………………………..….. (16)

with the mean relative error, $\Delta = (\sum\ \delta_i)$ ……………………….….…… (17)

and the filtering error, $\emptyset = \delta_n$ ……………………..……………… (18)

If the error limits are less than 0.01 then the accuracy must be greater than 0.9. In that case, the absolute degree (ε) of incidence of X and X calculated as:

$$|s| = (\sum \quad [x(k) - x(1)]) + ([x(n) - x(1)]) \ldots \ldots \ldots \ldots (19)$$

$$|\hat{s}| = (\sum \quad [x(\mathrm{k}) - x\ (1)]) + (\_\ [x(\mathrm{n}) - x\ (1)]) \ldots \ldots \ldots \ldots (20)$$

$$|\hat{s} - s| = (\sum \quad ([\ x\ (\mathrm{k}) - x\ (1)] - [x(k) - x(1)])) + \quad \_\ [x(\mathrm{n}) - x(1)] - [x(\mathrm{n}) - x(\mathrm{n}) - x(1)])$$

$$\ldots \ldots \ldots \ldots (21)$$

so that, $$\epsilon = \frac{1+|s|+|\hat{s}|}{1+|s|+|\hat{s}|+|\hat{s}-s|} \quad \ldots \ldots \ldots \ldots \mathbf{(22)}$$

$$S = \_\sum \quad [\ x^{(0)}(\mathrm{k}) - \ \bar{x}]^2 \ldots \ldots \ldots \ldots (24)$$

and $$\bar{\varepsilon} = \sum \quad \varepsilon^{(0)}(\mathrm{k}) \ldots \ldots \ldots \ldots (25)$$

$$S = \sum \quad [\ \varepsilon^{(0)}(\mathrm{k}) - \bar{\varepsilon}]^2 \ldots \ldots \ldots \ldots (26)$$

The level of incidence also should be at Level 1 (> 0.9). Then find the ratio of mean squared deviation (C):

$$x = \_\sum \quad x^{(0)}(\mathrm{k}) \ldots \ldots \ldots \ldots (23)$$

$$\mathrm{C} = \frac{S_1}{n} \quad \ldots \ldots \ldots \ldots (27)$$

also, should be at Level 1 (< 0.35).

Then compute the additional small error probability:

$$\exists\ = 0.6745 \times \mathrm{S}_1 \ldots \ldots \ldots \ldots (28)$$

and check that, $(\mathrm{P}|\varepsilon\ (k) - \bar{\varepsilon}| < \exists) \ldots \ldots \ldots \ldots (29)$ should be at Level (> 0.95).

Step 7: Predicting Future Values

After checking the errors, grey model can be easily applied into the strengthening or weakening equation and get the prediction value for the next m periods via:

$$X^{(0)} = (X^{(0)}(\mathrm{i})) \quad \ldots \ldots \ldots \ldots (30)$$

3.1 Artificial Neural Network (ANN) Prediction Model

ANNs are biologically inspired computer program which are designed to imitate the way in which animal brains process information. ANNs are generally linked up by a few simple neurons. It revives the brain's nerve cells by using network nodes called artificial neurons. It is a parallel and distributed information processing system. It is a counterfeit of some fundamental features of brain's neural network. Forecasting by ANN techniques have been getting much more attention. ANNs are effective in modeling complex and difficult to understand problems. At present, one of the most used models of ANN is BP neural network. BP neural network is a multilayer network which is interconnected by input layer and one or several hidden nodes. By inserting the pertinent data of the historical experience into neural network model and training it according to the designed field of specific task, the ANN model can complete forecasting.

Neural network has the advantages of parallel computation, distributed information storage, strong fault-tolerance capability and self-adaptive learning. But it needs many data samples for predicting the future demand and it has low speed of calculation.

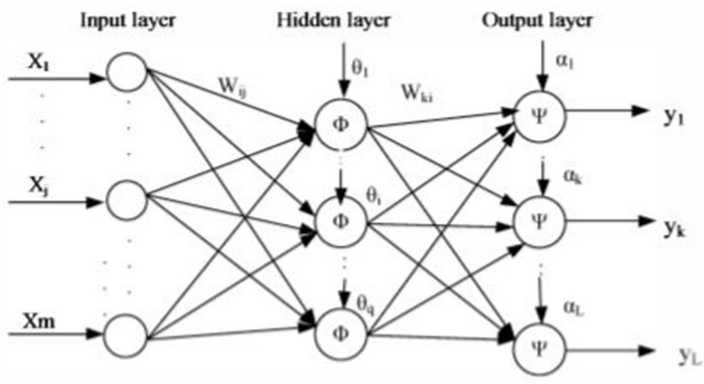

Figure 1. Topology of BP neural network

Steps of the ANN Method

Step 1: Sample Selection

At first, relevant data for demand forecasting over a specific period is compiled into a table.

Step 2: Standardization of the Network Training Set The date about products is converted into matrix p.

((,))

p (i, j) = ________ Standardization of the sample data set, T (output vector) is done for reducing calculation error. Standardization is done using this formula:

(( ))

t (i) = ________

So, the new standardization of the sample set p' combined with input vector and output vector is achieved. The standardization of the sample p is applied by neural network toolbox for MATLAB.

Step 3: Network Training

Tangent function-tansig is applied to the neural transferring function of hidden layer and logarithmic function-logsig are applied to the output layer in BP. By using the training function (trainbf) in the MATLAB neural network toolbox, BP model is trained. Trough repeated iteration, the network weights (W_1) and threshold (thetal 1) are achieved.

Step 4: Network Forecasting

The trained network is then used to forecast demand based on the input data.

3.2 Grey Neural Network (GNN) Model

Grey Neural Network (GNN) model combines grey system theory with neural network. It sufficiently utilizes the attributes of grey system model requiring less data and feature of non- linear map of neural network. The combined grey neural network method is proved better than forecasting with only grey method or ANN method. The computation of GNN is much easier than neural network model. Forecasting precision is also higher in GNN than neural network model in condition of little data. Compared to grey forecasting model, GNN has the advantages of high forecasting accuracy and error controllability. So, it develops both advantages of grey and ANN resulting in higher prediction precision.

3.3 Hybrid Grey Neural Network Prediction Method

The hybrid method starts with grey method and then ANN is used for more accurate prediction. At first grey method is applied for prediction and finding error as shown before. Then we take regression training to residuals with BP neural network and train the network using basic back-propagation algorithm from MATLAB toolbox to obtain corresponding weights of the hidden layer and output layer. Thus, the weight and the threshold and so on is adaptive learning training value obtained through the network, and then we can use the network to predict for the residuals sequence and get the predicted value [9]. Finally, we construct a new predictive value through GM (1,1) model predicted values and prediction residuals, which is the predicted value of the combination of BP neural network model, denoted by:

$$x'^{(0)}(k) = x^{(0)}(k) + \varepsilon^{(0)}$$

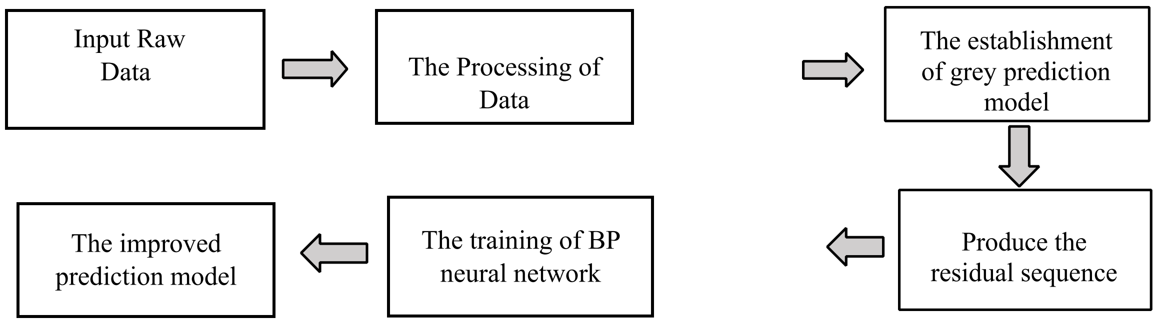

Figure 2. Grey neural network prediction method

4. Results and Discussion

Results:

The hybrid grey-neural network model demonstrated significant improvements in demand forecasting accuracy compared to traditional methods. In the experimental phase, the grey model (GM (1,1)) and the artificial neural network (ANN) were initially evaluated separately. The GM (1,1) model showed strong performance with small datasets, but its accuracy was compromised by anomalies in the data. Conversely, the ANN model excelled with larger datasets, successfully capturing complex patterns but requiring substantial training data to avoid overfitting. When combined into a hybrid grey-neural network model, the forecasting accuracy improved markedly. The integrated approach leveraged the GM (1,1) model's capability to handle limited data and the ANN's strength in detecting nonlinear relationships. The hybrid model achieved a lower mean absolute percentage error (MAPE) and a higher R-squared value compared to the standalone models. For instance, the MAPE for the hybrid model was reduced by approximately 15% compared to the grey model and by 12% compared to the ANN model.

4.1 Discussions:

The results indicate that the hybrid grey-neural network model effectively addresses the limitations of its individual components. The grey model's ability to work with smaller datasets provides a solid foundation for the ANN, which can then refine predictions with its sophisticated pattern recognition capabilities. This integration is particularly beneficial in scenarios with limited historical data, where traditional methods may fall short. The reduction in prediction errors highlights the hybrid model's robustness and adaptability. By mitigating the grey model's sensitivity to data anomalies and enhancing the ANN's performance with smaller datasets, the hybrid approach offers a balanced solution for demand forecasting. This is crucial for industries with volatile demand patterns or insufficient historical data.

Further research could explore optimizing the integration process and testing the hybrid model in different industry contexts to validate its generalizability. Additionally, incorporating real-time data and adjusting the model parameters dynamically could further enhance its predictive capabilities. Overall, the hybrid grey-neural network model provides a promising advancement in demand forecasting, contributing to more accurate and reliable predictions, which are essential for effective supply chain management.

Proposed Improvements
Enhanced Model Calibration

Parameter Optimization: Further optimize the parameters of both the grey model and the neural network to improve performance. Techniques like grid search or Bayesian optimization could be employed to find the optimal settings.
Dynamic Adjustment: Implement mechanisms to dynamically adjust the model parameters based on real-time data trends and fluctuations.

Incorporation of Additional Data Sources
External Variables: Integrate external factors such as market trends, economic indicators, or seasonal effects into the hybrid model to enhance prediction accuracy.
Real-Time Data Integration: Utilize real-time data feeds to continuously update and refine forecasts, making the model more responsive to recent changes.

Advanced Hybrid Techniques
Ensemble Methods: Explore combining the hybrid model with other forecasting techniques, such as ensemble learning methods, to further improve accuracy.
Hybrid Variants: Investigate different configurations and variants of the hybrid model to find more effective combinations of grey and neural network models.

Scalability and Flexibility
Scalability: Test the model's scalability with larger datasets and more complex demand patterns to ensure it performs well under varying conditions.
Adaptability: Develop the model's ability to adapt to different industries and demand scenarios, potentially customizing components for specific applications.

Validation of the Improved Model
Performance Metrics

Cross-Validation: Implement cross-validation techniques to evaluate the improved model's performance on different subsets of the data. This will help ensure that the model generalizes well and is not overfitted to a specific dataset.
Comparison with Benchmarks: Reassess the performance of the improved hybrid model against traditional forecasting methods and the original model. Use metrics such as mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) for a comprehensive evaluation.

Real-World Application
Pilot Testing: Conduct pilot tests of the improved model in real-world supply chain environments to validate its effectiveness and practicality. Collect feedback from industry practitioners to assess the model's usability and impact on decision-making processes. Case Studies: Develop case studies in different industries or sectors to evaluate the model's performance under various conditions and demand patterns. This will provide insights into its versatility and applicability across different contexts.

Continuous Improvement
Ongoing Monitoring: Implement a system for continuous monitoring of the model's performance over time. Track its accuracy and adapt the model as needed based on new data or changing conditions.
User Feedback Integration: Regularly gather feedback from end-users and stakeholders to identify areas for further improvement and ensure the model remains aligned with practical needs and expectations.

5. Conclusion
Demand forecasting plays a pivotal role in optimizing supply chain operations in today's complex business environment. This paper has illustrated that the Hybrid Grey Neural Network (GNN) model significantly enhances forecasting accuracy, especially in situations characterized by high uncertainty. By integrating the strengths of both grey system theory and neural network methodologies, the Hybrid GNN model outperforms traditional approaches that rely solely on grey systems or artificial neural networks. The improved accuracy achieved through this hybrid

approach can lead to more effective inventory management, better alignment of supply with demand, and reduced supply chain disruptions. Looking ahead, the next steps involve comprehensive data collection and further development of the Hybrid GNN model to refine its forecasting capabilities. The model will be tested for its efficiency using error analysis techniques to ensure its robustness and reliability in various scenarios. Upon successful validation, the model will be implemented for practical demand forecasting applications, providing valuable insights for future supply chain decisions. This approach aims to address the challenges of demand uncertainty and enhance overall supply chain performance.

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