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The negative impact of the COVID-19 on renewable energy growth in developing countries: Underestimated

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\textbf{A B S T R A C T}

According to the United Nations Environment Programme, the COVID-19 pandemic has created challenges for the economy and the energy sector, as well as uncertainty for the renewable energy industry. However, the impact on renewable energy during the pandemic has not been consistently determined. Instead of relying on data from year-to-year comparisons, this study redesigned the analytical framework for assessing the impact of a pandemic on renewable energy. First, this research designed an “initial prediction-parameter training-error correction-assignment combination” forecasting approach to simulate renewable energy consumption in a “no pandemic” scenario. Second, this study calculates the difference between the “pandemic” and “no pandemic” scenarios for renewable energy consumption. This difference represents the change in renewable energy due to the COVID-19 pandemic. Various techniques such as nonlinear grey, artificial neural network and IOWGA operator were incorporated. The MAPEs were controlled to within 5% in 80% of the country samples. The conclusions indicated that renewable energy in China and India declined by 8.57 mtoe and 3.19 mtoe during the COVID-19 period. In contrast, the rise in renewable energy in the US is overestimated by 8.01 mtoe. Overall, previous statistics based on year-to-year comparisons have led to optimistic estimates of renewable energy development during the pandemic. This study sheds light on the need for proactive policy measures in the future to counter the global low tide of renewable energy amid COVID-19.

1. Introduction

The COVID-19 pandemic has changed the global renewable energy market. However, to what extent the epidemic has impacted renewable energy consumption is not well determined. Part of the argument is that the COVID-19 pandemic’s blockade restrictions resulted in a 6% drop in energy demand, which increased the share of renewables in the generation mix (Klemeš et al., 2020). Additional evidence suggests that the pandemic-induced economic crisis impacted renewable energy manufacturing facilities, supply chains, and companies, slowing the global transition to sustainable energy (Wang et al., 2022c). From a macro perspective, the worldwide COVID-19 pandemic has increased uncertainty in the development of renewable energy.

There is an emerging consensus that a renewable energy-based energy transition is the only way to achieve the 2050 temperature control target (Tian et al., 2021). To ensure that this process proceeds smoothly, quantifying the specific impacts on renewable energy at this stage is a prerequisite for the formulation of future development policies. Most of the existing measures of impact are based on inter-annual comparisons. According to the International Energy Agency (IEA) (International Energy Agency, 2021), global renewable energy generation, including hydropower, wind power and photovoltaic power, increases by nearly 7% in 2020 compared to 2019. Renewable Energy Statistics 2021 annual report of International Renewable Energy Agency (IRENA) shows (International Renewable Energy Agency, 2021) that global installed renewable energy capacity reaches 260 GW in 2020, nearly 50% higher than the previous record. However, the measurement based on year-to-year comparisons only reflects historical fluctuations in 2020 compared to 2019 (Wang et al., 2022a). Specific changes in renewable energy consumption due to the pandemic cannot be determined.

To fill this gap, this study proposes a “scenario simulation” approach...
to characterize the renewable energy situation under “pandemic-free” and “pandemic” scenarios. In a comparative manner, the difference in renewable energy consumption between the “business-as-usual” scenario and the “real-world” scenario is considered as the real impact of the COVID-19 pandemic on renewable energy. This scenario-based measure is more scientific and rational than the traditional measure based on inter-year comparisons. Further, this research has innovated the methodology of the scenario simulation. This study employs the “initial prediction-error correction-operator weighting” prediction concept and integrates various tools such as metabolic nonlinear grey, artificial neural network, and IOWGA operator to simulate renewable energy consumption in a pandemic-free counterfactual in 2020. This study creates two categories of countries, the TOP 5 developing countries and the TOP 5 developed countries in terms of renewable energy consumption, with the aim of exploring whether COVID-19 has a heterogeneous impact on renewable energy across income groups. Data for the period 1990–2019 are used for modeling and extrapolation. Overall, this study aims to quantify the specific impact of COVID-19 pandemic on global renewable energy and provide pathway suggestions for renewable fuels under the pandemic. The results of the study contribute to the reduction of uncertainty in the impact of COVID-19 on the energy transition process.

The line structure of this study is as follows. The second section conceives the existing literature on renewable energy consumption and the forecasting methods. Section 3 displays the methods and data used in the scenario simulation. Section 4 shows the calculation process of the results and analyzes the findings. Section 5 summarizes the full text.

2. Literature review

2.1. Research on renewable energy consumption during the pandemic

In recent years, governments have introduced policies to support the development of solar, wind and other renewable energy. In 2019, installed capacity of renewable energy increased by 200,000 MW, breaking historical records. During the global pandemic in 2020, renewable energy is the only segment in the power generation sector to achieve growth during the global epidemic in 2020. However, the regional development of renewable energy sources shows large differences. European cities lead the way in renewable energy investment (Adedoyin et al., 2020), but renewable energy development is relatively diverse across countries (Papie et al., 2018). North American cities are among the world leaders in the use of renewable energy (Brodny et al., 2021). The development of renewable energy in Asian countries is mainly driven by the central government, and its development relies mainly on policy support and regulation (Muhammed and Tekbiyik-Ersoy, 2020). It is crucial to analyze the heterogeneity of renewable energy within countries of different income groups.

The COVID-19 pandemic outbreak causes a global health and economic crisis (Mofijur et al., 2021), which also hit the energy sector (Jiang et al., 2021). As a key to the future energy transition, the challenges facing in renewable energy during this period have received a great deal of academic attention (Gillingham et al., 2020; Schill, 2020). The uncertainty surrounding renewable energy during the COVID-19 pandemic, as reviewed by ACS Energy Letters (Jin, 2020), is enormous (Liu et al., 2021). With this awareness, many scholars have advocated for the energy research community to collaborate on the energy transition challenge with the most incredible sense of urgency.

One view was that renewables were negatively impacted during the pandemic (Tsao et al., 2021). And the reasons for this situation include several aspects. First, the economic recession caused by COVID-19 brought about financial barriers to investment in renewable energy projects, as renewable energy was heavily dependent on financial inputs at this stage. Studies had argued that tighter fiscal management during the pandemic led to fewer auctions for new renewable energy projects (Hoang et al., 2021). Second, the social shutdown caused by the pandemic affected the delivery of renewable energy equipment. The latest study found that (Eroglu, 2021) the outbreak had created serious problems for the renewable energy sector, such as delays in the supply chain, difficulties in the tax stock market, and the risk of not benefiting from government incentives. A large number of renewable energy projects were impacted by equipment delays. For example, up to 4 GW of renewable energy projects could be affected (Pradhan et al., 2020). Focusing on the technology sector, reduced investment in renewable energy technologies and employee layoffs have affected the continued progress and outlook for renewable energy (Siddique et al., 2021). Thirdly, the social impact caused by restrictive measures (e.g. travel, socialization) changed the demand for renewable energy at source. This view was also supported by various social data and Keras LSTM models (Bhuiyan et al., 2021).

Another view stated that the pandemic increased the share of renewable energy use through indirect means (Deswal et al., 2021). First, the change in renewable energy consumption during COVID-19 was related to the amount of substances in the air. As a result of the restrictions, COVID-19 reduced airborne pollutants, allowing more sunlight to reach photovoltaic panels and thus increasing the amount of renewable energy generated (Naderipour et al., 2020). By investigating the link between hydropower, the energy sector, and carbon emissions during the COVID-19 pandemic, scholars (Omo Olabiwonnu et al., 2021) demonstrated that the impact of COVID-19 on renewable energy was associated with a reduction in carbon emissions during the pandemic. Second, in addition to improving production conditions due to air pollution, changes in energy use patterns affected renewable energy consumption. The argument had been that the energy use patterns during COVID-19 (Tsai, 2021) and the lower energy demand caused by the embargo (Hoang et al., 2021) had inadvertently increased the share of renewables in the generation mix. Furthermore, the volatility of oil prices due to the pandemic also had a positive effect on the significant improvement of the position of renewable energy plants in the infrastructure (Hammoudeh et al., 2021).

In general, the pandemic created both opportunities and challenges for renewable energy development. Although there were short-term fluctuations in renewable energy development during the pandemic, as stated in the study by Hosseini (2020), estimating the magnitude of the impact was difficult. More research institutions are currently focusing on the measurement with numerical domain of inter-annual comparisons. There are, however, very few studies that measure the amount of change in renewable energy because of the pandemic.

2.2. Research on energy forecasting methods

The simulation of pandemic-free scenarios requires accurate forecasting tools. Proper simulation tools enable the fitting of future trends by learning from data characteristics (Debnath and Mourshed, 2018). Numerous analytical methods use different operational logics to extract information from existing data and define patterns. Therefore, method
selection around data characteristics becomes an important issue.

In the COVID-19 pandemic, many scholars have used a number of typical prediction models to make comprehensive forecasts of energy (Rahimi et al., 2021a). The different approaches can be generally categorized as time series models, neural network models, and combinatorial models. (1) The time series forecasting method is to use the data characteristics of a past period to predict the data characteristics of a future period. This method is effective for fitting small samples and short-term time-series data. In terms of the type of predicted series, ARIMA models are often used to deal with time series with a clear overall trend and uncertainty in individual data points. ARIMAX models with exogenous can improve the forecasting performance by capturing the non-smooth demand properties of probability-based models (Arias et al., 2021). In addition, scholars have developed pattern recognition-like (KNPTS) methods for the identification and processing of time series data (Gomez-Onella et al., 2020). Numerous scholars (Liu and Lin, 2021) have applied such time series methods to forecast energy demand during a pandemic. However, many real-world indicators present temporal autocorrelation and complex big data patterns, and time series models may not be able to effectively identify and model this series. Therefore, neural network models have been derived. (2) Neural network models are complex nonlinear dynamical learning systems composed of many neurons that mimic the operation of the human brain, providing a flexible computational framework for nonlinear modeling in various applications. With excellent predictive performance, this method is widely used in pandemic period prediction (Rahimi et al., 2021b). Artificial neural network models have proven to be applicable for dealing with the prediction of multiple types of energy sources such as renewable energy (Brodny et al., 2020). Some scholars (Zeroual et al., 2020) demonstrated the great potential of deep learning models in predicting COVID-19 cases and highlighted the superior performance of the Variational Autoencoder (VAE) compared to other algorithms. Furthermore, three deep learning methods, LSTM, convolutional LSTM, and GRU, have applicability in predicting new cases and new mortality of COVID-19 (Ayoobi et al., 2021). The above studies and applications demonstrate the powerful analytical processing and dynamic learning capabilities of artificial neural network models. Compared with traditional time series models, neural network models have good performance in dynamically simulating the changing characteristics of fluctuating series. (3) Compared with single method, combinatorial models can combine data with different types using different identification methods. In predicting energy consumption during a pandemic, ARIMA and Holt-Winters models were combined and applied to forecast natural gas consumption in industrial areas (Cihan, 2022). There were also studies that combined time series with machine learning methods to confirm the U.S. oil consumption under the pandemic was about 18.14% lower than in a normal non-pandemic scenario (Wang et al., 2022a). In addition, the combination of nonlinear autoregressive (NARX) and long short-term memory neural network has been applied to the prediction of electricity consumption species (Ozbay and Dalcali, 2021). Combinatorial modeling strategies can systematically consider multiple uncertainties and avoid the limitations caused by a single statistical or machine learning approach.

A review of the above energy forecasting literature reveals that time series forecasting model can simulate the overall trend of the data with a small number of samples but is weak in handling large samples and nonlinear information. The neural network model has good expressiveness in dynamically simulating the change characteristics of volatile series, but it ignores the discovery of linear factors in the series. Therefore, a combination of the two by means of improved modeling steps can achieve improved forecasting performance (Ahmad and Chen, 2018).

2.3. Contribution points of this study

Through literature combing, the pandemic has changed the development pattern of renewable energy to some extent. However, a clear determination of the impact of COVID-19 on renewable energy has not been obtained. Based on this gap, this study quantifies the specific impact of the COVID-19 pandemic on renewable energy consumption by constructing a “pandemic-free” scenario. To integrate the two types of models mentioned above using a suitable strategies, this study proposes a combined model with a time series model as the main predictor and a neural network for nonlinear residual training. This approach not only allows the full extraction of linear and nonlinear factors of the data, but supports the memorization of important features of the input series data, which could accurately predict the future.

The contributions of this study are as follows. (1) Instead of using previous measures based on inter-annual comparisons, this research innovatively develops an assessment method based on “scenario assumptions”. Specifically, this study compares renewable energy consumption in the “with pandemic” and “without pandemic” scenarios. The difference between the two is considered as the specific impact of COVID-19 on renewable energy consumption. (2) In order to make the data simulation under the “no pandemic scenario” more accurate, this study innovatively proposes an “initial prediction-parameter training-error correction-assignment combination” forecasting concept. The prediction technique incorporates a nonlinear grey model of metabolism, an artificial neural network model, and the IOWGA operator, equipped with error self-learning and self-correcting effects by correcting the fluctuation series, improving the power coefficients of the equations, and assigning weights according to the accuracy. (3) This study is conducted on the top five developing and top five developed countries in terms of renewable energy consumption. The performance of renewable energy consumption in these two types of countries can be used to assess whether there is a heterogeneous effect of income level on the stability of renewable energy.

3. Method and data

3.1. Data acquisition and methodological framework

This study evaluates the renewable energy consumption of 140 nations using BP energy statistics (BP, 2021), and visualizes the accessible data in 2005, 2010, 2015, and 2020 with a map (as shown in Fig. 1). The natural discontinuities classification method (Babic and Dolsek, 2019) is used perform a five-stage natural classification of global renewable energy. Various color blocks represent different levels of renewable energy consumption. The greater the value of renewable energy consumption, the darker the color.

The key contributors to renewable energy have shifted in the last 15 years. North and South America used to be the most critical region in global renewable energy development in 2005, while the center has shifted to Asia since 2010. Global renewable energy development becomes polycentric in 2020, with Asia and America at the center and Europe and Australia at the forefront. The highest levels of renewable energy consumption have increased six-fold in the last 15 years. For developing countries, China and India play an increasingly important role in the global energy market and cannot be ignored when studying renewable energy (Wang et al., 2018). Based on this, this study analyzes historical data from the top 10 renewable energy countries (top five developing countries and top five developed countries) and predicts the pandemic stage.

Table 1 depicts the temporal trends in renewable energy consumption in developing and developed countries during 1990–2020. China and the United States have the highest consumption level among the separate groups of developing and developed countries. The remaining eight countries show no considerable differences in renewable energy consumption. Furthermore, energy data from 1990 to 2019 are used as training samples to forecast consumption during 2020-25. Besides 2020, this study also predicts energy consumption for the next five years.

In constructing the method, a novel combination of “Initial
prediction-Error correction-Assignment combination” is proposed to solve the problem of fitting complexity and bias in the “pandemic-free scenario” assessment. Based on this new prediction idea, this study combines a metabolic nonlinear grey model (MNGM) with a backpropagation artificial neural network (BP) model. The new combined MNGM-BP model can bypass the large sample limitation and the error imbalance, and can also meet the prediction effect of renewable energy simulation in the pandemic context. Meanwhile, the fusion process of the model uses the IOWGA operator, a dynamic assignment theory, to perform a quadratic search for the result. The method framework diagram is shown in Fig. 2.

As shown in Fig. 2, the overall forecasting framework can be subdivided into three components: Preliminary prediction, Error correction, and Empowerment integration. This study describes the methodological steps and equations involved in these three subparts in detail within sections 3.2-3.4.

3.2. Preliminary prediction

This study uses a multi-step prediction method, including initial prediction, parameter training, and combined weight assignment. To be more specific, this study adopts the Metabolic Nonlinear Grey Model to make an initial prediction with historical data for ten countries. Then, use an artificial neural network to learn and correct the parameters and errors. Finally, use the induced ordered weighted geometric averaging operator (IOWGA) to improve forecast accuracy with the predicted results. In the following sections, this research goes over the intermediate principles of the three forecasting processes in greater detail.

| Type               | Country   | Time period:Training-Predicting | Primary Data Trends |
|--------------------|-----------|---------------------------------|---------------------|
| Developing Countries | China     | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Brazil    | [1990–2019]→[→ 2020–2025]       |                     |
|                    | India     | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Turkey    | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Mexico    | [1990–2019]→[→ 2020–2025]       |                     |
| Developed Countries | US        | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Germany   | [1990–2019]→[→ 2020–2025]       |                     |
|                    | UK        | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Japan     | [1990–2019]→[→ 2020–2025]       |                     |
|                    | Spain     | [1990–2019]→[→ 2020–2025]       |                     |
This study uses the improved grey model of the differential equation (Xu et al., 2017) in the initial prediction stage. The prediction equation is established using nonlinear parameters and multi-step iteration. The Metabolic nonlinear grey model’s criteria and prediction steps are depicted in Fig. 3. The preliminary forecast starts from preprocessing the data cumulatively. Then, the grey differential equation is established for the first-time accumulation of data, and nonlinear parameters are introduced to improve the equation. This study uses the Fourth Order

**Fig. 2.** The portfolio forecasting strategy and distribution process proposed in this study.

**Fig. 3.** Evolutionary principle and calculation process of metabolic nonlinear grey model.
Ronge-Kutta Method and Matlab software to solve nonlinear grey differential equations. After obtaining the initial prediction, this study continuously updates the input data and iterates out the new prediction values for each round. Each modeling round is a re-enactment of the previous prediction steps. Finally, iteration is terminated once all predicted values have been solved.

3.3. Error correction

Following the above preliminary prediction, this study uses the artificial neural network model to modify the parameters to lower the error further. The back-propagation artificial neural network model (BP) is a feed-forward network model with multiple layers. The input, intermediate, and output layers are configured to achieve mathematical equation mapping (Sadeghi, 2000). The artificial neural network model sets its training based on the input value and obtains the results closest to the expected output value using the internal BP algorithm with an analysis of errors using gradient descent (Amari, 1993). The essence of the gradient descent method is first to use the gradient search technique to adjust the input weight of each layer based on training error. Then determines the direction where the gradient vector decreases the fastest by taking partial derivatives of the weights until the minimum of the error function is found.

The multilayer feed-forward network model and the gradient descent algorithm are illustrated in Fig. 4. As shown in Fig. 4, the BP algorithm consists of two processes: signal forward propagation and error back propagation. The forward propagation process (shown in the upper part of Fig. 4) sends input nodes to output nodes via hidden layers. If the actual output does not match the expected output, the error propagation process is initiated (as shown in the lower part of Fig. 4). The error signal is used as the basis for adjusting the weight of each element in this process, and the error decreases along the gradient direction as the weight is adjusted. Fig. 4 depicts the gradient descent algorithm more intuitively. Assuming the initial error is at the top of the red mountain, the gradient descent algorithm descends to the bottom of the blue mountain via the black curve. The risk of a locally optimal solution is critical during this process; thus, it is necessary to run the algorithm many times to find the minimum value of the critical loss function.

3.4. Empowerment integration

This study adopts the combined weighting method established on the Induced ordered weighted Geometric mean operator (IOWGA) (Zheng and Wu, 2015). In this method, every model’s predicted value is assigned a weight coefficient based on prediction accuracy, and the final prediction result is computed. When combined with the IOWGA operator, the model reduces model deviation and achieves the best prediction effect. The IOWGA operator theory originated with the WGA and gradually progressed to the OWGA and then to the IOWGA. The weighted geometric average operator (WGA) was a traditional combinatorial method that assigned different weighted average coefficients to different model types. Following that, Yager proposed the ordered weighted geometric average operator (OWGA) to avoid the same weight coefficient at different times, considering the different accuracy of a single prediction method. The OWGA operator can provide a weighting factor based on the position of the accuracy of the predicted value. Finally, the Induced Ordered Weighted Geometric Average (IOWGA) operator was proposed to make the assigned weights more scientific. This method assigned different weight coefficients based on model prediction accuracy. The larger the weight coefficient, the better the prediction accuracy. This improved weighting method was practical, it also improved prediction accuracy.

The following is the specific operation procedure: To begin, this study defines \( p_i \) as the “\( i \)’th prediction method’s prediction accuracy at time \( t \), and \( x_i \) as the “\( i \)’th prediction method’s prediction result at time \( t \). As a result, variables \( p_i \) and \( x_i \) form a two-dimensional array. Then,
based on $p_a$ value, this study arranges the array positions and defines the order in the entire array as $p - \text{index}(i)$. Finally, as shown in Equation (1), the final combined prediction result at time $t'$ can be obtained:

$$G(t) = \left( <p_{t1}, x_{t1}>, <p_{t2}, x_{t2}>, \ldots, <p_{tn}, x_{tn}> \right) = \sum_{i=1}^{m} x_{\text{index}(i)}^{t'}, t = 1, 2, \ldots, N$$  \hspace{1cm} (1)

It should be noted that the power coefficient in Equation (1) corresponding to each predicted value is the key to the solution. This study defines $l_i$ as the weight of the predicted value of the $i$th bit sorted by accuracy, based on the principle that the higher the accuracy, the greater the weight. Once the weight coefficient is determined, the final unique prediction result corresponding to each time can be calculated using the calculation equation in Equation (1).

The linear programming method solves the weight coefficient $l_i$ in conjunction with the existing references. The logarithmic error corresponding to the actual value is as shown in Equation (2). If $x_i$ is the predicted value at $t'$ and $x_{\text{index}(i)}$ is the predicted value of the $i$th precision sorting at $t'$, the logarithmic error $e_{a - \text{index}(i)}$ of the $i$th method at $t'$ is:

$$e_{a - \text{index}(i)} = \ln x_i - \ln x_{\text{index}(i)}$$  \hspace{1cm} (2)

The sum of the logarithmic errors squared "S" was calculated by adding the logarithmic errors at each time, which is as shown in Equation (3):

$$S = \sum_{i=1}^{N} \left( \ln x_i - \ln \prod_{i=1}^{m} x_{\text{index}(i)} \right)^2$$

$$= \sum_{i=1}^{N} \left( \ln x_i - \sum_{i=1}^{m} l_i \ln x_{\text{index}(i)} \right)^2 = \sum_{i=1}^{m} \sum_{j=1}^{m} L_{ij} \left( \sum_{i=1}^{N} e_{a - \text{index}(i)} e_{a - \text{index}(j)} \right)$$  \hspace{1cm} (3)

The sum of the error squares is used to assess the model’s effectiveness. As shown in Equation (4) and Equation (5), it can be obtained by minimizing the sum of squares of logarithmic errors obtained above:

$$\min S(L) = \sum_{i=1}^{m} \sum_{j=1}^{N} L_{ij} \left( \sum_{i=1}^{N} e_{a - \text{index}(i)} e_{a - \text{index}(j)} \right)$$  \hspace{1cm} (4)

s.t \hspace{0.5cm} \begin{align*}
\sum_{i=1}^{m} L_{i} &= 1 \\
L_{ij} &\geq 0, \quad i = 1, 2, \ldots, m
\end{align*}  \hspace{1cm} (5)

As shown in Equation (6), the LINGO software is used to solve the optimal coefficient $l_i$ of the linear programming problem, and the corresponding weight coefficient is expressed as shown. Substitute this into (1) to calculate the final predicted value for each year.

$$L^* = \frac{E^{-1}R}{R^TE^{-1}R}$$  \hspace{1cm} (6)

As soon as the theory was proposed, it was cited by many scholars, and the accuracy-based weighting method became the most scientifically recognized method in combinatorial models. In terms of model benefits, this combination method applies to situations where the accuracy of multiple models is determined, and it is consistent with the principle of combination optimization to assign large weights to prediction results with high accuracy. In this study, comparing the three groups of prediction results during the fitting stage helps determine their respective accuracy. The linear programming weight coefficients fully reflect the prediction results and help reduce the final accuracy further.

4. Results and discussion

4.1. Construction of cyclic prediction equations

According to the initial predictive modeling principles shown in Section 3.2, this study constructs nonlinear differential equations based on the historical data on renewable energy consumption in ten countries. Each prediction round uses five numbers to establish a differential equation and generates a prediction result. Because the model uses the rolling modeling mechanism of metabolism, each round of equation building generates a set of parameters. A total of 26 sets of equations were built and solved for each country based on the 1990-2019 history period. Table 2 depicts the rolling mechanism of each round of prediction, and only the differential solution equations in the first, second, and final round of estimations are listed due to space constraints. The preliminary fitting results of MNGM from 1995 to 2020 are predicted using this equation. After this, the study performs a training correction on the error value between the predicted and the actual values. The final forecast incorporates the preliminary predictions and the correction error. The final two steps are detailed in the following sub-sections.

4.2. Training performance and error correction

Based on the preliminary prediction results of the metabolic nonlinear grey model, this study optimizes the parameters and errors using the BP neural network model. The neural network is trained over 5000 iterations, with each iteration (training) process utilizing all of the samples in the training set. The iterative process propagates the error of each calculation in reverse until the value of the error function is significantly reduced. Fig. 5 demonstrates the error iteration process for each sample and the mean squared error metric performance. The blue and green lines represent the training process, while the red line represents the results of the BP model. The dotted line (named 'Best') indicates that the training result of the error is the best when the BP network is trained to a specific generation. After training and learning the error curve for ten samples, the corrected error is calculated.

Fig. 6 depicts the original error predicted by the MNGM model (represented by orange and blue lines) and the corrected error following training with the BP model (shown by black lines). The error value after forecasting renewable energy consumption is represented by the ordinate (unit: Mt). The smaller the absolute value, the smaller the error. The correction amount is indicated by how close the black curve is to the abscissa. There is some variation in the double-error plots across countries. The effect of error correction is not noticeable in China, Brazil, or Turkey but shows notable power in the remaining countries. However, Fig. 6 only provides a rough representation of the initial and corrected errors. More specific prediction effects require numerical estimates from the error equation.

This study uses the relative error to represent the prediction accuracy as the mean of relative error is a term that reveals prediction accuracy. The prediction accuracy of different models each year is reflected by the different colored lines in Fig. 7. The higher the prediction accuracy, the closer the line is to the outer side of the spider diagram. The sample curves of ten countries show that the MNGM-BP model has more high-precision nodes than the other two single models, indicating that the error-corrected model outperforms in predictions.

4.3. Precision prioritization and result assignment

This study fits the integrated results of three models, i.e., the nonlinear grey model of metabolism (MNGM), the artificial neural network model (BP), and the combined model of metabolic nonlinear grey-artificial neural network (MNGM-BP) with the historical energy consumption data. This research uses the IOWGA operator method to rank the fitting errors of different models to integrate the prediction results of the three models above. Weights are assigned based on the principle that the smaller the error, the larger the weight.

This study adopts the standard calculation indicators of Mean Absolute Percentage Error (MAPE) and Mean Squared Percentage Error (MSPE) to measure forecast error, as shown in Equation (7) and Equation (8). According to the evaluation criteria, the smaller the value of the
Table 2
Rolling forecast equation and preliminary forecast results.

| Country | 1990-1994 → 1995 | 1991-1995 → 1996 | 1992-1996 → 1997 | --- | 2015-2019 → 2020 |
|---------|------------------|------------------|------------------|----|------------------|
| China   | \( \frac{dx^{(1)}(t)}{dt} = 0.71(x^{(3)}(t))^{0.009} - 0.0002 \) | \( \frac{dx^{(3)}(t)}{dt} = 1.13(x^{(3)}(t))^{1} = - \) | \( \frac{dx^{(3)}(t)}{dt} = 3.19(x^{(3)}(t))^{0.061} = - \) | \( \frac{dx^{(3)}(t)}{dt} = 4.35(x^{(3)}(t))^{0.562} = - \) | 
| Brazil  | \( \frac{dx^{(3)}(t)}{dt} = -0.04(x^{(3)}(t))^{1} = 6.5538 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.05(x^{(3)}(t))^{1} = 6.6248 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.14(x^{(3)}(t))^{0.768} = 6.5384 \) | 
| India   | \( \frac{dx^{(3)}(t)}{dt} = -0.0227 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.55(x^{(3)}(t))^{1} = 0.0053 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.49(x^{(3)}(t))^{3.95} = -0.0338 \) | 
| Turkey  | \( \frac{dx^{(3)}(t)}{dt} = -0.04(x^{(3)}(t))^{1} = 0.0269 \) | \( \frac{dx^{(3)}(t)}{dt} = -0.39(x^{(3)}(t))^{1} = 0.0041 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.21(x^{(3)}(t))^{5.838} = -0.0169 \) | 
| Mexico  | \( \frac{dx^{(3)}(t)}{dt} = -93.52(x^{(3)}(t))^{0.001} = - \) | \( \frac{dx^{(3)}(t)}{dt} = 0.02(x^{(3)}(t))^{1} = 1.5318 \) | \( \frac{dx^{(3)}(t)}{dt} = 49.38(x^{(3)}(t))^{0.001} = - \) | 
| United States | \( \frac{dx^{(3)}(t)}{dt} = 2028\text{ln}(x^{(3)}(t))^{0.001} = - \) | \( \frac{dx^{(3)}(t)}{dt} = -567(x^{(3)}(t))^{0.001} = - \) | \( \frac{dx^{(3)}(t)}{dt} = 0.02(x^{(3)}(t))^{1} = 19.6597 \) | 
| Germany | \( \frac{dx^{(3)}(t)}{dt} = -0.21(x^{(3)}(t))^{1} = 0.2503 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.23(x^{(3)}(t))^{1} = 0.2994 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.31(x^{(3)}(t))^{0.773} = -0.3025 \) | 
| United Kingdom | \( \frac{dx^{(3)}(t)}{dt} = -0.33(x^{(3)}(t))^{0.006} = 0.0848 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.63(x^{(3)}(t))^{0.294} = - \) | \( \frac{dx^{(3)}(t)}{dt} = -0.79(x^{(3)}(t))^{1.177} = - \) | 
| Japan   | \( \frac{dx^{(3)}(t)}{dt} = -0.04(x^{(3)}(t))^{1} = 2.5288 \) | \( \frac{dx^{(3)}(t)}{dt} = -0.07(x^{(3)}(t))^{1} = 2.4231 \) | \( \frac{dx^{(3)}(t)}{dt} = 720(x^{(3)}(t))^{0.001} = - \) | 
| Spain   | \( \frac{dx^{(3)}(t)}{dt} = -0.19(x^{(3)}(t))^{0.317} = 0.0173 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.24(x^{(3)}(t))^{1} = 0.0883 \) | \( \frac{dx^{(3)}(t)}{dt} = 0.25(x^{(3)}(t))^{1} = 0.1053 \) | 

Fig. 5. The process of decreasing the value of the error function by data iteration and node calculation.
average relative error and the mean square relative error, indicating the higher the prediction accuracy of the selected method. Table 3 lists the MAPE and MSPE values for the three models in each country. The accuracy ranking of the three models at each prediction node is identified based on the size of the error value.

\[
\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{x}_t - x_t}{x_t} \right|
\]  

(7)

\[
\text{MSPE} = \frac{1}{n} \sqrt{\sum_{t=1}^{n} \left( \frac{\hat{x}_t - x_t}{x_t} \right)^2}
\]  

(8)

where: “\(\hat{x}_t\)” means predictive value; “\(x_t\)” means original value; “n” means the number of all forecast years.

This study assigns the corresponding weights to the predicted values of the three models in the order of accuracy using the IOWGA operator’s combination principle. The weights calculated by IOWGA for the ten country samples are shown in Table 4. Using China as an example, a weight coefficient of 0.466 is assigned to the forecast value \(x_{\text{index}(1)}\)
ranked first in accuracy, a weight coefficient of 0.306 is assigned to the predicted value $x_{\text{index}(2)}$ ranked second in accuracy, and a weight coefficient of 0.228 is assigned to the predicted value $x_{\text{index}(3)}$, ranked third in precision. The combined equation after weighting is shown in the last column. Results from four models, MNGM, BP, MNGM-BP, the weighted IOWGA operator models. Fig. 7 depicts the error value of the final combined model after calculating the average relative error and the mean square relative error. The remaining countries’ average relative forecast error is less than 5%, except for China and Turkey. This value satisfies the predictive model’s highest accuracy requirements. Table 5 shows that the combined prediction error is less than the single prediction error, which supports the validity of the combined effect.

4.4. Gap between the pandemic year and the historical trajectory

After studying the data from 1990 to 2019, this study uses the above three models to predict the renewable energy consumption of ten countries in 2020. Since this result is simulated based on historical trajectories, this forecast is also considered the 2020 renewable energy consumption under the assumption of a no-pandemic scenario. Fig. 8 shows the renewable energy change curve for five developing countries under different scenarios. The black curve represents renewable energy consumption in the absence of a pandemic, and the grey represents actual renewable energy consumption. The difference between the hypothetical and actual value represents the true impact of the pandemic on renewable energy consumption. Existing statistics frequently use the difference between 2020 and 2019 to evaluate the performance of renewable energy consumption during the pandemic, which corresponds to the year-to-year impact. Energy consumption estimated from two statistical methods differ; this study further explores this distinction in detail.

The figure’s bar chart shows changes in renewable energy consumption due to the pandemic using two measures. The yellow histogram, for example, represents the impact of renewable energy consumption based on an inter-annual comparison, which is accomplished by comparing renewable energy consumption from 2020 to 2019. Based on the scenario assumptions, the green histogram represents the impact of renewable energy consumption, accomplished by subtracting the forecast model’s simulated renewable energy consumption in the no-pandemic scenario and the actual renewable energy consumption in 2020. According to the figure, China’s renewable energy consumption increased by 24.85 Mtoe in 2020 compared to the previous year. However, based on scenario assumptions, the actual decrease in renewable energy consumption during the pandemic was 8.57 Mtoe. This demonstrated that, while renewable energy consumption increased during the pandemic compared to previous years, it decreased compared to the typical trajectory. This phenomenon can also be found in India, Turkey, and Mexico. Based on the reported values in existing statistics, the pandemic is still slowing renewable energy development in these developing countries.

During the pandemic, renewable energy in Brazil has increased by 0.91 Mtoe. The gap is formed by subtracting the yellow histogram’s value from the green one. This disparity can be used to calculate the specific value of overestimated renewable energy consumption during the pandemic. The gaps’ specific values and order from high to low are shown in the lower right corner of Fig. 8. During the pandemic, China’s renewable energy consumption was overestimated by the most significant amount, reaching 33.43 Mtoe. China is followed by India, which is overvalued by 5.68 Mtoe. Turkey (1.83 Mtoe) ranked third, followed by Mexico (0.56 Mtoe).

Fig. 9 shows the change curves of renewable energy in five developed countries under different scenarios. The increase in renewable energy during the pandemic was overestimated in all five developed countries based on year-to-year comparisons. The United States is the most overvalued, with 8.01 Mtoe. Renewable energy consumption in the

### Table 3
Error values of the three models.

| Country | MAPE | MSPE |
|---------|------|------|
|         | MNGM | MNGM-BP | BP | MNGM | MNGM-BP | BP |
| China   | 13.03% | 13.27% | 22.96% | 0.0359 | 0.0372 | 0.1116 |
| Brazil  | 6.90%  | 3.98%  | 4.32%  | 0.0159 | 0.0104 | 0.0124 |
| India   | 9.64%  | 7.32%  | 6.43%  | 0.0235 | 0.0191 | 0.0196 |
| Turkey  | 17.18% | 16.06% | 23.36% | 0.0445 | 0.0425 | 0.0167 |
| Mexico  | 5.32%  | 4.74%  | 3.85%  | 0.0118 | 0.0115 | 0.0134 |
| United  | 3.43%  | 1.66%  | 2.76%  | 0.0079 | 0.0052 | 0.0070 |
| States  |       |       |       |       |       |       |
| Germany | 6.33%  | 3.95%  | 4.10%  | 0.0154 | 0.0096 | 0.0128 |
| United  | 5.98%  | 5.57%  | 4.55%  | 0.0147 | 0.0140 | 0.0126 |
| Kingdom |       |       |       |       |       |       |
| Japan   | 5.40%  | 4.81%  | 3.88%  | 0.0124 | 0.0115 | 0.0105 |
| Spain   | 7.39%  | 7.05%  | 3.32%  | 0.0180 | 0.0194 | 0.0133 |

### Table 4
Assignment value and combination equation based on IOWGA.

| Country | Weight coefficient | Rank 1 | Rank 2 | Rank 3 |
|---------|--------------------|--------|--------|--------|
| China   | 0.4660             | 0.3060 | 0.2280 |
| Brazil  | 0.6554             | 0.3446 | 0.0000 |
| India   | 0.4713             | 0.3486 | 0.1802 |
| Turkey  | 0.5520             | 0.4480 | 0.0000 |
| Mexico  | 0.4201             | 0.3101 | 0.2698 |
| United States | 0.5414 | 0.2751 | 0.1835 |
| Germany | 0.5691             | 0.2408 | 0.1901 |
| United Kingdom | 0.3955 | 0.3690 | 0.2355 |
| Japan   | 0.5530             | 0.3975 | 0.0495 |
| Spain   | 0.6788             | 0.3212 | 0.0000 |

**Note:** $x_{\text{index}(1)}$ represents the predicted value with the highest accuracy among the three predicted values. $x_{\text{index}(2)}$ represents the second-ranked predicted value. $x_{\text{index}(3)}$ represents the third-ranked predicted value.
United States under a counterfactual without the COVID-19 pandemic has 2.5 Mtoe less than the actual situation. With the pandemic outbreak, the increase in renewable energy consumption was only 2.5 Mtoe, not 10.51 Mtoe. Following that, renewable energy consumption in Germany and the United Kingdom has increased by 0.05 Mtoe and 0.56 Mtoe, respectively, during the pandemic, which was overestimated by 2.44 Mtoe and 2.09 Mtoe. Because of the pandemic, renewable energy consumption in Japan and Spain has fallen by 0.99 Mtoe and 0.48 Mtoe, respectively. The growth in renewable energy consumption in both countries is overestimated by 1.96 Mtoe and 0.41 Mtoe, respectively, compared to inter-annual statistics.

Data from China and India illustrate that renewable energy consumption in developing countries was severely damaged during the pandemic. But the damage is underestimated. And data from places like the U.S., Germany, and the U.K. imply that renewable energy consumption is showing slightly increasing in some developed countries. This finding supports the view that, although the renewable energy path faces obstacles in the pandemic period, its development may show significant differences depending on income levels. It is worth noting that the use of renewable energy is affected by many factors, and the pandemic is only one of many. Therefore, this study comprehensively analyzes the reasons for the changes in renewable energy after the COVID-19 pandemic from the perspective of renewable energy project financing and stakeholder interests.

From what has been seen, the COVID-19 pandemic has exposed the vulnerability of the renewable energy sector in developing countries. This phenomenon may be closely related to local project financing woes (Shekhar et al., 2021). Scholars have found that the ongoing economic downturn caused by the pandemic has triggered uncertainty about financing renewable energy projects (Hoang et al., 2021). According to a recent publication by Wood Mackenzie, 3000 MW of combined solar and wind projects have been put on hold in India (Deshwal et al., 2021); up to 150 GW of renewable energy projects in Asia are expected to be delayed or canceled by 2024 if the recession continues further (Hosseinir, 2020). Adding insult to injury, stakeholders are even more concerned that continued job losses and capital loss are further elevating the financial risk of renewable energy investments (Ji et al., 2020). In addition, developing countries have taken on significant production of components, which has led to significant production disruptions and supply chain delays. This further affects the deployment of renewable energy stimulus programs.

While COVID-19 has had a negative impact on renewable energy development, the slight increase in developed countries also conveys a potential opportunity for the clean energy sector. On the one hand, some developed countries have established relatively well-established clean energy supply systems. The prevalence of smart grids and integrated energy storage systems invariably brings additional resilience to renewable energy systems (Li et al., 2022a, 2022b). At the enterprise level, developed countries have also achieved a natural transition to a circular economy across sectors and countries (Marino and Pariso, 2021). On the other hand, developed countries have more aggressive investment efforts and incentives for clean energy. Market prices for oil

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**Fig. 8.** Deficient values of renewable energy consumption from two calculations (Developing countries).
and natural gas have long been volatile because they are subject to multiple factors (Mehrotra et al., 2020). The recent drop in oil prices has made the return on investment in fossil fuels unpredictable, triggering a boom in investment in renewable energy in developed countries (Donovan et al., 2020). Thus, multiple factors convey the possibility that renewable energy investments have long-term returns. There is reason to believe that the crisis has led to volatility in conventional energy markets, which has accelerated energy infrastructure transition to renewables. This is consistent with countries meeting their carbon reduction targets and enhancing national energy systems’ security resilience.

4.5. Forecast of differentiated countries

This study uses historical values to predict short-term future values of renewable energy consumption, in line with the forecast ideas mentioned above. Fig. 10 and Fig. 11 demonstrate the future trends in renewable energy consumption in developing and developed countries, respectively. The dotted line in the figure represents the boundary between the past fitting stage and the future prediction stage. The forecasting results of the three base models are represented by the three-dotted lines in blue, yellow, and green, respectively. The solid red line represents the combined trend graph for the three forecast combinations. Because the combination principle is based on higher precision and more significant weight, the red solid line trajectory map determines the final development trend.

China and Mexico show a dynamic trend of periodic growth among the top five developing countries regarding renewable energy consumption. On the other hand, Brazil and India exhibit a dynamic trend of explosive growth. Turkey exhibits no prominent fluctuation characteristics, indicating stable growth. China, India, Turkey, and Mexico will experience rapid increases in renewable energy consumption. China and India show the highest annual growth rates and increments, with average annual growth rates of 1.72 Mtoe and 0.47 Mtoe, respectively. That is to say, China and India will continue to demonstrate a stable upward trajectory based on their current high levels of renewable energy consumption. Turkey and Mexico have an average annual growth rate of around 1.5 Mtoe, a high growth rate with a low increment. This means that Turkey’s and Mexico’s high growth rates result from low development bases. This rapid growth rate will not result in significant changes in renewable energy development in the future. However, due to Brazil’s volatile development characteristics in recent years, the growth rate in the next five years will be low. Although the development level used to rank second among developing countries, the future net increase will have a slow development rate.

The United States ranks first among the top five developed countries in renewable use, with an average annual growth rate of 6.8% (at a maximum level of 10.48 Mtoe annually). Following the United States, Germany demonstrates a dynamic trend of fluctuating growth, with an average annual incremental level of 3.84 Mtoe, ranking second place. In
contrast, the United Kingdom and Japan are experiencing rapid growth, at 9.05 percent and 10.15 percent, respectively. Both are among the club with high growth rates. However, Spain grows slower, with an average annual growth rate of 6.32 percent (1.12Mtoe), the lowest level among the top-five nations. According to their current high levels of renewable energy consumption, the United States and Germany have a stable upward prospect (Li, R. et al., 2022). Based on their current development, the United Kingdom and Japan will enter a period of rapid growth. Spain, which has been affected by a sluggish trend in recent years, will grow slowly over the next five years.

5. Conclusions

This study creates a research framework for ‘scenario forecast-difference analysis’ to address the specific impact of the COVID-19 pandemic on renewable energy consumption. The most important findings to emerge from this study were as follows.

First, this research developed the integrated MNGM-BP-IOWGA model with samples of ten countries. We learned the historical data trajectory from 1990 to 2019, and finally predicted the pandemic-free counterfactual for 2020. Results have shown that 80% of national samples have an average relative error of less than 5% over the last 30 years. This estimation demonstrated the applicability of the constructed model and the goodness of the prediction effect.

Second, the disparity in the results indicated more negative impacts on renewable energy in developing countries. The amount of underestimated renewable energy impact in China and India reached 33.43 Mtoe and 5.68 Mtoe, respectively. However, renewable energy consumption in the United States and Japan have increased by about 2.5 Mtoe and 0.99 Mtoe, respectively. This is also underestimated by about 8.01 Mtoe and 1.96 Mtoe compared to the official statistics of year-to-year growth figures. The different performance of developing and developed countries is related to the differences in clean energy infrastructure and the share of low-carbon energy use. This also means that the level of the economy will play a role in the stress-bearing nature of renewable energy.
Finally, the results of the comparison between the two scenarios indicated that the growth of renewable energy during the pandemic was overestimated. This viewpoint is consistent with the viewpoint of IEA that ‘global renewable energy growth is being hampered, but not halted, by the COVID-19 pandemic’ (International Energy Agency, 2020). On the positive side, developed-country renewable energy markets have shown resilience in the face of the pandemic, which serves to remind that the pandemic’s changes present both opportunities and challenge. In the future, China, the United States, and India remain the top three countries in terms of growth in renewable energy consumption. The average annual growth of the three countries will reach 17.24, 10.48 and 4.07mtoe. Continuous policy incentives are needed to make the global renewable energy industry more prosperous. Next, this research will continue to follow up with updated data to assess the impact of the outbreak in more real time. In addition, this research will also focus on the performance of additional types of energy in COVID-19, which is key to making this series of studies more complete.

CRediT authorship contribution statement

Shuyu Li: Methodology, Software, Data curation, Investigation, Writing – original draft, Writing – review & editing. Qiang Wang: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Supervision, Writing – review & editing. Xue-ting Jiang: Investigation, Writing – original draft, Writing – review & editing. Rongrong Li: Conceptualization, Methodology, Software, Methodology, Data curation, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Data availability
Data will be made available on request.

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