Using grey models for forecasting Vietnam's renewable energy consumption

Nguyen Dinh Tien*

VNU University of Economics and Business, Vietnam National University - Hanoi, 144 Xuan Thuy Street, Cau Giay Ward, Hanoi, Vietnam

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Abstract:

Vietnam has actively pursued its commitments under the 2030 Agenda for Sustainable Development and has been an engaged participant in the Paris Agreement under the United Nations Framework Convention on Climate Change (COP21). One of Vietnam's key obligations is to drive a significant energy transition aimed at reducing greenhouse gas emissions. The development of renewable energy sources is an essential global endeavour, given their crucial role in reducing greenhouse gas emissions, protecting the environment, and decreasing reliance on fossil fuels. This study employs grey forecasting models (GM(1,1), NGBM(1,1), and DGM(1,1)) to predict Vietnam's renewable energy consumption from 2023 to 2030. The analysis reveals a substantial increase in renewable energy demand, with forecasts indicating considerable growth: GM(1,1) predicts 632.2 TWh, DGM(1,1) anticipates 602.5 TWh, and NGBM(1,1) projects 557.7 TWh by 2030. Among the models, DGM(1,1) yields the most accurate results, with the lowest mean absolute percentage error (MAPE) of 6.76%. This forecast aligns with Vietnam's ambitious renewable energy development goals, aimed at diversifying its energy mix and meeting climate mitigation targets. The findings highlight the importance of continued investment in renewable energy technologies, infrastructure, and supportive policies to secure a sustainable energy future while balancing economic growth and environmental preservation. This research offers valuable insights for policymakers in shaping Vietnam's energy transition strategies over the coming decades.

Keywords: **grey model, renewable energy, Vietnam.**

Classification numbers: **2.2, 7**

1. Introduction

Vietnam stands out as one of Asia's most notable economic success stories, with an average GDP growth rate of 5.9% between 2016 and 2022 [1]. Notably, in 2020, Vietnam was one of the few countries to maintain a positive GDP growth rate of 2.91% amidst the global pandemic, earning its place as one of the 16 most successful emerging economies during COVID-19. With a population ranking as the 40th largest in the world and the 4th largest in ASEAN, Vietnam's GDP per capita is ranked 6th in the region [1]. Alongside these impressive economic achievements, there is an increasing demand for traditional energy sources, which has become a primary contributor to environmental pollution in the country. In 2019, emissions from fuel combustion in Vietnam totalled 262 million tonnes of CO_2, representing a 17.6% increase from 2018 and 1.8 times higher than in 2010 [2]. Comparative emission indicators show that Vietnam's per capita emission rate is relatively low, but its emissions per unit of GDP are notably high. Thus, the challenge of balancing economic growth with environmental sustainability is an urgent concern not only for Vietnam but for other nations as well.

Renewable energy is widely regarded as a key driver of sustainable development and a solution for reducing greenhouse gas emissions [3], particularly in response to the Paris Agreement, which aims to limit global warming to below 2°C [4]. According to the 2019 Energy Outlook report, renewables accounted for 19.3% of global energy consumption and 24.5% of electricity production in 2017 and 2018. Vietnam

*Email: ndtien.up@gmail.com

has significant potential to harness renewable energy sources such as solar, biomass, hydroelectric, and wind power. Over the years, the Vietnamese government has implemented policies and strategies to promote renewable energy development, including the country's renewable energy development strategy for 2050, support mechanisms for grid-connected biomass power projects, and incentives for solar and wind power development. However, the reality is that Vietnam has not fully capitalised on its potential due to barriers faced by investors in areas such as institutional frameworks, legal issues, investment climate, technical and commercial challenges, and workforce capabilities. According to Vietnam's Renewable Energy Report (2018), the combined output of small hydroelectric, wind, and solar energy stood at 1.65, 0.19, and 0.01 MW, respectively [5]. This study aims to predict the future consumption of renewable energy in Vietnam, which is essential to providing valuable insights and solutions for managing and optimising the country's renewable energy resources.

2. Literature review

Grey model theory is a powerful tool for system modelling in contexts where information is incomplete, behaviours are unclear, or operating mechanisms are undefined [6]. This theory facilitates in-depth analyses, allowing for the observation of system developments and changes, and supports long-term forecasting [7]. A distinctive feature of grey model theory is its ability to construct models using a minimum of just four data samples, without requiring strict assumptions regarding sample distribution. Numerous studies have demonstrated that the basic grey model GM(1,1) delivers exceptionally high predictive accuracy when applied to small sample data sets [8]. However, the predictive accuracy of GM(1,1) is generally observed when the test sample data follow a steady growth trend. D.C. Li, et al. (2009) [9] and Y.C. Lee, et al. (2014) [10] have proposed that, in cases where sample data exhibit significant fluctuations, the use of nonlinear Bernoulli models and Markov models can significantly improve forecast accuracy. To address the limitations identified in previous studies and to enhance prediction accuracy, several studies have integrated the GM(1,1) model with the nonlinear grey Bernoulli model (NGBM) and the grey Verhulst model for theoretical computations and empirical validation. P. Herbig, et al. (1993) [11] emphasised that forecasting is a crucial tool for estimating future events or conditions that lie beyond an organisation's control, thus providing managers with vital data for planning. Therefore, accurate prediction is a fundamental element in the decision-making process.

D. Gielen, et al. (2019) [12] confirmed that renewable energy sources could meet two-thirds of global energy demand and make a substantial contribution to reducing greenhouse gas emissions, which are necessary to limit the global average surface temperature increase to below 2°C by 2050. H.T.H. Xuyen (2018) [13] used data from 2010 to 2014 to forecast CO_2 emissions, renewable energy consumption, and economic growth in Vietnam from 2015 to 2019 using the grey model. The results indicated a 3% increase in CO_2 emissions, a negligible rise in renewable energy consumption, and a 5% GDP growth by 2019 compared to 2010. H. Zhao, et al. (2020) [14] applied the grey model to forecast non-renewable energy consumption in countries within the Asia-Pacific Economic Cooperation (APEC) forum. Their findings suggest an upward trend in oil consumption across 15 countries, with coal consumption showing significant growth in South Korea, Indonesia, Vietnam, Malaysia, and the Philippines, while the United States, Canada, and Australia exhibited a decreasing trend. Natural gas consumption is expected to increase in the United States, Mexico, Singapore, China, Vietnam, and Peru. For nuclear energy, consumption is projected to rise in China, while it is expected to decrease in South Korea.

H.T. Pao, et al. (2012) [15] used the grey Bernoulli model to forecast CO_2 emissions, renewable energy consumption, and economic growth in China. The results showed that from 2011 to 2020, China's annual emissions, energy consumption, and real GDP growth rates were 4.47, -0.06, and 6.67%, respectively. Based on these findings, it was recommended that China adopt a dual strategy to enhance energy efficiency, reduce losses in electricity transmission and distribution, and promote energy-saving policies to mitigate unnecessary energy waste.

C.H. Wang (2004) [16] applied an improved GM(1,1) model to forecast the number of tourists from Hong Kong (China), the US, and Germany visiting Taiwan (China) between 1989 and 2000. The study concluded that the improved model demonstrated high predictive accuracy, significantly reducing both the cost and time required for data collection due to its minimal sample size requirement.

E. Kayacan, et al. (2010) [17] employed NGBM and grey Markov models to forecast the exchange rates of the US dollar and the euro from 2005 to 2007. The study revealed high accuracy in these models when the test sample data exhibited a steady growth trend. D. Akay, et al. (2013) [18] applied various models to forecast electricity demand in Turkey, concluding that grey theory provided the most optimistic predictions. P.Y. Hu (2004) [19] developed a GM(1,1) model to assist consumers in making optimal decisions when purchasing new cars, allowing them to input preferences such as brand, price, safety, functionality, and fuel consumption to make an informed choice.

3. Data and methodology

3.1. Data collection

Data on renewable energy consumption in Vietnam from the period 2019 to 2023 were collected from the website ourworldindata.org (Table 1). The procedure for setting the data in the grey model is provided in Section 3.2.

Table 1. Data description used for the Grey model.

Year	Renewable energy consumption (TWh)
2019	190
2020	223
2021	284
2022	341
2023	309

Source: ourworldindata.org (2024).

3.2. The Grey model

GM(1,1): The GM(1,1) forecast model is the fundamental component of the grey forecast model system. Renowned for its computational simplicity and high precision, this model is extensively utilised across various domains, including economics, management, and transportation. In this study, series prediction, involving the direct formulation of grey prediction models based on available data, has been addressed. The detailed computational steps for the GM(1,1) forecasting model are outlined as follows:

First, the given data is defined as the original series, where $X^{(0)}$ is a non-negative data series:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots x^{(0)}(n)) \quad (1)$$

In the second step, a single AGO is applied to accumulate the established original series. The following generated sequence is obtained:

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

where $x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i)$, k=2, 3, ..., n

For the third step, GM(1,1) is established as a differential equation of order one and one variable, as follows:

$$\frac{dx^{(0)}(k)}{dk} + ax^{(1)}(k) = b \quad (3)$$

where *b* is a constant.

For the fourth step, the least squares method along with differential and difference equations is used to obtain the parameters a and b of the GM(1,1) model:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y$$
$$Y = \left[X^{(0)}(2), X^{(0)}(3), \dots X^{(0)}(n)\right]^T \quad (4)$$

where

$$B = \begin{bmatrix} -0{,}5 \times \left(x^{(1)}(2) + x^{(1)}(1)\right) & 1 \\ -0{,}5 \times \left(x^{(1)}(3) + x^{(1)}(2)\right) & 1 \\ \dots & \dots \\ -0{,}5 \times \left(x^{(1)}(n) + x^{(1)}(n-1)\right) & 1 \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \\ x^{(0)}(n) \end{bmatrix} \quad (5)$$

In step five, the grey differential equation is used to obtain the grey AGO equation:

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, k = 1, 2, 3, \dots, n, n+1, \dots \quad (6)$$

For step six, the forecast values of the GM forecast model (1,1) is calculated based on the following formula:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), \ k = 1, 2, 3, \dots$$

or

$$\hat{x}^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1 - e^{a}) \quad (7)$$

Nonlinear grey Bernoulli Model (NGBM (1,1)): The nonlinear grey Bernoulli model (NGBM) extends the traditional GM(1,1) model by introducing a nonlinear component based on the Bernoulli differential equation, enabling it to capture more complex system dynamics for enhanced forecasting performance. As a variant of the grey forecasting models, the NGBM incorporates the Bernoulli equation to accommodate nonlinear forecasting functions, allowing for more accurate predictions of time series data exhibiting nonlinear fluctuations-something that traditional GM(1,1) models cannot achieve. C.I. Chen, et al. (2011) [7] conducted an empirical study comparing the NGBM(1,1) with the traditional GM(1,1) model using unemployment rate data from ten countries. The results showed that the NGBM(1,1) significantly improved prediction accuracy. S.B. Tsai, et al. (2017) [20] applied the traditional GM(1,1), NGBM(1,1), and the Grey Verhulst model to forecast renewable energy consumption trends. They then compared the results to those from a standard linear regression model to validate the NGBM(1,1)'s precision and applicability. The NGBM(1,1) retains two basic advantages of the GM(1,1): a simple derivation process and the requirement of only four data points for modelling. Additionally, the NGBM(1,1) reduces the prediction error common in GM(1,1) and improves its accuracy for nonlinear data.

The GM (1,1) is a special case of the NGBM. The calculation steps and procedures for deriving the NGBM equation are as follows:

(a) The original data are defined as the original series. A new series is then obtained using the Accumulated Generating Operation (AGO) for calculation. The first three equations for the NGBM are identical to Eqs. (1)-(3) in GM(1,1).

(b) The NGBM equations differ from those of GM(1,1). The Bernoulli equation is used to establish both the differential and difference models for the NGBM. The NGBM differential equation is as follows:

$$\frac{dx^{(0)}(k)}{dk} + ax^{(1)}(k) = b[X^{(1)}]^r \quad (8)$$
$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y$$

(c) The grey differential equation is used to derive the grey AGO equation:

$$B = \begin{bmatrix} -0,5 \times \left(x^{(1)}(2) + x^{(1)}(1)\right) & \left\{0,5 \times \left(x^{(1)}(2) + x^{(1)}(1)\right)\right\}^r \\ -0,5 \times \left(x^{(1)}(3) + x^{(1)}(2)\right) & \left\{0,5 \times \left(x^{(1)}(3) + x^{(1)}(2)\right)\right\}^r \\ \cdots & \cdots \\ -0,5 \times \left(x^{(1)}(n) + x^{(1)}(n-1)\right) & \left\{0,5 \times \left(x^{(1)}(n) + x^{(1)}(n-1)\right)\right\}^r \end{bmatrix} \quad (9)$$

$$\hat{X}^{(1)}(k+1) = \left[\left[X^{(0)}(1)^{(1-r)} - \frac{b}{a}\right] e^{-ak(1-r)} + \frac{b}{a}\right]^{\left(\frac{1}{1-r}\right)} \quad (10)$$

k=1, 2, 3, ..., n, n+1, ...

(d) Equation (10) is reduced using the IAGO to obtain the required forecasting model (Eq.(11)):

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), k=1, 2, \ldots \quad (11)$$

The discrete grey DGM (1,1): The DGM(1,1) model is often used to address problems involving uncertain information and small sample sizes. The DGM(1,1) model offers a distinct advantage over the GM(1,1) model in that it can accurately predict data series exhibiting exponential growth [64].

Suppose $X^{(0)}$ is a non-negative data series.

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots x^{(0)}(n)) \quad (12)$$

A single AGO is used to sum the established $X^{(1)}$. The following generating sequence is obtained:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots x^{(1)}(n)) \quad (13)$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k=2, 3, \ldots, n$$

From this, we have the formula:

$$x^{(1)}(k+1) = ax^{(1)}(k) + b \quad (14)$$

Equation (14) is the basic DGM (1,1). The least squares method along with the differential and difference equations are used to obtain parameters *a* and *b*.

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (15)$$

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

Suppose $x^{(1)}(1) = x^{(0)}(1)$, we have Eq. (16):

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{1-a}\right] a^k + \frac{b}{1-a} \quad (16)$$
$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), k = 1, 2, \ldots$$

Predictive accuracy measurement: The prediction error, defined as the estimated difference between actual values and predicted values generated by a forecasting model, serves as a crucial metric for assessing model performance [8]. Evaluating the prediction error is essential for determining the efficacy of a forecasting model. In this study, the mean absolute percentage error (MAPE) was employed to evaluate the accuracy of the forecasting models [21]. The error metrics for GM(1,1), NGBM(1,1), and DGM(1,1) are defined as follows:

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

where $x^{(0)}(k)$ is actual value, $\hat{x}^{(0)}(k)$ is predicted value, and n is the observation.

According to C.D. Lewis (1982) [22], lower error rates are indicative of higher accuracy. Therefore, MAPE values below 10% signify predictions with high predictive accuracy (Table 2).

Table 2. MAPE forecasting accuracy reference criteria.

Ranges of MAPE (%)	Forecasting accuracy
≤10	Superior
10-20	Good
20-50	General
≥50	Poor

4. Results and discussion

4.1. Situation of renewable energy consumption in Vietnam

Vietnam is among the countries most affected by climate change. Over the years, Vietnam has actively fulfilled its commitments under the 2030 Agenda for Sustainable Development and has participated in the Paris Agreement within the framework of the United Nations Framework Convention on Climate Change (UNFCCC). One of the key requirements for Vietnam, as part of its participation, is to promote a robust energy transition to reduce greenhouse gas emissions. Investment decisions and policies must be implemented to decarbonise the energy sector. Developing renewable energy sources is considered an inevitable global trend due to their significant contribution to reducing greenhouse gas emissions, protecting the environment, and decreasing dependence on fossil fuels. Additionally, as the quality of life improves, the demand for energy consumption increases. Continued dependence on fossil fuels will deplete resources and increase greenhouse gas emissions. Therefore, forecasting future demand for renewable energy will support the formulation of policies to effectively exploit and utilise renewable energy sources for sustainable development.

The demand for renewable energy, including solar power, wind power, geothermal energy, and hydropower, has generally increased both worldwide and in Vietnam over time. Data on per capita renewable energy consumption from 1965 to 2023 show a marked increase in renewable energy use beginning in the 2000s (Fig. 1). Globally, the United States and China are the countries with the highest growth rates in renewable energy. Vietnam is a country experiencing high economic growth, rising urbanisation, and industrialisation, leading to an increasing demand for energy consumption. With environmental protection policies and the goal of achieving net zero by 2050, the Vietnamese government has implemented various actions to improve the environment, with a focus on renewable energy development. Vietnam's renewable energy consumption in the period 2019 to 2023 peaked in 2022 at 341 TWh, before dropping to 309 TWh in 2023. It can be explained that in 2022, due to the full operation of solar and wind projects commissioned under Vietnam's FIT policies, post-pandemic economic recovery increased electricity demand, favorable hydropower output, and still-manageable grid congestion. After 2022, curtailment pressures and reduced new investments led to lower renewable energy consumption in 2023.

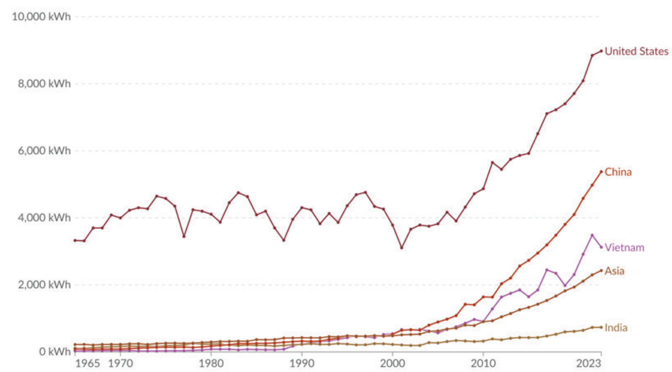

Fig. 1. Energy consumption from renewable sources from 1965 to 2023. Source: ourworldindata.org.

4.2. Predicting the value of renewable energy in Vietnam until 2030

The forecast for Vietnam's renewable energy consumption demand up to 2030, calculated using three grey forecasting models - GM(1,1), NGBM(1,1), and DGM(1,1) - is presented in Table 3. The results from the three models predict that Vietnam's renewable energy consumption will approximately double by 2030, reaching about 632.2 TWh according to GM(1,1), 602.5 TWh according to DGM(1,1), and 557.7 TWh according to NGBM(1,1).

MAPE (Mean absolute percentage error): The MAPE values for all models are below 10%, indicating a good fit and relatively accurate forecasts, as suggested by C.D. Lewis (1982) [22]. The MAPE values show that the GM(1,1) and DGM(1,1) models offer similar forecasting accuracy, while NGBM(1,1) performs slightly less well. Among these, DGM(1,1) yields the lowest MAPE (6.76%), suggesting it provides the most accurate prediction. The GM(1,1) model, due to its high accuracy (lower MAPE), is recommended for policymakers and stakeholders seeking reliable forecasts for planning renewable energy infrastructure and investment.

Table 3. Renewable energy consumption of Vietnam till 2030 (Terawatt-hours).

Year	Actual value	GM(1,1)	DGM(1,1)	NGBM(1,1)
2019	190	190	190	190
2020	223	246.8	243.8	205.5
2021	284	273.3	269.1	290.2
2022	341	302.7	297.1	329.5
2023	309	335.2	327.9	312.2
2024		371.2	361.9	357.7
2025		411.1	399.5	365.1
2026		455.3	440.9	405.4
2027		504.2	486.7	417.1
2028		558.4	537.2	459.5
2029		618.5	592.9	512.3
2030		632.2	602.5	557.7
MAPE (%)		6.88	6.76	7.2

Source: Results based on the author's calculation.

The results from this table suggest that renewable energy consumption in Vietnam is expected to continue growing over the next decade, with each of the three models predicting significant increases.

With the projected GDP growth target of 8% in 2025 and over 10% from 2026 to 2030, Vietnam's energy sector will face significant challenges in ensuring environmental protection and combating climate change. Fig. 2, based on the grey model results, indicates that the demand for renewable energy consumption is expected to increase substantially after 2025. Vietnam is prioritising renewable energy sources by increasing their share in the electricity mix, such as raising wind power from 1 to 22% (2020-2045), while reducing coal-fired power and hydropower from 29.6 and 30% (2020) to 18 and 9.3% (2045), respectively. However, to mitigate the risk of energy shortages and their impact on economic development, the structure of gas- and oil-fired power plants will be maintained, with their share increased to ensure effective supply to the national grid (rising from 13.1% in 2020 to 24% in 2045). During the period from 2021 to 2045, total investment in developing power sources is estimated to reach 5.27 trillion VND, with 2.97 trillion VND allocated for renewable energy sources. The government has increased the capital share for renewable energy in each period (from 44.4% in 2021-2025 to 70.9% in 2041-2045), with the largest investment package of 719 trillion VND allocated for the period 2030 to 2035.

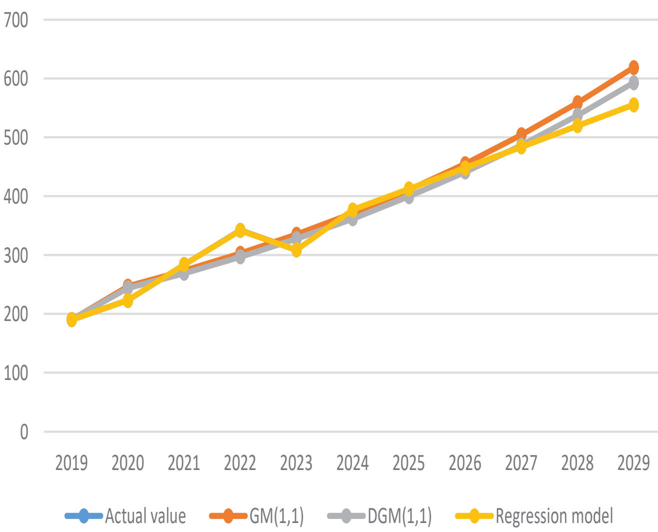

Fig. 2. Value prediction of renewable energy in Vietnam.

To effectively implement the Paris Agreement and advance its long-term climate strategy, Vietnam has issued a comprehensive plan for the period 2021-2030 aimed at reducing greenhouse gas emissions, particularly in the energy sector, which is projected to account for more than 70% of national emissions by 2030. In the Nationally Determined Contribution (NDC) submitted to the UNFCCC Secretariat in September 2020, Vietnam pledged to reduce total greenhouse gas emissions by 9% through domestic efforts, with the possibility of increasing this reduction to 27% conditional on international support. These commitments were further strengthened when Vietnam announced its ambition to achieve Net-Zero emissions by 2050 at the COP26, placing even greater emphasis on accelerating renewable energy development, improving energy efficiency, and reducing reliance on fossil fuels. As Vietnam continues to experience rapid economic growth and rising energy demand, promoting the sustainable transformation of the energy sector is essential not only for achieving climate goals but also for ensuring national energy security and social well-being. To this end, the government has fostered a favourable environment for domestic and foreign investment, encouraged technology transfer, and implemented policies to enhance energy conservation and efficiency-thereby supporting the country's transition toward a low-carbon, resilient, and sustainable energy system.

5. Conclusions

Vietnam's renewable energy consumption demand by 2030 shows that the demand for renewable energy will continue to increase with predictions around 632.2, 602.5 and 557.7 TWh in the GM(1,1), DGM(1,1), and NGBM(1,1), respectively. Among the models, DGM(1,1) achieves the most accurate predictions with the lowest MAPE (6.76%). Vietnam is striving to fulfil its commitment to phase out coal-fired power plants at the COP26 conference. In this context, participating countries will gradually eliminate coal-fired power plants, halt the construction of new plants both domestically and internationally, and expand clean energy. However, with the current high demand, Vietnam needs to make efforts to promote and harness renewable energy sources. Some key solutions to consider are as follows:

- It is essential to create a comprehensive legal framework. A Renewable Energy Law is crucial to enable favourable conditions for growth. Such legislation should aim to standardise technical regulations, ensure a transparent and competitive market, and uphold high standards in the operation and maintenance of all installations.

- Technological innovation in the renewable energy sector requires significant investment in research and development, particularly in the improvement and application of renewable energy technologies. Special attention should be given to the development of infrastructure and systems for the collection, treatment, and recycling of end-of-life solar panels and wind turbines to ensure environmental sustainability.

- It is necessary to adopt a rational and flexible energy strategy to adapt to the weather conditions and landscape of different regions of Vietnam. In the context of Vietnam, this necessitates the concurrent maintenance of conventional power generation systems to ensure a stable and reliable electricity supply.

- Finally, the introduction of effective electricity pricing mechanisms and investment guarantee policies is essential. This includes the adoption of feed-in tariff (FIT) schemes for grid-connected renewable energy projects, under which power companies are obligated to purchase all generated electricity through power purchase agreements. The associated costs should be integrated into the overall electricity pricing structure. Renewable energy projects should be granted priority access to the national grid, and the costs of the grid should be included in transmission and distribution fees.

Since Vietnam's renewable energy data remain limited with annual fluctuations influenced by policy changes, weather conditions, and grid congestion, this may reduce statistical reliability. The Grey model, while effective for small datasets, assumes relatively stable trends and therefore struggles to capture sudden policy shifts or market disruptions that commonly occur in Vietnam, which is rapidly transitioning in energy sector. In addition, the model's reliance on accumulated data smoothing may overlook short-term volatility caused by curtailment or irregular renewable output. Consequently, forecast results should be interpreted with caution, particularly in a dynamic policy and infrastructural environment like Vietnam.

COMPETING INTERESTS

The author declares that there is no conflict of interest regarding the publication of this article.

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