A Multicriteria Decision-Making Approach in Exploring the Nexus Between Wind and Solar Energy Generation, Economic Development, Fossil Fuel Consumption, and CO$_2$ Emissions

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Environmental degradation has been identified as a major worldwide concern in recent decades, with CO$_2$ emissions considered as one of the primary drivers of this catastrophe. This study creatively analyzes the underlying impact of wind and solar energy generation, economic development, fossil fuel consumption on CO$_2$ emissions to mitigate the environmental degradation in the world's top three largest energy consumers and CO$_2$ emitters nations namely, China, India, and the USA. To investigate the integrated impact of CO$_2$ emission, a grey relational analysis (GRA) technique is adopted for the year 1990–2017. The Grey technique for order of preference by similarity to ideal solution (G-TOPSIS) technique was employed for further optimization by prioritizing the explanatory factors that have potential influence on CO$_2$ emissions in the selected nations. The outcomes through the GRA technique discovered that India is a major contributor of carbon emission caused by economic development, and China appeared to be the more afflicted nation for raising its carbon emissions owing to fossil fuel consumption. Whereas, the generation of solar and wind energy are grounded factors in the reduction of carbon emissions for China and the USA. In addition, the generation of wind energy showed a considerable impact in the reduction of CO$_2$ emissions, based on the G-TOPSIS analysis. This suggests that reducing CO$_2$ emissions would require a compendious transition from nonrenewable to renewable resources, while the United States and China appear to be on a more promising direction to environmental sustainability than India. As a growing renewable energy pioneer, India should increase the utilization of minimal carbon sources of energy in its electricity grid while limiting its reliance on fossil fuels. The findings of the study potentially aid governments and policymakers in making better decisions and investments to mitigate CO$_2$ emissions while fostering a more environmentally friendly atmosphere.

Keywords: CO$_2$ emissions, grey relational analysis, G-TOPSIS, fossil fuel consumption, GDP per capita, wind energy, solar energy

INTRODUCTION

Fossil fuel combustion is widely regarded as a major contributor to climate change and global warming because carbon dioxide is emitted directly into the atmosphere, which causes global warming (IPCC Working Group et al., 2013). And this is a growing source of concern. While the atmospheric concentrations of carbon dioxide peaked in 2016, it was revealed that 2015, 2016, and 2017 were the three hottest years in human history (Yang et al., 2020). A growing percentage of these Greenhouse Gas (GHG) emissions now comes from emerging nations, necessitating the implementation of immediate energy regulatory measures (Liu et al., 2019). Likewise, low-carbon energy sources have sparked the interest of academics, enterprises, and industries throughout the world, with experts predicting that renewables will be the driving force behind long-term growth (Charfeddine and Kahia, 2019; Chien et al., 2021). Electricity generation is a major source of greenhouse gas emissions, which explains why this is the case (Pfeiffer and Mulder, 2013). As a result, renewable energy based on electricity would continue to expand primarily through solar, wind, biomass, hydro and geothermal, etc. (Xia and Wang, 2020). The Renewable Global Status Report has compiled a list of the world's top renewable energy investor economies (REN21, 2020). As a result, India, China, and the United States are among the world's leading renewable energy developers. China, India, and other emerging nations are deliberately embracing renewable energy technologies from developed countries, which is far from a coincidence. For three contradictory reasons, this study focuses on China, India, and the United States. They are the world's largest coal consumers, the world's top Greenhouse gas emitters, and the three potential leaders in renewable energy. In contrast, the upsurge of such economies is causing observable changes in the global economic system, necessitating more detailed analyses (Dechezleprêtre et al., 2011; Khattak et al., 2020; Ahmad M et al., 2020). Consequently, it appears to be true especially for India and China, who share important and unresolved socioeconomic traits that threaten US supremacy. According to the BRICS paradigm, India and China together accounts for 36% of the global population in 2019 due to massive infrastructural development and growing per capita income (Zakarya et al., 2015; Davis et al., 2018). To begin, India, China, and the United States are the world's top three black coal producers with 765 million tons, 3,683 million tons, and 685 million tons of coal in 2018 respectively (BSPR, 2018). Such economies continue to rely heavily on fossil fuels for energy for generating electricity, their energy decisions have a significant impact on global GHG emissions (Mahmoodi, 2017; Farhani et al., 2014; Khan et al., 2021). In 2017, coal accounted for 71% (India), 74% (China), and 30% (the USA) of the total energy generation, respectively (IEA, 2019a). In regards to the United States, we must recognize that coal-based electricity production has decreased in recent times, despite remaining relatively high (IEA, 2020). China and India, as the world's two largest rising economies, have seen significant economic development in the recent decade. Yet, this growth has indeed been associated with a substantial boost in their power consumption particularly power-based coal for industries, clearly making India and China, respectively, the world's top and fourth-biggest coal consumers (Sridhar, 2018; Fareed et al., 2020). As a result, unless substantial changes are made, emissions from India, China, and the United States are projected to continue to cause global warming, despite the fact that other parts of the globe are alarmed about the issue (Nathaniel and Iheonu, 2019; Rehman et al., 2019).

Second, being the world's largest emitters of air pollution, these three nations are important determinants of environmental change accounting for 29.3 percent (China), 13.7 percent (the USA), and 6.6 percent (India) of global carbon emissions in the year 2017. As a result, extensive environmental initiatives implemented in all of these three nations are likely to be highly effective (Wu et al., 2019; Shahbaz et al., 2020). This emission from fossil combustion in China have increased at an exponential rate, about 789 million tonnes of CO_2 in 1971 to 9,257 Mt/CO_2 in 2017. Likewise, in the United States, this metric increased from 4,289 Mt/CO_2 to 4,761 $MtCO_2$ during the same period. Finally, between 1971 and 2017, this was magnified 10 times in India, from 181 to 2,161 Mt/CO_2 (Sinha and Shahbaz, 2018; IEA, 2019b). Nonetheless, they are projected to significantly lessen their ecological influence in the future, despite their continued reliance on fossil fuels, these nations burned over 45 percent of global fuels in the year 2016 (Xia and Wang, 2020; Anser et al., 2020; Murshed, 2021). In spite of the Trump administration's withdrawal from the Paris Accord, several American states have proceeded to undertake green (Hildreth and Anderson, 2018). At the 2015 Paris Climate Change Conference, India and China, as members of the BRICS nations, confirmed their abatement objectives (Fareed et al., 2016; Haseeb et al., 2018). In actuality, they agreed to reduce intensity of GHG emissions by approximately 43–60% in 2030 (Bogner et al., 2008). Thirdly, these economies have moved to the top 3 worldwide competitors in installed renewable power generation and energy generation (especially wind, solar photovoltaic, and hydropower), according to the (IEA, 2018). Furthermore, by 2022, these nations will add up to two-thirds of worldwide renewable growth. This is not unexpected, given that increasing the percentage of clean energy technologies in the energy supply has been proven to be an effective strategy for reducing pollution while also generating large economic advantages (Rehman et al., 2020). Following President Xi Jinping's push for an "energy revolution," China's electrical industry has experienced significant changes. Between 2000 and 2018, China's renewable energy generation increased sevenfold: from 21,770 to 169,510 thousand tons of oil equivalent (ktoe). Looking at disaggregated figures, the wind has grown exponentially from 615–295,023 GWh in energy generation. Likewise, solar photovoltaic capacity has increased significantly since 2000, rising from 22 GWh in 2000 to 130,658 GWh in 2018. This is a pattern that is likely to prevail. China, as the world's largest renewable energy investor, will contribute 40% of global capacity increase by 2024 (Xu et al., 2020). In the United States, the energy policy environment has radically shifted during the last decade. Due to the rise of natural gas-powered generators, coal-based electricity

output has plummeted. Over the period 2000–2018, the percentage of renewable energy in electricity generation climbed from 8 to 17% (IPCC, 2019). Wind and solar PV have seen the most growth at the disaggregated energy level. In the case of India, the nation is coping with a surge in energy consumption, which is being driven by the country's significant population expansion (~1.36 billion people in 2019) and its rapidly expanding economy. To improve access to electricity for everyone, the government has been working hard for 2 decades to incorporate a major percentage of renewable sources of energy into the national power network (Vidyarthi and Mishra, 2020; Li et al., 2021). Renewable energy generation (wind, solar, and hydro) increased from 6,583 (ktoe) in 2000 to 19,662 (ktoe) in 2017. Moreover, in 2000, wind and solar photovoltaic generated 1,684 GWh and 2 GWh, respectively. India ranked sixth in the world in terms of solar photovoltaic capacity in 2018 (International Renewable Energy Agency, 2019). Due to support from the national and state government, solar photovoltaic production in India is predicted to exceed about 1×10^5 MW by 2022 (Muniyoor, 2020). As a labor-intensive industry, the renewable energy sector is predicted to provide more jobs globally, despite the fact that long-term employment creation growth in India is not assured (Reddy et al., 2020). Finally, improving renewables development across US, Indian, and Chinese domains is impossible without tackling a significant impediment. Globally, the absence of economic incentives, the significant startup costs, and inadequate return on medium-term renewable energy expenditures (particularly solar) (Karaeva et al., 2020; Shahzad et al., 2021). However, Elavarasan et al. (2020) found that problem of inadequate usage are two main impediments to renewable power in China, whereas the underexploited generating potential is expected to undermine hydropower and solar power implementation in the United States. Eventually, the literature highlights extreme challenges in India, such as a shortage of sustainable energy infrastructure along with appropriately qualified and competent staff (INCCA, 2010; Menyah and Wolde-Rufael, 2010; MoSPI, 2013; Wang and Feng, 2017).

Consequently, this research is motivated by the need to analytically validate the influence of economic variables on environmental degradation as assessed by CO_2 emissions for the top three biggest energy consumers and CO_2 emitters nations of the world namely, China, India, and the USA. Annual data from 1990 to 2017 are used for study objectives. Our analysis contributes to the present literature in terms of both empirically and methodologically. Theocratically, it seeks to assess the degree of proximity (closeness) of the selected factors with CO_2 emissions using an advanced mathematical grey relational analysis (GRA) model. Implementing the multicriteria decision-making (MCDM) approaches in this study will enable healthcare policymakers in making rational decisions on the best strategy to mitigate CO_2 emissions in the selected countries by focusing on the worse factors.

The contribution of this article is mirrored in the following three aspects. First, the grey relational analysis (GRA) i.e., Deng GRA, absolute GRA, and second synthetic (SS-GRA) are employed to demonstrate that it outperforms traditional
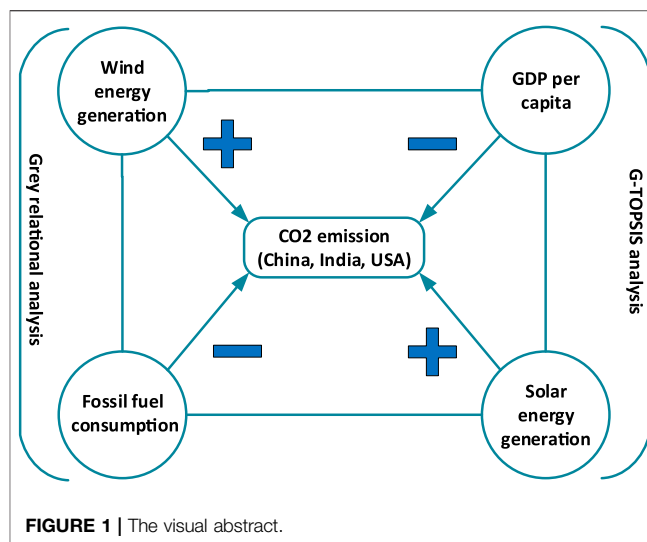

FIGURE 1 | The visual abstract.

statistical models. Traditional statistical models simply evaluate the relationship between two data sequences; they do not offer the degree of closeness (proximity). As a result, it is an excellent contribution to the current literature because GRA has an advantage over conventional techniques in that it not only provides the relationship between explanatory and response variables but also the degree of proximity (closeness). More extensively, the Deng GRA model explores the partial proximity of two data sequences, whereas A-GRA shows the integral proximity. While the SS-GRA approach incorporates the benefits of both Deng and absolute GRA models and illustrates inclusive proximity. Also, it provides a weighting scheme and ranking criteria, which is quite useful when several variables are included in the research with equal worth. Consideration of endogeneity concerns in the acquisition of carbon emission-related variables is the main contribution to this type of study. Secondly, a grey-based Technique for Order of Preference by Similarity to Ideal Solution (G-TOPSIS) has been deployed to identify the key influencing factor that intensifies the carbon emissions in the selected regions. The visual abstract of the study is presented in **Figure 1**.

MATERIALS AND METHODS

Data Source

Solar energy generation, wind energy generation, economic growth (in terms of GDP), consumption of fossil fuel, and environmental pollution (CO_2). The time period was determined by the availability of wind and solar data for each country, which covered different periods. This is because wind and solar development strategies in all three countries (India, China, and the United States) did not begin at the same time. As a result, we kept the dataset span consistent across all nations, i.e., 1990–2017. GDP data is accessed from the World Development Indicators (WDI) and is given in constant LCU (World Developement Indicator, 2019). Carbon emissions (CO_2)

TABLE 1 | Description of the study variables.

Variable	Measurement	Unit	Source
Wind energy generation	Renewable energy resource	Thousand tons of oil equivalent (Ktoe)	IEA
Solar energy generation	Renewable energy resource	Thousand tons of oil equivalent (Ktoe)	IEA
Fossil fuel consumption	Non-renewable energy resource	Thousand tons of oil equivalent (Ktoe)	IEA
GDP	Economic growth	Local currency unit (LCU)	WDI
CO_2 emissions	Environmental pollution	Thousand tons	IEA

from fuel-burning are used as an indicator for pollution in the environment. Pollution figures are presented in thousand tonnes and are based on the International Energy Agency's (IEA) CO_2 Emissions from Fuel Combustion Statistics (2019) (IEA, 2019a). In terms of energy variables, we employ fossil fuel consumption as well as wind and solar energy generation (thousands of tonnes of oil equivalent (ktoe)). Both sets of energy statistics are obtained via the IEA World Energy Statistics and Balances database (2019) (IEA, 2019b). The description of all the selected study variables is summarized in **Table 1**.

Grey System Theory

GRA methods are one of the core area subjects of the grey system theory (GST), introduced by Deng Julong, a Chinese scholar, in 1982 (Ng, 1994) to manage dubious systems with limited input. GST belongs to the category of uncertainty theories, that also incorporates rough set theory, fuzzy theory, interval theory, and other related theories. Additionally, GST, as led by its methodology, addresses the vulnerability in a manner distinct from previous vulnerability suppositions. The grey framework categorizes the world's systems into three different groups which are white, black, and grey. If there is no information provided it refers to black data. Whereas, if complete information is accessible, it is described as white data or structure. Thusly, a GS turns into a framework that is partially known and rather cryptic (Kalyon et al., 2018; Liu, 2018; Sun et al., 2020). The grey theory and related models are well-known for their potential to predict and develop choices based on smaller sample sizes, poor and inadequate data. The GRA models attempt to grasp unclear correlations between GST features. The implications of GST have been applied so far in various field successfully (Sallehuddin et al., 2008; Kalyon et al., 2018; Rehman et al., 2021b; Rehman E et al., 2021). The general concept behind GRA is the degree/intensity of proximity or closeness of the geometrical framework of the data series suggests that the structured parameters might be implemented to predict the proximity of a link among the system variables. This proximity is known as correlation in the literature. D-GRA, A-GRA, and SS-GRA are the three components of the GRA model. In essence, the D-GRA model assesses the effect of one variable reflected by a data series on the other. Whereas, the absolute GRA model evaluates the relationship between the two. Moreover, the second synthetic GRA model estimates an overall degree of the relationship among the parameters under consideration. A comprehensive review of GRA models can be found in the work of Liu Sifeng (Liu et al.,

2017). The algorithms involved with the grey methods are explained in the following sections.

Grey Relational Decision Analyses

Deng's GRA model was employed to measure the partial closeness (a measure of influence) of the selected variables, whereas the absolute GRA model was used to evaluate the integral closeness (degree of correlation) of the selected variables. The second synthetic GRA model was performed to obtain an overall estimate (weight) of inclusive proximity by accompanying the methods outlined in (Javed and Liu, 2018). The diagrammatic framework of the grey methodology is shown in **Figure 2**. The algorithms involved with the grey methods are explained in the following sections.

Deng's GRA Model

Let $Y_i = (y_{i(1)}, y_{i(2)}, \cdots, y_{i(m)})$ be the basic or reference data sequence addressing a dependent variable, whereas $Y_j = (y_{j(1)}, y_{j(2)}, \cdots, y_{j(m)})$ be the arrangement of comparative sequences addressing independent variables, in the wake of going through initialing operator then, at that point GRA, the real number degree addressing the output of GRA model, is depicted as γ_{ij} or $\gamma(Y_i, Y_j)$ and can be accompanied by:

$$\gamma(Y_i, Y_j) = \frac{1}{m} \sum_{h=1}^{m} \gamma(y_{i(h)}, y_{j(h)}) \qquad (1)$$

Where,

$$\gamma(y_{i(h)}, y_{j(h)}) = \frac{min_k min_h |y_{i(h)} - y_{j(h)}| + \zeta \, max_k max_h |y_{i(h)} - y_{j(h)}|}{|y_{i(h)} - y_{j(h)}| + \zeta \, max_k max_h |y_{i(h)} - y_{j(h)}|} \qquad (2)$$

Here, $\zeta \epsilon (0, 1)$ represent as a distinguishing coefficient, and its value is generally considered to be $\zeta = 0.5$. The implementation of the Deng GRA model for evaluating the effect of one parameter/variable over the other has been highlighted in the literature (Javed and Liu, 2018; Javed, 2019).

Absolute GRA Model

Let $Y_i = (y_{i(1)}, y_{i(2)}, \cdots, y_{i(m)})$ and $Y_j = (y_{j(1)}, y_{j(2)}, \cdots, y_{j(m)})$ be two data sequences denoting two variables linked to a system, then the algorithm to calculate the absolute GRA is listed below.

$$\epsilon_{ij} = \frac{1 + |r_i| + |r_j|}{1 + |r_i| + |r_j| + |r_i - r_j|},$$
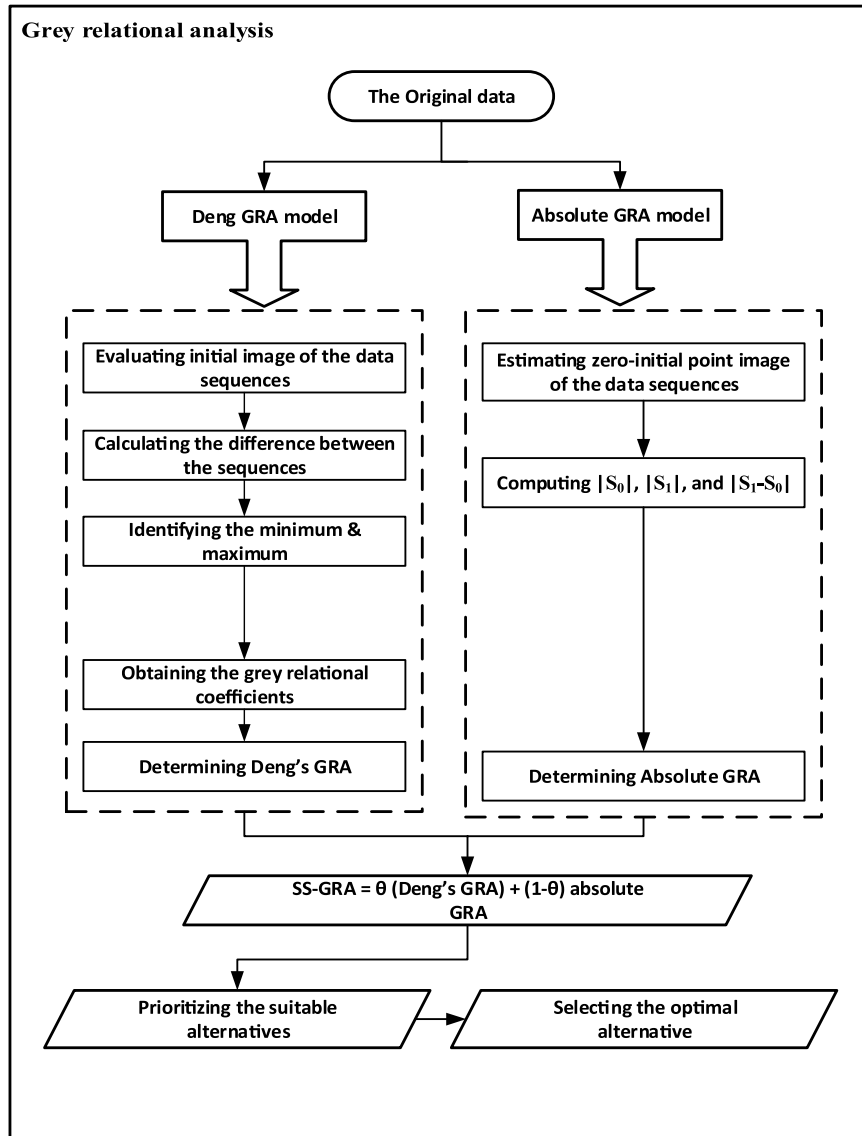
FIGURE 2 | Framework for the proposed grey methodology.

where, $r_i = \int_1^m Y_i^0 dt$, $r_j = \int_1^m Y_j^0 dt$, $r_i - r_j = \int_1^m \left(Y_i^0 - Y_j^0\right) dt$

$$Y_i^0 = \left(y_{i(1)}^0, y_{i(1)}^0, \cdots, y_{i(m)}^0\right)$$

$$Y_j^0 = \left(y_{j(1)}^0, y_{j(1)}^0, \cdots, y_{j(m)}^0\right)$$

$Y_{i(h)}^0 = y_{i(h)} - y_{i(1)}$ and $Y_{i(h)}^0 = y_{i(h)} - y_{i(1)}$ $h = 1, 2, \cdots, m$

Second Synthetic GRA Model

The second synthetic GRA model is an approach to estimate SS-GRA and can be acquired by utilizing the accompanying equation.

$$\mathscr{P} = \vartheta \epsilon_{ij} + (1 - \vartheta) \gamma_{ij} \quad \vartheta \in [0, 1]$$

where $'\mathscr{P}'$ stands for the SS-GRA, $'\epsilon'$ for the absolute GRA, and $'\gamma'$ for the Deng GRA between the two grey data sets Y_i and Y_j.

When a decision-maker desires a holistic assessment that evenly integrates the benefits of both $'\epsilon'$ and $'\gamma'$ without preferring one over the other we may keep ϑ at 0.5. In the case of preferring is fundamental, then, at that point, the value of $'\vartheta'$ can be adjusted. In the event that one desire to prefer $'\gamma'$, then $'\vartheta'$ can be diminished, and assuming one desires to prefer $'\epsilon'$, then $'\vartheta'$ can be increased. In the present investigation, we put $\vartheta = 0.5$. Furthermore, when the interactions within the frameworks/systems are ambiguous, it is likewise advised that the absolute GRA can be supplanted by the bidirectional absolute GRA (Javed, 2019). Deng's GRA is established on grey incidence/relational coefficients of specific points, while absolute GRA is based on an integral perspective, however, the SS-GRA is based on specific points and integral perspectives and shows overall proximity (closeness).

Grey Numbers

A grey number represents an interim with unspecified information but a well-defined range of possibilities which is depicted by a sign $\otimes$. In the GST, there are multiple forms of grey numbers; however, the present study introduces the following three forms (Rehman et al., 2021a):

Description 1: If $\otimes E$ represent a grey number whose lower limit can only be evaluated, it is termed a grey number with a lower limit only and is expressed as $\otimes E = [\underline{E}, \infty)$.

Description 2: If $\otimes E$ represent a grey number whose upper limit can only be evaluated, it is termed a grey number with an upper limit only and is expressed as $\otimes E = (\infty, \bar{E}]$.

Description 3: If $\otimes E$ represent a grey number whose lower and upper limit can only be evaluated, it is termed an interval grey number is expressed as $\otimes E = [\underline{E}, \bar{E}]$.

Let $\otimes E = [\underline{E}, \bar{E}]$ and $\otimes H = [\underline{H}, \bar{H}]$ are two Grey numbers, then arithmetic operations ought to be composed in the manner as follows:

$$\otimes E + \otimes H = [\underline{E} + \underline{H}, \underline{E} - \bar{H}] \quad (14)$$

$$\otimes E - \otimes H = \otimes E + (- \otimes H) = [\underline{E} - \bar{H}, \bar{E} - \bar{H}] \quad (15)$$

$$\otimes E \times \otimes H = [Min\{\underline{E}\underline{H} \ \bar{E}\bar{H} \ \bar{E} \ \underline{H}\underline{E} \ \bar{H}\} \ Max\{\underline{E}\underline{H} \ \bar{E}\bar{H} \ \bar{E} \ \underline{H}\underline{E} \ \bar{H}\}] \quad (16)$$

$$\frac{\otimes E}{\otimes H} = \otimes E \times \otimes H^{-1}$$
$$= \left[Min\left\{\frac{\underline{E}}{\underline{H}} \ \frac{\underline{E}}{\bar{H}} \ \frac{\bar{E}}{\underline{H}} \ \frac{\bar{E}}{\bar{H}}\right\}\right] Max\left\{\frac{\underline{E}}{\underline{H}} \ \frac{\underline{E}}{\bar{H}} \ \frac{\bar{E}}{\underline{H}} \ \frac{\bar{E}}{\bar{H}}\right\} \quad (17)$$

The length of the grey number $\otimes E = [\underline{E}, \bar{E}]$ is introduced by the following equation:

$$R(\otimes E) = \bar{E} - \underline{E} \quad (18)$$

If there are two Grey numbers $\otimes E = [\underline{E}, \bar{E}]$ and $\otimes H = [\underline{H}, \bar{H}]$, the degree of Grey synthetic assessment between these two numbers can be estimated utilizing **Eq. (19)**

$$P\{\otimes E \le \otimes H\} = \frac{Max\{0, R^* - Max(0, \bar{E}, \underline{H})\}}{R^*}, \ where$$
$$R^* = R(\otimes E) + R(\otimes H) \quad (19)$$

Grey TOPSIS Method

Huang and Yun proposed the TOPSIS idea in 1981, in which "n" alternatives are evaluated using "m" number of criteria. The TOPSIS method's main goal is to find +ve and −ve ideal solutions (variants) to a situation that have the greatest relative proximity to the pattern (+ve) and the least relative proximity to the anti-pattern (−ve). The +ve ideal solution portrays the raise in the response variable, while, the −ve ideal solution portrays the decline in the response variable. Since data is not always precise in reality, the GT is employed to account for ambiguities. As new techniques emerge, the TOPSIS method continues to evolve. We employed this approach in conjunction with grey numbers from grey system theory in the current investigation (GST). This technique is solved using the steps listed below (Ren et al., 2007; Tabor, 2019).

Stage-1: Initially, grey numbers with the accompanying values are assigned to verbal judgments of criteria significance by the decision makers: highly insignificant [0.0, 0.2], insignificant [0.2, 0.4], moderately significant [0.4, 0.6], significant [0.6, 0.8], highly significant [0.8, 1.0] (Mahmoudi et al., 2019).

Stage-2: We use the arithmetic mean technique to aggregate the results after determining the level of significance of the decision-making criteria (h) by assuming the number of decision-makers as p:

$$\otimes w_h = \frac{1}{p}[\otimes w_h^1 + \otimes w_h^2 + \cdots + \otimes w_h^p], \ where:$$
$$\otimes w_h^p = [\underline{w}_i^p, \bar{w}_h^p] \quad (20)$$

Stage-3: To establish the state of each of the criteria, the linguistic variables ought to be employed. The score of alternative k in the criteria h is determined by the accompanying relation, presuming that the frequency of decision-makers is p:

$$\otimes R_{kh} = \frac{1}{p}[\otimes R_{kh}^1 + \otimes R_{kh}^2 + \cdots + \otimes R_{kh}^p] \quad (21)$$

where; $\otimes R_{kh}^p$, $(k = 1, 2, \cdots, n; h = 1, 2, \cdots, m)$ is an estimation of the criterion by the pth decision-maker, which is displayed in a structure by a grey number: $\otimes R_{kh}^p = [\underline{R}_{kh}^p, \bar{R}_{kh}^p]$.

Stage-4: In the fourth stage, constructing the grey decision matrix in the following structure:

$$R = \begin{bmatrix} \otimes R_{11} & \otimes R_{11} & \cdots & \otimes R_{1m} \\ \otimes R_{21} & \otimes R_{11} & \cdots & \otimes R_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes R_{n1} & \otimes R_{n2} & \cdots & \otimes R_{nm} \end{bmatrix} \quad (22)$$

Stage-5: Established the normalized grey decision matrix in the accompanying structure:

$$R^* = \begin{bmatrix} \otimes R_{11}^* & \otimes R_{12}^* & \cdots & \otimes R_{1m}^* \\ \otimes R_{21}^* & \otimes R_{22}^* & \cdots & \otimes R_{2m}^* \\ \vdots & \vdots & \ddots & \vdots \\ \otimes R_{n1}^* & \otimes R_{n2}^* & \cdots & \otimes R_{nm}^* \end{bmatrix} \quad (23)$$

If the variable attribute is beneficial, the normalization equation is as follows:

$$\otimes R_{kh}^* = \left[\frac{\underline{R}_{kh}}{R_h^{max}}, \frac{\bar{R}_{kh}}{R_h^{max}}\right], \ and \ R_h^{max} = \max_{1 \le k \le m}\{\bar{R}_{kh}\} \quad (24)$$

And, on the off chance that the variable attribute is non-beneficial, the data is normalized using the accompanying equation.

$$\otimes R_{kh}^* = \left[\frac{\underline{R}_{kh}}{R_h^{min}}, \frac{\bar{R}_{kh}}{R_h^{min}}\right], \ and \ R_h^{min} = \min_{1 \le k \le m}\{\bar{R}_{kh}\} \quad (25)$$

The grey matrix's range will remain within $[0, 1]$ after normalization.

Stage-6: Assemble the weighted normalized grey decision-making matrix in the accompanying structure:
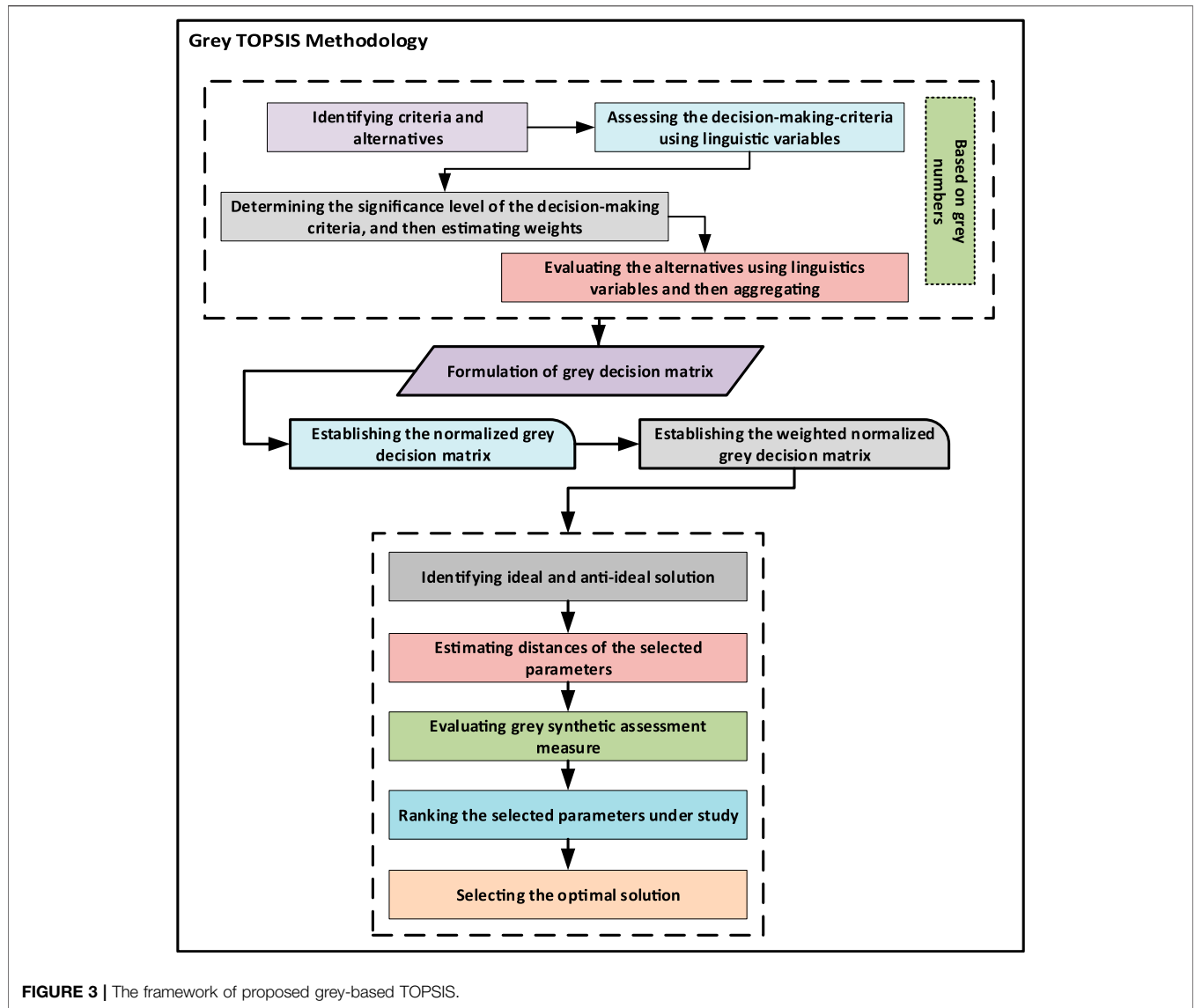
FIGURE 3 | The framework of proposed grey-based TOPSIS.

TABLE 2 | Grey relational assessment for wind energy generation and CO_2 emission.

Nation	Deng GRA (Partial proximity)	Absolute GRA integral proximity)	Second synthetic GRA (inclusive proximity)	Rank
China	0.9865	0.9903	0.9884	1st
India	0.7388	0.7428	0.7408	3rd
USA	0.8533	0.8597	0.8565	2nd

TABLE 3 | Grey relational assessment for GDP per capita and CO_2 emission.

Nation	Deng GRA (Partial proximity)	Absolute GRA (integral proximity)	Second synthetic GRA (inclusive proximity)	Rank
China	0.8606	0.8690	0.8648	3rd
India	0.9143	0.9261	0.9202	1st
USA	0.8774	0.8836	0.8805	2nd

TABLE 4 | Grey relational assessment for fossil fuel consumption and CO_2 emission.

Nation	Deng GRA (Partial proximity)	Absolute GRA (integral proximity)	Second synthetic GRA (inclusive proximity)	Rank
China	0.9592	0.9634	0.9613	1st
India	0.9020	0.9140	0.9080	2nd
USA	0.8765	0.8811	0.8788	3rd

TABLE 5 | Grey relational assessment for solar energy generation and CO_2 emission.

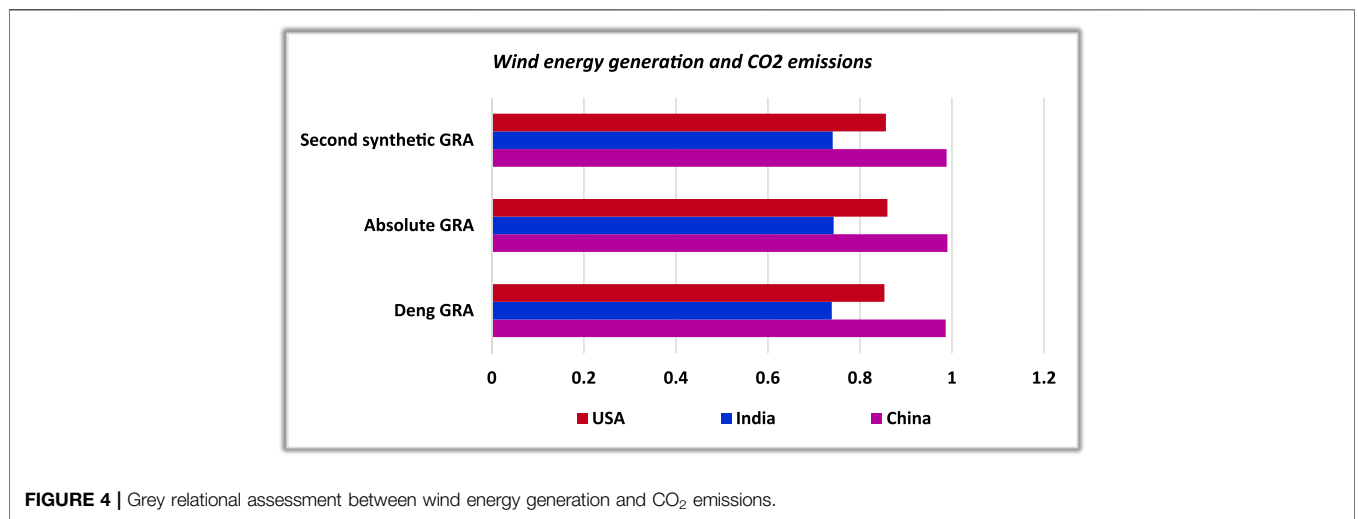| Nation	Deng GRA (Partial proximity)	Absolute GRA integral proximity)	Second synthetic GRA (inclusive proximity)	Rank
China	0.8603	0.8815	0.8709	1st
India	0.6800	0.7206	0.7003	3rd
USA	0.7599	0.7815	0.7707	2nd

FIGURE 4 | Grey relational assessment between wind energy generation and CO_2 emissions.
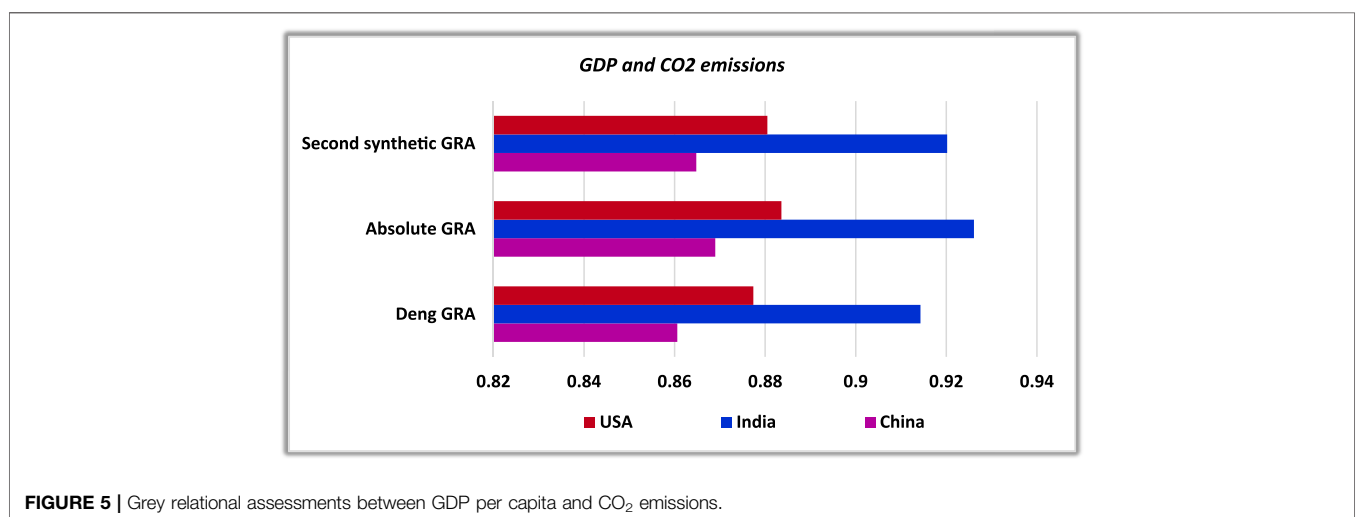

FIGURE 5 | Grey relational assessments between GDP per capita and CO_2 emissions.
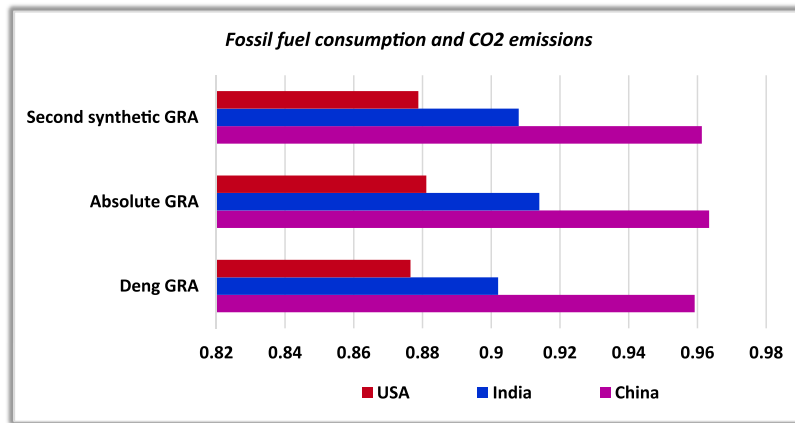
FIGURE 6 | Grey relational assessment between fossil fuel consumption and CO_2 emissions.

$$R^*_\omega = \begin{bmatrix} \otimes C_{11} & \otimes C_{12} & \cdots & \otimes C_{1m} \\ \otimes C_{21} & \otimes C_{22} & \cdots & \otimes C_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes C_{n1} & \otimes C_{n2} & \cdots & \otimes C_{nm} \end{bmatrix}, \; where;$$

$$\otimes C_{kh} = \otimes R^*_{kh} \times \otimes \omega_h \qquad (26)$$

Stage-7: Determine the ideal solution based on the assumption that given the set of "n" prospective alternatives $V = \{V_1, V_2, V_3, \cdots, V_n\}$, pattern V^{max} should be identified as follows:

$$V^{max} = \{\otimes C_1^{max}, \otimes C_2^{max}, \cdots, \otimes C_m^{max}\} \qquad (27)$$

where, $V^{max} = \{[\max\limits_{1\le k\le n} \underline{C}_{k1}, \max\limits_{1\le k\le n} \bar{C}_{k1}], [\max\limits_{1\le k\le n} \underline{C}_{k2}, \max\limits_{1\le k\le n} \bar{C}_{k2}], \cdots,$
$[\max\limits_{1\le k\le n} \underline{C}_{kn}, \max\limits_{1\le k\le n} \bar{C}_{kn}]\}$

Stage-8: Determine the anti-ideal solution based on the assumption that given the set of "n" prospective alternatives $V = \{V_1, V_2, V_3, \cdots, V_n\}$, anti-pattern V^{min} should be identified as follows:

$$V^{min} = \{\otimes C_1^{min}, \otimes C_2^{min}, \cdots, \otimes C_m^{min}\} \qquad (28)$$

where, $V^{min} = \{[\min\limits_{1\le k\le n} \underline{C}_{k1}, \min\limits_{1\le k\le n} \bar{C}_{k1}], [\min\limits_{1\le k\le n} \underline{C}_{k2}, \min\limits_{1\le k\le n} \bar{C}_{k2}], \cdots,$
$[\min\limits_{1\le k\le n} \underline{C}_{kn}, \min\limits_{1\le k\le n} \bar{C}_{kn}]\}$

Stage-9: Estimate the distances between the alternatives under consideration, as well as the ideal (V^{max}) and anti-ideal (V^{min}) solutions, employing the following formulas:

$$D_h^+ = \sum_{h=1}^{m} D(C_{kh}, C_h^{max}), \; and \; D_h^- = \sum_{h=1}^{m} D(C_{kh}, C_h^{min}) \; for \; h$$

$$= 1, 2, \cdots, m; \qquad (29)$$

where, $D(\otimes C_A, C_B) = \sqrt{\frac{1}{2}[(\underline{C}_A - \underline{C}_B) + (\bar{C}_A - \underline{C}_B)]}$

Stage10: Create a synthetic assessment metric for variations D_k based on the relative proximity of variant evaluations to the ideal and anti-ideal solutions:

$$D_k = \frac{D_k^-}{D_k^+ + D_k^-}, \; k = 1, 2, 3, \cdots, n \qquad (30)$$

The closer the value of the measure is to one, the minimal the interval of the assessment of the variant away from the ideal solution (D_k^+), and, simultaneously, the maximum the interval away from the anti-ideal solution (D_k^-).

Stage-11: Then, in decreasing order, generate a rating for "n" alternatives based on linear streaming synthetic assessment metrics. The alternative with the lowest degree of grey synthetic evaluation will end up contributing more adversely to the response variable, whereas, alternative with the highest degree of grey synthetic evaluation will end up contributing positively to the response variable. The diagrammatic view of the G-TOPSIS methodology is presented in **Figure 3**.

RESULTS

The present research utilized grey relational techniques to estimate the degree of proximity between solar energy generation, wind energy generation, economic growth, fossil fuels consumption, and carbon (CO_2) emissions among China, India, and the USA for the years 1990–2017. **Table 2–5** demonstrates the findings of the grey relational models, namely, the Deng GRA, absolute GRA, and the SSGRA for CO_2 emissions for each selected variable. The absolute GRA and the SS-GRA models have values ranging from [0, 1]. Whereas, Deng GRA has values in the range of [0.5–1]. If it is close to 1, it is regarded as potentially associated and if diverges from 1, considered to be weak. While, **Figures 4–7** show a graphical representation of the proximity between the studied variables based on GRA findings.

Wind energy generation: In the present analysis, as indicated by Deng GRA model findings (**Table 2**), a more grounded measure of influence (partial proximity) between wind energy generation and carbon emission (0.9865:1st) is observed in China whereas, a most fragile connection (integral proximity) is seen for
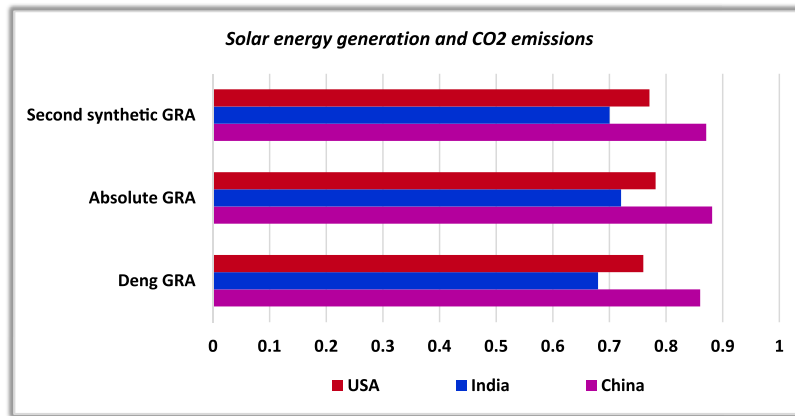
FIGURE 7 | Grey relational assessment between solar energy generation and CO_2 emissions.
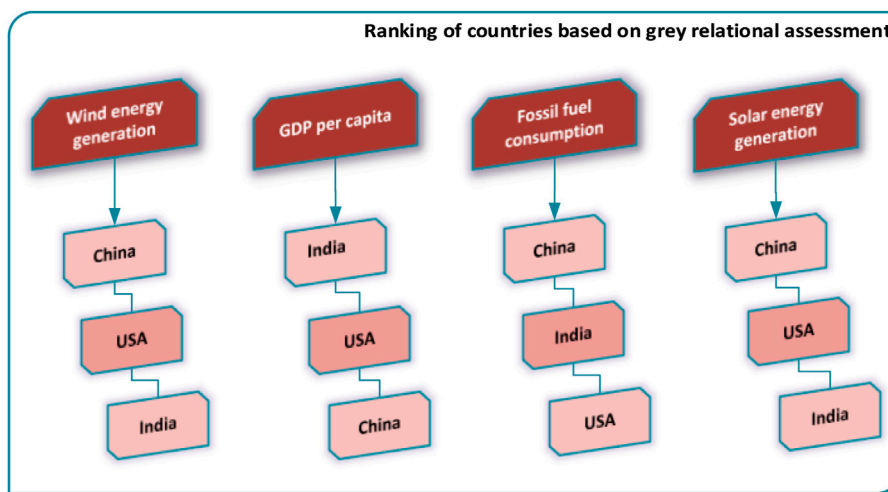

FIGURE 8 | Ranking sequences of selected nations based on GRA modeling.

India (0.7388:3rd). The higher measure of the influence of wind energy generation on CO_2 emission portrays that the factors are unequivocally interconnected with one another. Then again, the same succession showed up from the findings of the absolute GRA model. The degree of inclusive proximity (strength of association) is found much higher for China with an estimated weight of 0.9903. At a more aggregate level, as per SS-GRA findings, wind energy generation is distinguished as the major contributor in reducing carbon emission when compared with solar energy generation in China. After China, the USA appeared to be more influenced by wind energy generation in mitigating carbon emission with an estimated grey degree of 0.8565.

GDP per capita: Considering the impact of economic development on CO_2 emission, all selected nations sustained their ranking order across all grey incidence models; however, the degree of proximity (closeness) was determined to be greater for India. As per Deng GRA estimates, carbon emission tends to be

more strongly influenced by economic growth in India (0.9143) when compared with China (0.8606) and the USA (0.8774). Nonetheless, as per absolute GRA model findings, the measure of association is observed much higher in India with a grey degree of 0.9261 due to economic growth. Overall, the degree of proximity between CO_2 emission and GDP per capita was observed exceptionally high in India trailed by the USA and China with an estimated weight of 0.9202, 0.8805, and 0.8648 respectively. Broadly speaking, GDP per capita had all the earmarks of being a potential factor in raising CO_2 emission in India when compared with the USA and China (**Table 3**).

Fossil fuel consumption: China is distinguished as the most grounded contributor of carbon emission among the selected countries due to fossil fuel consumption with an estimated weight of 0.9592, though the least influence is seen with the USA (0.8765) under Deng GRA model results. In addition, the degree of integral closeness for China (0.9634) is found exceptionally high as

TABLE 6 | Formation of a grey decision matrix to identify the potential factor.

	China	India	USA
Normalized grey decision matrix			
Wind energy generation	[0.28, 1.00]	[0.41, 0.91]	[0.65, 1.00]
GDP per capita	[0.42, 0.86]	[0.20, 0.72]	[0.22, 0.52]
Fossil fuel consumption	[0.16, 0.49]	[0.11, 0.69]	[0.31, 0.83]
Solar energy generation	[0.21, 0.66]	[0.35, 0.85]	[0.51, 1.00]
Weighted normalized grey decision matrix			
Wind energy generation	[0.087, 0.540]	[0.045, 0.446]	[0.137, 0.650]
GDP per capita	[0.130, 0.464]	[0.022, 0.353]	[0.046, 0.338]
Fossil fuel consumption	[0.050, 0.265]	[0.012, 0.338]	[0.065, 0.540]
Solar energy generation	[0.065, 0.356]	[0.039, 0.417]	[0.107, 0.652]
Ideal and anti-ideal patterns			
Ideal	[0.130, 0.540]	[0.045, 0.446]	[0.137, 0.652]
Anti-ideal	[0.050, 0.265]	[0.012, 0.338]	[0.046, 0.338]

TABLE 7 | Estimated distances from the ideal and anti-ideal pattern.

	China	India	USA
D^+			
Wind energy generation	0.022	0.000	0.001
GDP per capita	0.038	0.058	0.189
Fossil fuel consumption	0.178	0.071	0.092
Solar energy generation	0.125	0.018	0.015
D^-			
Wind energy generation	0.161	0.071	0.202
GDP per capita	0.140	0.013	0.000
Fossil fuel consumption	0.000	0.000	0.111
Solar energy generation	0.053	0.053	0.188

compared to the USA (0.8811) and India (0.9140) for absolute GRA findings. Notably, with the SS-GRA model, China (0.9613) kept up with its position and ranked first among all selected nations, portraying that fossil fuel consumption is profoundly persuasive in raising carbon emission, trailed by India (0.9080) and the USA (0.8788) (**Table 4**).

Solar energy generation: According to GRA findings (**Table 5**), China (Deng GRA:0.8603, absolute GRA:0.8815, SS-GRA:0.8709, rank:1st) has the high proximity between solar energy generation and CO$_2$ emission trailed by USA (Deng GRA:0.7599, absolute GRA:0.7815, SS-GRA:0.7707), whereas the weakest proximity is observed for India (Deng GRA:0.6800, absolute GRA:0.7206, SSDGIA:0.62450, rank:3rd), and all countries sustained their position under all grey incidence models. Altogether, the estimates from the SS-GRA model uncover that among all three countries, China appears to be the main country where

solar energy generation is observed highly linked with CO$_2$ emission. The findings show that solar energy generation is contributing to reducing carbon emissions in China when compared to India and the USA.

The GRA findings are depicted graphically in **Figure 8** in descending order. The graph depicts a ranking sequence of the studied nations based on each explanatory variable separately. The weights calculated by GRA models (shown in **Tables 2–5**) are used to establish a ranking pattern.

G-TOPSIS Analysis

For this subsection, we implemented G-TOPSIS to measure and provide a ranking order to the intensity of the explanatory variables (wind energy generation, GDP per capita, fossil fuel consumption, solar energy generation) on carbon emission for all the selected countries. Based on expert opinion, we first constructed an initial grey decision matrix for all studied explanatory variables using **Eqs 20, 21**. We transformed the decision matrix into grey numbers through linguistic variables and we then built a standardized grey decision matrix against each of the explanatory factors across all countries, independently (using **Eq. 22**). After evaluating the weights for each criterion (countries), we then built a weighted normalized grey decision matrix using equation using **Eqs 24, 25**. Next, we determined the patterns for the ideal and anti-ideal solutions using **Eqs 27, 28**. All these findings are summarized in **Table 6**.

Using **Eq. 29**, we computed distances of the alternatives (wind energy generation, GDP per capita, fossil fuel consumption, solar energy generation) from ideal and anti-ideal patterns against each criterion (countries) and results are presented in **Table 7**.

Based upon distances calculated in **Table 7**, we established grey synthetic assessment measures of the factors (wind energy generation, GDP per capita, fossil fuel consumption, solar energy generation) for carbon emissions in the selected countries and then created a ranking pattern in descending order which can be seen in **Table 8**. The graphical representation of grey based TOPSIS assessment can be seen in **Figure 9**.

The variable with the least value of G-TOPSIS evaluation will contribute more negatively to the response variable which is carbon emissions, whereas the variable with the maximum value of G-TOPSIS evaluation will contribute more positively to the response variable. Therefore, it is reasonable to conclude that fossil fuel consumption (0.25) appeared as the worst factor in accelerating carbon emission in the selected countries followed by GDP per capita (0.35). Whereas, wind energy generation (0.95) contributes emphatically to reducing carbon emission in the selected countries led by solar energy generation (0.65).

TABLE 8 | Estimated grey degree of synthetic assessment.

Parameters	$\sum D_k^+$	$\sum D_k^-$	$\sum D_k^+ + \sum D_k^-$	$D(A_h) = \frac{\sum D_k^-}{\sum D_k^+ + \sum D_k^-}$	Optimal solution
Wind energy generation	0.023	0.434	0.457	0.95	
GDP per capita	0.285	0.153	0.438	0.35	
Fossil fuel consumption	0.341	0.111	0.452	0.25	Min
Solar energy generation	0.158	0.294	0.452	0.65	
Ranking sequence	Wind energy generation > Solar energy generation > GDP per capita > Fossil fuel consumption				

FIGURE 9 | The G-TOPSIS assessment.
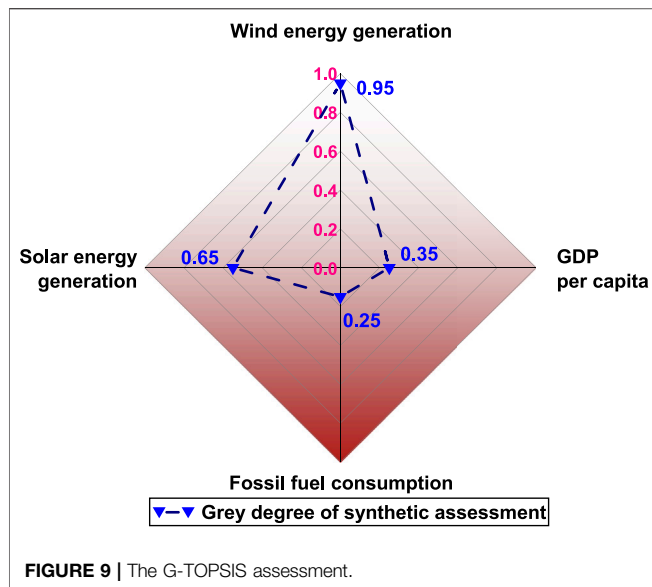
DISCUSSION AND CONCLUSION

In terms of environmental degradation, the most important environmental challenge confronting the globe today is climate change, with over usage of conventional fossil fuels regarded as the root cause of the problem. According to this preliminary research, environmental improvement and economic growth are inconsistent since economic growth is achieved at the price of environmental degradation. As a result, environmentally acceptable techniques are required to meet the societal goals of regulating carbon emissions while allowing economic expansion to proceed. Adequate policies are those that provide incentives for enhancing efficiency and productivity or for deploying pollution-reduction technologies. Certain sustainable development theories contend that a lack of critical environmental protection rules and regulations accelerates the degradation process. Hence, the present study takes a step forward in evaluating the degree of proximity (closeness) between wind energy generation, GDP per capita, fossil fuel consumption, and solar energy generation with carbon emissions among the top three biggest energy consumers and CO_2 emitters nations of the world (China, India, and the USA) utilizing time series data for the period 1990 to 2017. The research has been carried out using three grey relation models i.e., Deng GRA, absolute GRA, and second synthetic GRA models which may be implemented as a viable alternative to conventional data analysis approaches. According to GRA's results, China and India appeared as the biggest emitter of CO_2 emissions in terms of fossil fuel consumption and economic development, respectively. Whereas, in terms of renewable energy consumption, China ranked top among all selected nations, followed by USA and India. To manage such emissions that have negative effects on environmental degradation and economic development, China and India must put up several measures to restrict the utilization of fossil fuel consumption for their energy demand. While China's energy use plays a vital role, its energy consumption needs to be sustained to minimize emissions and therefore, lessen

environmental damage. The obvious low cost of conventional fossil resources and China's fossil fuel-dominated energy endowments have provoked China to burn a considerable amount of coal. This scenario is not only hampering China's low-carbon economy but can also impede the technological advancement of renewable energy (Wang et al., 2020; Xu and Lin, 2021). Technological innovation is a driving force in the advancement of renewable energy (Xin-gang and Wei, 2020). Despite recent significant advancement in China's renewable energy technology, however, there is a synergic link between the emissions of CO_2 and advancement level, demonstrating that massive carbon emissions have facilitated renewable energy technological innovation (Lei et al., 2021). Renewable energy development is critical to China's energy safety and autonomy, and climate mitigation (Chen et al., 2019; Ahmad F et al., 2020; Godil et al., 2021).

In case of India, the present research discovered that when assessing the effect of GDP on carbon emissions among the selected nations, India came out on top, and under G-TOPSIS analysis, fossil fuel consumption appeared to be a strong influencing factor when compared to GDP. This implies that the use of fossil fuels is a greater risk factor for environmental degradation, while green energy generation, particularly wind energy generation, is more effective at mitigating the effects of carbon emissions. Our findings are consistent with previous studies that found a strong positive effect of renewable resources on environmental quality (Balsalobre-Lorente et al., 2018; Shahzad et al., 2021). Because of its fast-growing status, the Indian economy is heavily reliant on energy consumption. India requires more energy to achieve growing production demands and ensure long-term economic development (Ahmad et al., 2016; Sinha and Shahbaz, 2018; Fareed et al., 2018). Policymakers should take into account disaggregated sources of energy in order to establish a strategy for the best mix of energy sources to strengthen environmental quality without compromising economic growth. Pollution has a negative impact on public health. By identifying a substitute for fossil fuel emissions, the Indian government could perhaps attain its objective of optimum economic growth with minimal carbon emissions. According to the analysis, wind energy generation is more beneficial in terms of strengthening environmental quality since it emits fewer pollutants into the environment than other non-renewable resources.

On a broad level, this finding would emphasize the need for policymakers participating in the energy sector by harnessing clean energy resources to meet an increasing requirement for energy fluctuations by changes in economic output. It is clearly defined and depicted by the present analysis, that the fossil fuel explanatory variable is the principal driver of carbon emissions in China and India. However, we discovered that even green energy technology, especially wind and solar are trending towards a direction signalized by carbon emissions in India. Based on the study outcomes, policy suggestions can be offered. First, because fossil fuel utilization is a significant contributor to carbon dioxide emissions in all three economies, governments might have to reinforce sustainable energy subsidies with additional measures aimed at lowering power-based fossil fuel consumption. This may

be accomplished, in particular, by strict fossil-based energy conservation regulations or additional energy-efficiency initiatives. Besides, despite increased expenditures in the wind and solar energy, these sources of energy (particularly wind) may become increasingly significant in the energy portfolio. However, nonrenewable fuels continue to dominate their respective proportions, and more regulations promoting low-carbon energy alternatives are recommended. Third, the government should supervise and assist businesses in their technological innovation efforts, as well as expand the volume of technology expenditures. The fact that CO_2 emissions have a beneficial influence on technical innovation suggests that renewable technologies are proactively responding to changes in the climate. The policy implications suggest that we must recognize the significance of renewable energy technology innovation in carbon emissions mitigation, and monetary assistance is essential to increase the level of innovation. On the other hand, the significance of the energy pricing system in fostering technological innovation must be gradually rationalized. Technological innovation is critical in promoting the expansion of renewable energy.

The present investigation only includes the top three nations responsible for carbon dioxide emissions, which limits the scope of the investigation. For further research, it is advised that more nations and other economic variables influencing CO_2 emissions to be investigated. Furthermore, it is vital to broaden the study by investigating the impact of COVID-19 on energy demand transitions. Evidence suggests that when industries closed, energy use reduced swiftly, but air traffic and public transportation usage decreased significantly. However, the use of surgical masks and their massive manufacture might have severely negative environmental consequences. As a result, we anticipate that the data's expansion will address these concerns in depth.

DATA AVAILABILITY STATEMENT

The data used to support the findings of this study are included within the article.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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