Mathematical Modeling to Anticipate the Global Growth Trends of Renewable Energy

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Abstract
Energy is prerequisite for the competitive economic growth or for the livelihoods of the increasing population of any nation but around 80% percent of the energy comes from fossil fuel which creates many environmental hazardous. The renewable energy which can save the planet is still a far cry. In this paper different models were analyzed to forecast the growth rate of renewable energy. To forecasting the trends, wide-range of data is not suitable always for prediction. The most latest only 20 years of data is considered for the analysis here in order to get the exact scenarios of the trends. Four models GM(1,1), NGBM(1,1), Holt's, Nonlinear Regression were analyzed here and compare their accuracy. By the Mean Absolute percentage Error (MAPE) method the accuracy and fitness were justified. This study reveals that among all the above four models the nonlinear regression model shows the highest accuracy which is 1.3%, and next grey model with 2.96% accuracy. From the nonlinear regression model it is predicted that 52% energy may come from renewable sources by 2035.

Key Words: Grey Model, Renewable energy, Fossil fuel, Forecasting, Mathematical model.

I. INTRODUCTION

There is no alternative but renewable energy to save the globe. The production of excessive fossil fuel which discharges huge green house gases (GHG) is responsible for rising the temperature of the globe. Besides this, the dependence on traditional energy definitely will deepen the crisis of future energy. Renewable energy is the solution of future energy crisis as it mitigates the climate change impacts by reducing the emissions of green house gases (GHG) to the atmosphere [1-3], as well as it is cost effective [4-5]. Despite many advantages of renewable energy such as environment friendly, job creation, economical benefit, reduction of excessive dependence on fossil fuel; the space of using the non-fossil fuel is not significant. According to the Paris Agreement, the rise of temperature should be well below 2^0 C preferably 1.5^0 C above the industrial level [6] by the end of this century; to achieve this goal net –zero emissions is mandatory by this time. Fossil fuel is mainly responsible for these emissions along with deforestation, agricultural activities [7].

Scientists, environmentalists and policy makers appealing to all the nations, stake holders to stop the further investment in traditional energy. Despite all these scenarios the share of renewable energy will be 36% of total energy by 2030[8].

II. METHODOLOGY

Here existing 20 years of data is considered for predicting next 15 years. Data source is our world in data. Four models, Grey Model GM(1,1), Nonlinear Grey Bernoulli Model NGBM (1,1) model, Nonlinear Regression Analysis are used for predicting the trends. Excel and MATLAB were used for computing the parameters and solving the equations.

A. GM (1,1) Model

In present days grey model GM(1,1) is widely used in many fields for predicting such power, CO_2 emissions in the atmosphere, climate forecasting etc. This model is popular as only a handful of data can predict significantly other then probability, fuzzy logic etc. In grey analysis two methods were applied for increasing the similarity and to raise the regularity of data. For Accumulated Generation Operation (AGO) a fresh sequence is formed by accumulating the data as in the given series. Inverse Accumulated Generation Operation (IAGO) which is actually opposite of previous AGO as this is a series of difference between 1st and last datum.

In fact, the GM(1,1) model is a 1st order differential equation that have one independent variable.

The data series is

$$P^{(0)} = \{P^{(0)}(1), P^{(0)}(2), \dots \dots \dots \dots \dots P^{(0)}(n)\} \qquad (1)$$

Adding together with one AGO the sequence is

$$P^{(1)} = \{P^{(1)}(1), P^{(1)}(2), \dots \dots \dots \dots \dots P^{(1)}(n)\} \qquad (2)$$

$$X^{(1)}S = \sum_{i=1}^{k} X^{(0)}(i),\ S = 1,2,3 \dots \dots \dots .\, n \qquad (3)$$

In GM(1,1) the 1st order differential equation is in the following form [9]

$$\frac{dP^{(1)}}{dt} + aP^{(1)} = b \qquad (4)$$

The derivative of the above equation is as follows

$$\frac{dP^{(1)}}{dt} \cong \frac{P^{(1)}(S+\Delta t) - P^{(1)}}{\Delta t} \qquad (5)$$

$\Delta t = 1$ leads to

$$\frac{dP^{(1)}}{dt} \cong P^{(1)}(S + \Delta t) - P^{(1)} = P^{(0)}(S) \qquad (6)$$

Moreover, $P^{(1)} \cong Z^{(1)}$

$$Z^{(1)}(S) \cong \frac{P^{(1)}(S) + P^{(1)}(S+1)}{2}, S = 2,3,4 \dots \dots, n \qquad (7)$$

Equation (4)-(7) gives that

$$P^{(0)}(S) + aZ^{(1)} = b \qquad (8)$$

(d) Applying the least square method and differential and difference equations to have two unknowns a, b. We assume

$$\theta = [a, b]^T = (B^T B)^{-1} B^T Y, Y = B\theta \qquad (9)$$

$$Y = \left[P^{(0)}(2), P^{(0)}(2), \dots\ P^{(0)}(n)\right]^T \qquad (10)$$

$$B = \begin{bmatrix} -\frac{1}{2}\left[P^{(1)}(1) + P^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[P^{(1)}(2) + P^{(1)}(3)\right] & 1 \\ \vdots & \\ -\frac{1}{2}\left[P^{(1)}(n-1) + P^{(1)}(n)\right] & 1 \end{bmatrix} \qquad (11)$$

(e) The Grey AGO equation is from grey differential equation and the Inverse AGO (IAGO) is employed for reduction to get the demand model as in below:

$$\hat{p}^{(1)}(S+1) = \left[P^{(0)}(1) - \frac{b}{a}\right] e^{-aS} + \frac{b}{a},\ S = 1,2,3 \ldots \ldots n \qquad (12)$$

$$\hat{p}^{(0)}(S) = \left[P^{(0)}(1) - \frac{b}{a}\right](1 - e^{a})e^{-a(S-1)},\ S = 1,2,3 \ldots \ldots n \qquad (13)$$

GM(1,1) model is employed to forecast in grey theory from the existing data. This model can be used for the small size of data and mathematically it's very convenient.

B. The NGBM(1,1) model

This model is b based on Bernoulli differential equation and previous model GM(1,1).
The model is of the form

$$\frac{dP^{(1)}}{dt} + aP^{(1)} = b\left[P^{(1)}\right]^{r} \qquad (14)$$

Using GM(1,1) equations (4)-(7) the NGBM difference equation is

$$P^{(1)}(S) + aP^{(1)}(S) = b\left[Z^{(1)}(S)\right],\ S = 2,3,4 \ldots \ldots n \qquad (15)$$

By least square method the NGBM differential and difference equation is to be determined a and b

Suppose $\theta = [a, b]^{T} = (B^{T}B)^{-1}B^{T}Y,\ Y = B\theta$ (16)

$$Y = \left[P^{(0)}(2), P^{(0)}(3) \ldots, P^{(0)}(n)\right]^{T} \qquad (17)$$

$$B = \begin{bmatrix} -\frac{1}{2}\left[P^{(1)}(1) + P^{(1)}(2)\right] & \left\{-\frac{1}{2}\left[P^{(1)}(1) + P^{(1)}(2)\right]\right\}^{r} \\ -\frac{1}{2}\left[P^{(1)}(2) + P^{(1)}(3)\right] & \left\{-\frac{1}{2}\left[P^{(1)}(1) + P^{(1)}(2)\right]\right\}^{r} \\ \vdots & \vdots \\ -\frac{1}{2}\left[P^{(1)}(n-1) + P^{(1)}(n)\right] & \left\{-\frac{1}{2}\left[P^{(1)}(n-1) + P^{(1)}(n)\right]\right\}^{r} \end{bmatrix} \qquad (18)$$

From the grey differential equation we have the grey accumulation equation is as

$$\overline{P}^{(1)}(S+1) = \left[\left[P^{(0)}(1)^{(1-r)} - \frac{b}{a}\right]^{e^{-a(1-r)S}} + \frac{b}{a}\right]^{\left(\frac{1}{1-r}\right)},\quad S = 1,2,3,\ldots n \qquad (19)$$

Reducing the above equation by IAGO to get the demand model

$$\widehat{P}^{(0)}(S) = \widehat{P}^{(1)}(S) - P^{(1)}(S-1), S = 1,2,3 \ldots \ldots n \qquad (20)$$

C. Holt's Model

The governing equations for Holt' Model [10] are

$$Y_{t+1} = L_t + (h)T_t \qquad (21)$$

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad (22)$$

$$T_t = \beta(L_t + L_{t-1}) + (1-\beta)T_{t-1} \tag{23}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|(A_t - Y_t)|}{A_t}100$$

Where, Y_{t+1} = value time at $t+1$, L_t =level value at time t , T_t=trend value at time t

α and β is the smoothing parameter, h is the forecast horizon.Here $\alpha = 0.2, \beta = 0.3$

D. Nonlinear Regression Model

The nonlinear regression model is described by the following equation

$$y = a + bt + ct^2 \tag{24}$$

The calculated values are $a = 17.8658,\ b = -0.0528,\ c = 0.029496$

Table 1: Shares of renewable energy (raw data)

Year	Shares of renewable energy (%)
2001	18.68307699
2002	18.48353104
2203	18.11712455
2204	18.48864808
2005	18.68801502
2006	18.70894432
2007	18.41384224
2008	19.16940129
2009	19.81413469
2010	20.06067337
2011	20.39520827
2012	21.53578969
2013	22.30395704
2014	23.12176133
2015	23.61885003
2016	24.6616607
2017	25.54301313
2018	26.26046773
2019	27.27854084
2020	28.98463451

Source: Our World in Data

III. FORECASTING ACCURACY ASSESSMENT:

The difference of existing data and the estimated data from the model is treated as an error. Here we used the followings to measure the error. The lower value of the each measurement indicates the suitable prediction.

(1) Mean Absolute Error, $MAE = \frac{\sum|e|}{n}$

(2) Mean Absolute Percentage Error,MAPE $= \frac{\sum\left|\frac{e}{a}\right|}{n} \times 100\%$, a =actual value

Table 2: MAPE(%) forecasting accuracy level

Range	Meaning
≦10%	Highly forecasting
10–20%	Reasonable
20–50%	Feasible
≥50%	Inaccurate

IV. RESULTS AND DISCUSSION

GM(1,1) results :

It is calculated by excel the share of renewable energy is 17.71% in 2005, 20.91% in2010, 24% in 2015, 27.5% in 2020.

NGBM(1,1) results:

It is calculated by excel the share of renewable energy is 15.47% in 2005, 21.68% in2010, 24.21% in 2015, 23.87% in 2020.

Holt's Model results:

It is calculated by excel the share of renewable energy is 19.79% in2005, 19.78% in2010, 22.11% in 2015, 27.14% in 2020.

Nonlinear Regression Results:

It is calculated by excel the share of renewable energy is 18.33% in 2005, 20.28% in2010, 23.71% in 2015, 28.60% in 2020.

Table 3: Forecasting accuracy of the four models

Forecast indicators	GM(1,1)	NGBM(1,1)	Holt's Model	Nonlinear Regression
MAPE%	2.9604	9.1519	5.3756	1.2950

Among the four models nonlinear regression model gives the highest accuracy. It is also observed that GM(1,1)model gives higher accuracy in comparing with the other two models NGBM(1,1) and Holt's model. GM(1,1) model has map value 2.9604 accuracy which is the 2nd highest accuracy, shows in table 3. All the three models GM(1,1), Holt's model, nonlinear Regression model is predicted with increasing growth rate except NGBM(,11) which is shown in figure 1. The growth rate of NGBM model shows only 23.87% at 2020. In figure 2 nonlinear regression model shows the highest increase in the same time.

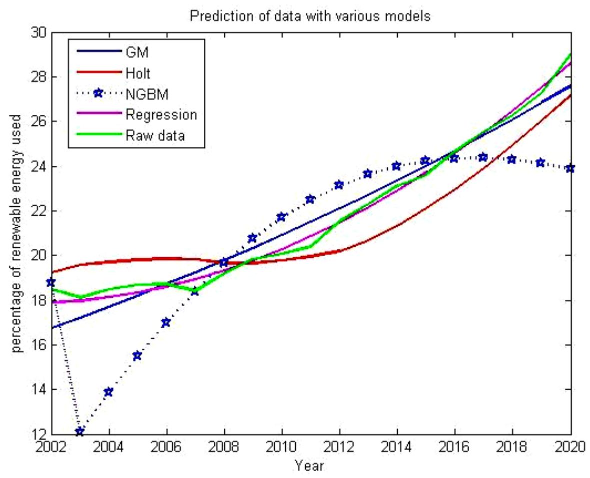

Figure 1: Prediction of four different models

3.4 Prediction graph

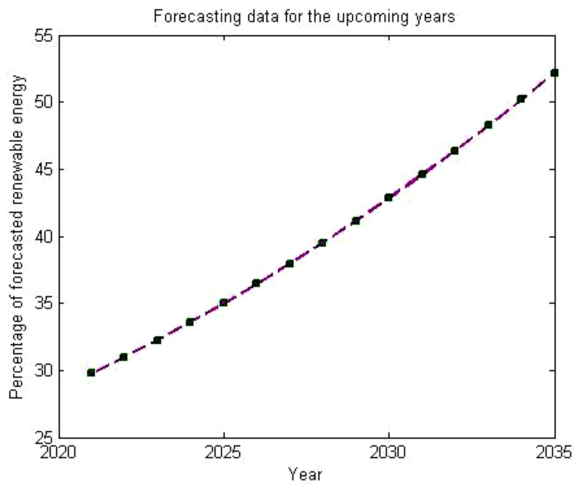

Figure 2: Forecasting the growth rates of renewable energy

CONCLUSION

Renewable energy is replenished by the nature. Although the renewable energy treated as green energy its share is very little over the conventional energy. It is found that the nonlinear regression model has the highest accuracy over the other three models namely GM(1,1), NGBM(1,1) and Holt's model. The MAPE value 1.29% shows the high accuracy in nonlinear regression model. According to the nonlinear regression model the renewable energy share will be more than 52% by the year 2035.If we want to save the planet the share of the renewable energy must to be increased. The high ambitious net-zero emission is achievable if all the bodies work together. In order to achieve this goal the stake holder of the nation, policy maker's even individual level needs to work to shift the primary energy into renewable energy without further delay. Investment in fossil fuel based power plant must be stopped as early as possible. Growth rate of different renewable energy can be studied in future is suggested.

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