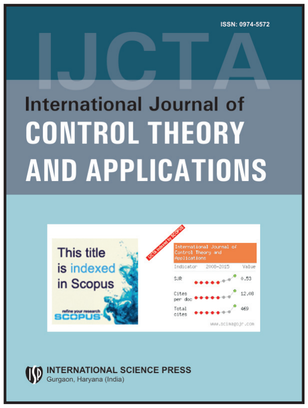

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Forecasting of Electricity Production using NGBM Special Reference to India

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Abstract: Thus the average production of electricity is getting increased due to the increasing demand of electricity. In this paper Grey Model (GM) and Nonlinear Grey Model (NGM) with the concept of the Bernoulli differential equation (BDE) is introduced to obtain higher predictive precision, higher accuracy rate and the validation of a differential equation using this model. To improve the predicted accuracy related to the GM, the best response is achieved by using NGBM. The NGBM model is having the capability to produce the more reliable outcome easily. The NGBM with power r is a nonlinear differential equation. By using r we control the expected result and adjust this solution to fit the result of 1-AGO of historical raw data. NGBM has been a recent new applicable grey prediction model which is easy to adjust for the correctness of GM (1, 1) stable with a BDE. The differentiation of desired outcome with the actual GM (1, 1) has been displayed through a feasible forecasting model NGBM (1, 1) by accumulating the decisive variables.

Keywords: Grey model GM (1, 1); Nonlinear grey Bernoulli model NCBM (1, 1), electricity production; *Bernoulli model*; forecasting.

1. INTRODUCTION

1982 grey system theory was first proposed by Deng. In recent year the grey system theory his also been successfully employed in various prediction applications. It has become a very effective method of solving uncertainty problem under discrete data and incomplete information. In education information and measurement, when the number of data in the system is not enough for traditional statistical method, the application of grey system theory can gate good result and which grey prediction models play a very important role for prediction problem. However, in Grey Model they did not satisfied the problem that the predicted accuracy in Grey forecasting [1] is one topic of grey theory proposed by Deng [2].

When the data are few, most forecasting models are restricted fortunately, the grey forecasting merely needs four data to construct model and its forecasting performance is satisfactory. We have applied in many fields, including Economics [3] finance, agriculture [4], air transportation [5], electric load [6], industry [7], and industrial waste water [8] and so on. In this present era our day to day life fully increasing dependence on energy, because electricity energy is effective factor in economic and playing the very important and remarkable role in various areas of the economy. Energy is known as one of the strongest factors in the economic growth theories, but its importance differs from one model to one another.

We overall introduction of the Indian electricity production. In this paper we use the nonlinear grey Bernoulli model for prediction and its application in use educational information and measurement. The method of improving the predicted accuracy related to the grey model are introduced. Grey prediction models have the advantages of establishing a model with few data and uncertain data has become the core of grey system theory. Prediction is to analyze the developing tendency in the future according to the past facts. Statistical methods are the most commonly used method for production forecasting. In classical predicting way, the predictor are produced on the hypothesis of performing the format of the system to be predicted. These are only part of the system design could be totally executed, after all, because of the limitation of information and knowledge. The grey system theory was first proposed by Deng [8] [11], mainly for a system with incomplete or uncertain information, to construct a grey forecasting and decision-making. As a superiority to conventional statistical models, grey models require only a limited amount of data to estimate the behavior of unknown systems. In recent years, the grey system theory has been success- fully adapted in several fields and has authenticated suitable output [12–20].

Its widely use of classical grey forecasting model GM(1, 1) still could be enhanced despite for the predicting efficiently principle by resultant function. The latterly elaborated grey forecasting model of the NGBM(1, 1) is a taken by Chen [18], the Bernoulli differential equation there are easily joining with adaptation of GM(1, 1). The finally modifies the accuracy of the NGBM model for actual data of nonlinear characteristics of actual system and adjustably arbitrate the shape of the model's curve proposed to the strengthens with a exponentially power. NGBM is a laterally established nonlinear grey Bernoulli model NGBM(1, 1) because there are a latest grey predicting model . Its exponent power r acceptable clearly the nonlinear features of actual system and realistic define the outline of the ideal curve. The power exponent and structural parameters in the model are known. Therefore, predicting of the variation series can be performed by the variation quality as long. Dissimilar GM(1, 1) and the grey Verhulst model which is actually proceeding a constant integer 0 or 2 but NGBM(1, 1) does not necessary such as a integer. The NGBM(1, 1) was magnificently used to assume and predict the result to yearly redundancy rates of many selected countries, This favorable outcome signify to NGBM(1, 1) indictable advanced veracity of duplication and forecasting predictions of the traditional GM(1, 1).

This NGBM(1, 1) model appropriate an operator obtained by 1-AGO to evaluate on the non-negative actual series. The GM(1, 1) has been authenticated and generally used in the unrestricted [19],. It determines the almost accurate exponential progress rules and acquire temporary estimating accuracy. The model acquire significant meaningful in forecasting certainty specifically with respects the following conditions: the series generation background value, parameter estimation [19], the time response function, the differential equations, and non-linear grey model. In accumulation, various composite models established on GM(1, 1) we repurposed. There are containing to grey econometric mode. However, No. matter how much change for the better to completed the GM(1, 1), the grey model is constantly continuous for the forecasting approach. But finally we can say that the solution, GM(1, 1) is not appropriate for actual data which holds remarkable instability.

However, studies on both the initial condition and the two adjustable parameters in the NGBM(1, 1) model are scarce [32]. The initial condition in grey models is also an important factor affecting the simulation and forecasting precision. According to grey system theory, the model should give priority to new information. Thus, the initial condition should not be limited to the first item in the first-order accumulated generating sequence, and the last item was taken to be the initial condition used the weighted sum of the first item and the last item as the initial condition. [21] [22] between the simulated values and the observed values minimized the sum of the square error, and between the simulated accumulating generation values and the original accumulating generation values, respectively. In this study, different initial conditions [23] combined with the optimized model were tested to research the effectiveness of the NGBM (1, 1)model.

The considering the simulated value and giving to the better results the linear model to nonlinear one, that's called nonlinear grey Bernoulli model (NGBM) the past works. After simulation of raw data to predicting accuracy is actually make to better comparison to grey model and gives to the perfect accuracy in NGBM(1, 1) with parameter *r*. Before every, to clarity of the authentic model is kept. This concept to apply to the actual raw data and simulated to gives the predicted value for development is more succeeded by applying non-linear grey Bernoulli model concept in several area as like that economics, agriculture, market analysis and etc.. for the future plan. A ideal model with variable *r* and *p* is proposed for prediction. Consequently, a unique model with two adaptable parameters *n* and *p* is projected and his named nonlinear grey Bernoulli model (NGBM). In this research, A simple pattern to indication that an ideal model is productive and applied to predict the Indian electricity production. The results could provide production of electricity energy of future strategy and the initiated process could be also simply used by the electricity or experimenter to forecast the future production of electricity not only in India but in globally.

2. METHODOLOGY

In grey theory, the AGO technique is truly relevant in the historical data to reduce randomized allocation of raw data. To complies the refined data there are grow up series by using first order linear ordinary differential equation with the solution. This model is broadly applied in various area of practical application of grey system theory. In this model there are satisfied the some condition. The information density is infinitely large. The sequence process the intension of grey differentiation. The mapping from the set of background values to the component of the grey model derivative satisfy the parallel mapping connection or relation. Our proposed modified grey forecasting model GM(1, 1) together with the NGBM(1, 1) theory to further developed the prediction attention. Now apply to the mathematical approach and briefly describe to GM and NGBM in to given in to the following:

3. CASE STUDY: LONG TERM PRODUCTION FORECASTING

A. Grey Model, GM (1, 1)

Assume that the original sequence of row data with n entries:

$$\mathrm{Q}^{(0)} = \left(q^{(0)}(1), q^{(0)}(2), \ldots, q^{(0)}(k), \ldots, q^{(0)}(n)\right) \tag{1}$$

where, $\mathrm{Q}^{(0)}$ stands for the non-negative original historical time series data and $q^{(0)}(m) \geq 0$, $m = 1, 2, ..., n$

$$\mathrm{Q}^{(1)} = \left(q^{(1)}(1), q^{(1)}(2), \ldots, q^{(1)}(m), \ldots, q^{(1)}(n)\right) \tag{2}$$

where, n is the whole number of modelling data. The 1-AGO creation of $q^{(1)}$ is defined as:

$$q^{(1)}(m) = \sum_{i=1}^{m} q^{(0)}(i), m = 1, 2, \ldots, n \tag{3}$$

where, $q^{(1)} = q^{(0)}$, an

Suppose that, 1-AGO generated sequence is $\mathrm{Q}^{(1)}$, a non-negative sequence is $\mathrm{Q}^{(0)}$, and the consecutive neighbours of $\mathrm{Q}^{(1)}$ the sequence generated with mean $\mathrm{Z}^{(1)}$.

$$\frac{dq}{dt} + \alpha Q = \beta \tag{4}$$

Where variable α and β are called the growing incident and grey model input, correspondingly. Now calculating in practice, coefficient α and β does not directly considered from Eq. (4). Simple uniform mapping relation elements in set satisfy the background value. So, the result of Eq. (4) can be achieved by using the least square method. Then the discrete form of the GM(1, 1) differential equation model express as:

$$q^{(0)}(m) + \alpha q^{(1)}(m) = \beta,\ m = 2, 3, \ldots, n., \tag{5}$$

$m = 1, 2, ..., n$ and $Z^{(1)}$ is the mean generated sequence of consecutive neighbours of $Q^{(1)}$ given by

$$Z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(n)\right) \tag{6}$$

where,

$$z^{(1)}(m) = 0.5q^{(1)}(m) + 0.5q^{(1)}(m-1) \tag{7}$$

The grey input and developing coefficient α and β are respectively. In Eq. (4) we can't directly calculated to Coefficient α and β. So, now solving the Eq. (8) and find the individual value of α and β. After calculating the parameter α and β then apply to the Eq. (4).

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{8}$$

Where are B and Y defined as fallows:

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix},\ Y = \begin{bmatrix} -q^{(0)}(2) \\ -q^{(0)}(3) \\ \vdots \\ \vdots \\ q^{(0)}(n) \end{bmatrix} \tag{9}$$

$$Y = Y = \left[q^{(0)}(2), q^{(0)}(3), \ldots, q^{(0)}(n)\right]^T \tag{10}$$

From Eq. (8) to give the value of parameter and solved the Eq. (4) for finding the appropriate solution with find out the sufficient result together:

$$\hat{q}^{(1)}(m+1) = \left(q^{(0)}(1) - \frac{\beta}{\alpha}\right)e^{-\alpha m},\ m = 1, 2, \ldots \tag{11}$$

So, the finally we calculate the prediction result at m step with valuation by IAGO there are describe in given below:

$$\hat{q}^{(0)}(m+1) = \left(1 - e^{-\alpha}\right)\left(\hat{q}^{(1)}(m+1)\right) - \hat{q}^{(1)}(m) \tag{12}$$

$m = 1, 2, ...$

or

$$\hat{q}^{(0)}(m+1) = \left(1 - e^{-1}\right) = \left(q^{(0)}(1) - \frac{\beta}{\alpha}\right)e^{-\alpha m} \tag{13}$$

$m = 1, 2, 3, ...$

B. Non-Linear Grey Bernoulli Model, NGBM (1, 1)

Describe and elaborate the Nonlinear Grey Bernoulli Model NGBM(1, 1). There are an inserted coefficient in the background value with first-order single variable grey Bernoulli model. According to Zhou et. al., [24], the methodology elaborate in using. The procedures of NGBM(1, 1) can be mathematically describe as given below.

Let $Q^{(0)}$ be a non-negative data sequence

$$Q^{(0)} = \left(q^{(0)}(1), q^{(0)}(2), \ldots, q^{(0)}(m), \ldots, q^{(0)}(n)\right) \tag{14}$$

where, $Q^{(0)}(m)$ is the m^{th} value of $q^{(0)}$, m = 1, 2, ..., n. Perform the accumulated generating operation on $Q^{(0)}$ as:

$$Q^{(0)} = \left(q^{(1)}(1), q^{(1)}(2), \ldots, q^{(1)}(k), \ldots, q^{(1)}(n)\right) \tag{15}$$

$$Q^{(1)}(m) = \sum_{i=1}^{m} q^{(0)}(i),\ m = 1, 2, \ldots, n\,, \tag{16}$$

The NGBM(1, 1) is defined by grey differential equation as:

$$q^{(0)}(m) + \alpha z^{(1)}(m) = \beta\left[z^{(1)}(m)\right]^{r} \tag{17}$$

and its whitenization differential equation is as follows:

$$\frac{dq^{(1)}}{dt} + \alpha\left[q^{(1)}\right] = \beta\left[q^{(1)}\right]^{r}, \tag{18}$$

where,

$$z^{(1)}(m) = pq^{(1)}(m) + (1-p)q^{(1)}(m-1),\ m = 2, 3, 4, \ldots, n.$$

p is called the production coefficient of the background value with a close interval [0, 1]; r is an adjustable parameter or adoptable variables, belonging to any real number excluding $r = 1$. To estimated variable α and β, using the least squares method, Eq. (17) is approximated as:

$$[\alpha \quad \beta]^{T} = (B^{T}B)^{-1}\, B^{T}Y \tag{19}$$

where,

$$B = \begin{bmatrix} -z^{(1)}(2) & [z^{(1)}(2)]^{r} \\ -z^{(1)}(3) & [z^{(1)}(3)]^{r} \\ -z^{(4)}(4) & [z^{(1)}(4)]^{r} \\ \vdots & \vdots \\ -z^{(1)}(n) & [z^{(1)}(n)]^{r} \end{bmatrix},\ Y = \begin{bmatrix} q^{(0)}(2) \\ q^{(0)}(3) \\ q^{(0)}(4) \\ \vdots \\ q^{(0)}(n) \end{bmatrix} \tag{20}$$

Set the initial condition $\hat{q}^{(1)} = q^{(1)}(1)$ and the solution of Eq. (18) can be expressed as:

$$\hat{q}^{(1)} = \left[\left(q^{(1)}(1)^{1-r} - \frac{\beta}{\alpha}\right)e^{-\alpha(1-r)(m-1)} + \frac{\beta}{\alpha}\right]^{1/(1-r)} \tag{21}$$

$r \neq 1, m = 1, 2, 3, \ldots$

Let the initial condition $\hat{q}^{(1)}(m) = q^{(1)}(m)$ where $m = 2, 3, \ldots, n$ and the particular solution of Eq. (18) is:

$$\hat{q}^{(1)} = \left[\left(q^{(1)}(m)^{(1-r)} - \frac{\beta}{\alpha}\right)e^{-\alpha(1-r)(k-m)} + \frac{\beta}{\alpha}\right]^{1/(1-r)} \tag{22}$$

$r \neq 1, m = 1, 2, 3, \ldots$

The inverse accumulated generating operation is performed on $\hat{q}^{(1)}(m)$ and $\hat{q}^{(0)}$ the forecasted value of can be estimated as:

$$\hat{q}^{(0)}(1) = q^{(0)}(1) \tag{23}$$

$$\hat{q}^{(0)}(m) = \hat{q}^{(1)}(m) - \hat{q}^{(1)}(m-1), \; m = 2, 3, \ldots \tag{24}$$

The adaptable variables r and p need to be fixed by the original data sequence. Therefore, how to acquire the appropriate values of r and p is an important issue in NGBM(1, 1) applications.

4. VARIABLE OPTIMIZATION FOR NGBM

Evaluate to historical raw data to find out the efficiency and properties of different forecasting models, after simulating the data now check and errors analysis of simulated data or forecast data: There are two types of errors first one is Relative Percentage Error and second one is Average Relative Percentage Error. Now using to the mathematical approach and calculating RPE and ARPE they are shown in fallowing Eqs. (24) and (25).

- RPE (Relative Percentage Error)

$$\text{RPE} = \frac{\hat{q}^{(0)}(m) - q^{(0)}(m)}{q^{(0)}(m)} \times 100\% \tag{24}$$

- ARPE (Average Relative Percentage Error)

$$\text{ARPE} = \frac{1}{m-1}\sum_{m=1}^{n} \text{RPE}(m) \tag{25}$$

Or

$$\text{ARPE} = \frac{1}{n}\sum_{m=1}^{n} \frac{\left|\hat{q}^{(0)}(m) - q^{(0)}(m)\right|}{q^{(0)}(m)} \times 100\%$$

A. Parameters NGBM model

Observing Eq. (1). to take the raw data of time series $Q^{(0)} = \left(q^{(0)}(1), q^{(0)}(2), \ldots, q^{(0)}(k), \ldots, q^{(0)}(n)\right)$ and analyzing the data and apply the 1-AGO and evaluated the new sequences and apply the GM(1, 1). Now apply the Bernoulli derivation equation $\frac{dq}{dt} + \alpha Q = \beta$ and find out the value of α and β then put the probabilistic value of $p = 0.5$.

From Eq. (11, 12, 13) too find out the simulated data and analysis of this scenario to find out the new data series with the help of estimated by inverse accumulated generating operation (IAGO). But we try to simulated of historical time series raw data to apply the nonlinear grey Bernoulli model for forecasting GM(1, 1) and NGBM(1, 1) both are given to the nearly corresponding or almost identical predicting solution, while the proposed model on the same series compression based of the appropriate effect its greater than that of the previous models. In other word we say that, the GM(1, 1) model is additional equitable and effective in the prediction at the time instants m. Its for the reason that the GM(1, 1) model especially the primary situation they are minimizes the sum of square error of new accumulated data.

The prediction precision of the NGBM(1, 1) are perfect and so, the recommended simulated approaches are effective for using this method. This method apply in the application and gives to the perfect and best result.

B. Data Preparation

Now we take to the historical data of the Indian electricity production and prepared the raw data for simulation. We take the yearly data of Indian electricity production for given Table 1 below.

Table 1
Actual data of electricity production of India

Year	*Actual data*
2000-01	560842
2001-02	579120
2002-03	596543
2003-04	633275
2004-05	665873
2005-06	697459
2006-07	752454
2007-08	813102
2008-09	842531
2009-10	905974
2010-11	959070
2011-12	1051375
2012-13	1111722

5. RESULTS AND ANALYSIS

The parameter computation are categories GM(1, 1) with two variables α and β for calculation, that find the result is actual GM(1, 1) only variable α and β require to be simulated with $r = 0$. And other one is calculated by the three variables of NGBM(1, 1) α, β and r are unknown. After computation of Grey Model and Non-linear Grey Bernoulli Model with raw historical data of electricity and predict or forecast of electricity production. In Table 2 shown to the elaborate variables consistent of the best response resultant value for the different model are shown in Table 2.

Table 2
Extract variable of GM and NGBM model

System	*Forecasting Parameter*	*Coefficient*	*ARPE*
GM(1, 1)	($\alpha = 0.0634$, $\beta = 496330$)	$r = 0$	1.7143
NGBM(1, 1)	($\alpha = -0.3212$, $\beta = 6745600$)	$r = 0.2$	1.5021

In this above table are shown to real compression result of forecasting between original GM(1, 1) and NGBM(1, 1). Compare to the find two value and validate the output of the two method. Using different technique and compute the parameter and compare to the Average Relative Percentage Error ARPE of the simulated data. The percentage relative error between GM (1, 1) and NGBM(1, 1) shown in Figure 2 and average percentage relative error comparison of GM(1, 1) and NGBM(1, 1) is also shown in Figure 3.

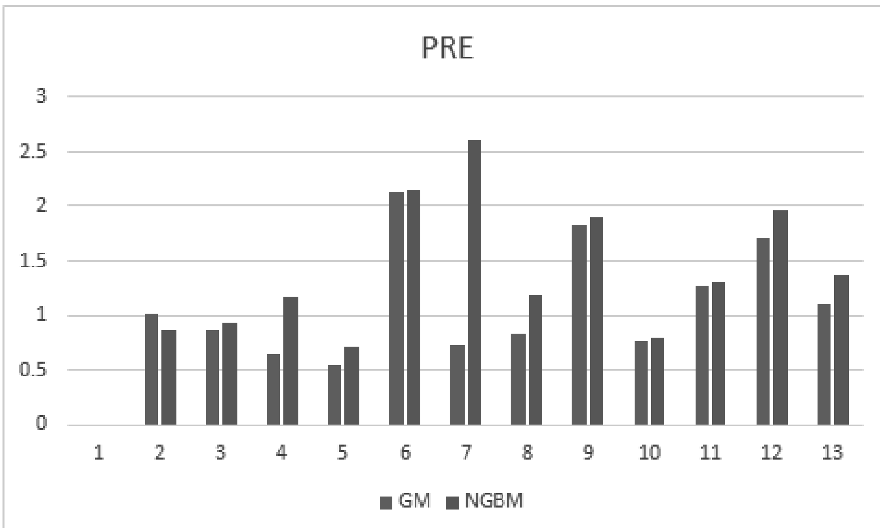

Figure 3: Models PRE comparision

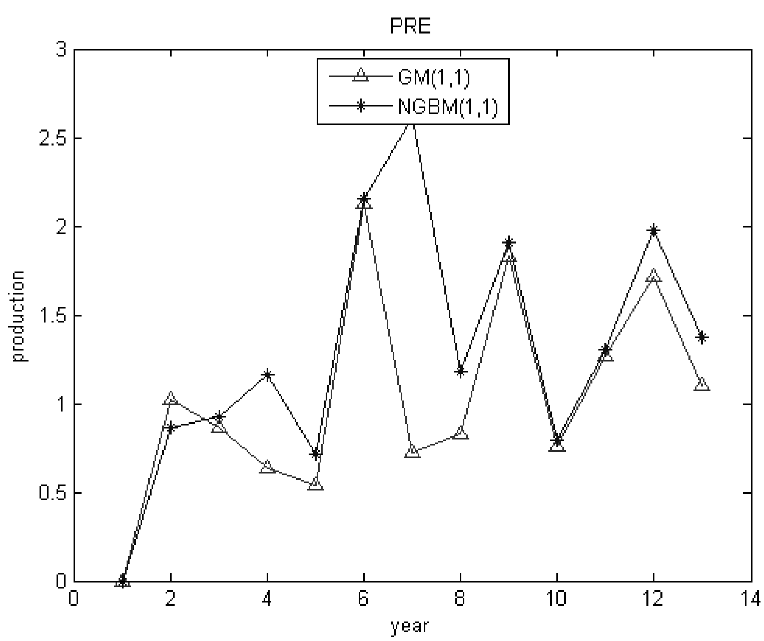

Figure 2: Models PRE comparision

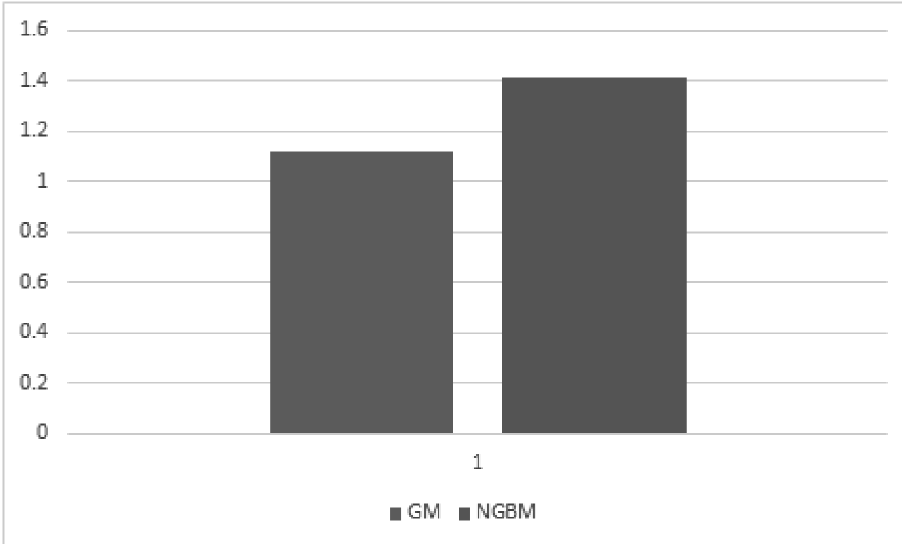

Figure 3: Models PRE comparision

Table 3
Extract variable of GM and NGBM model

Year	*Actual Value*	*Forecast Value*		*PRE*	
		GM	NGBM	GM	NGBM
2000-01	560842	560842	560842	0	0
2001-02	579120	555800	574120	1.0203	0.8626
2002-03	596543	555838	591031	0.8626	0.9293
2003-04	633275	591397	625914	0.6386	1.1637
2004-05	665873	629231	661127	0.5425	0.7133
2005-06	697459	669485	682449	2.13	2.1534
2006-07	752454	712315	732830	0.7217	2.6085
2007-08	813102	757885	803519	0.828	1.1796
2008-09	842531	806370	826478	1.8308	1.9062
2009-10	905974	857956	898816	0.7582	0.7904
2010-11	959070	912843	946591	1.2691	1.3011
2011-12	1051375	971241	103065	1.712	1.9741
2012-13	1111722	1033375	1096539	1.1008	1.3722
2013-14	- - - -	1099485	1110985	- - - -	- - - -
2014-15	- - - -	1169823	1250633	- - - -	- - - -
2015-16	- - - -	1244661	1319458	- - - -	- - - -
2016-17	- - - -	1324287	1468578	- - - -	- - - -
2017-18	- - - -	1409007	1493640	- - - -	- - - -
2018-19	- - - -	1499147	1542599	- - - -	- - - -
2019-20	- - - -	1595053	1687033	- - - -	- - - -
2020-21	- - - -	1697095	1894470	- - - -	- - - -
2021-22	- - - -	1805665	2092775	- - - -	- - - -
2022-23	- - - -	1921180	2229084	- - - -	- - - -

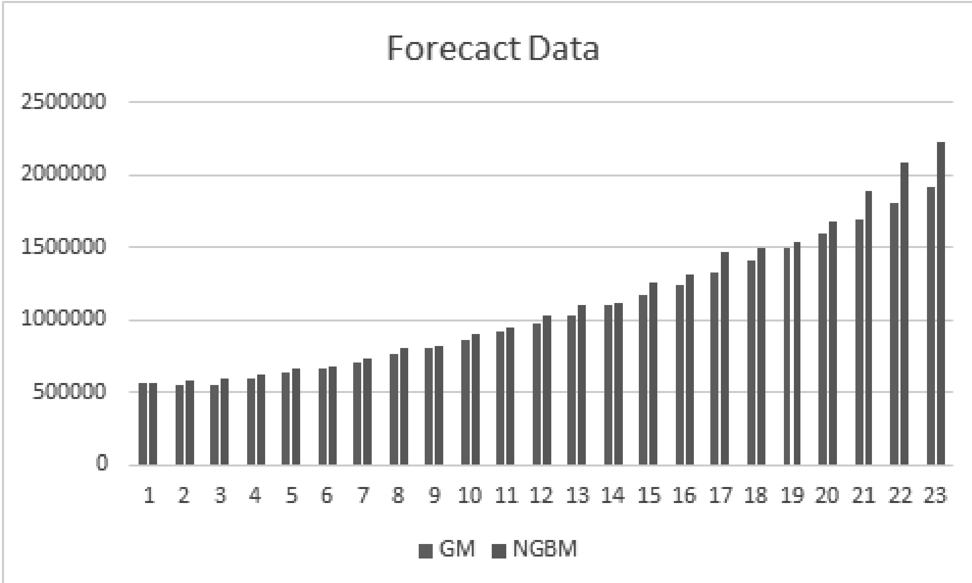

Figure 4: Comparison of predictive data, GM(1, 1) and NGBM(1, 1)

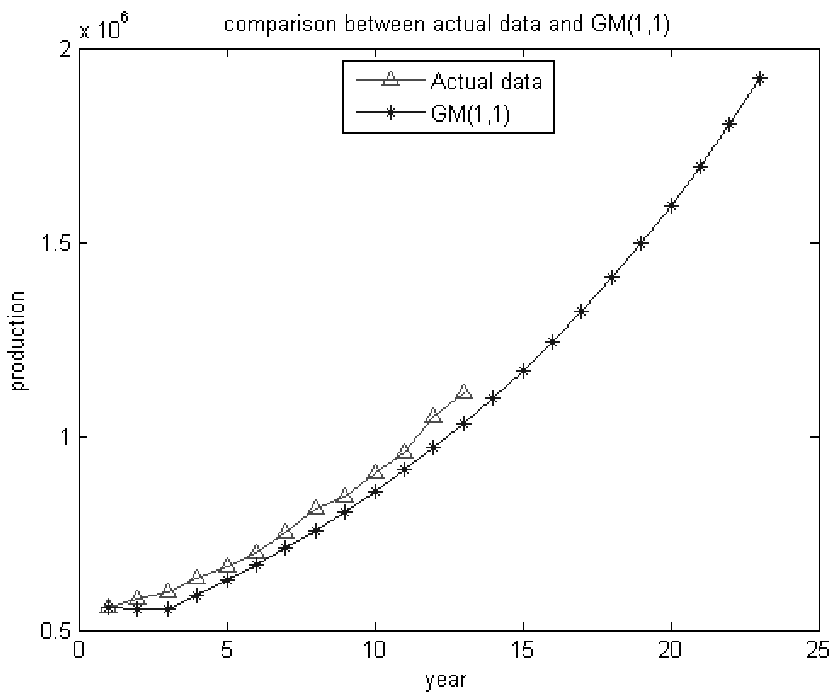

Figure 5: Model Forecast value by using GM(1, 1)

We clearly describe and show the compression of the relative percentage errors in the Figure 1 and Figure 2. In this figure we clearly simulate and justify the deference of RPE. Now in Table 1 and Table 2 to take the parameter *a* and *b* for GM(1, 1) there are two dimensional, NGBM(1, 1) is three dimensional coefficient parameter *a*, *b* and *r* with compression for ARPE of both model and show in the Figure 3 is clearly justify. In Figure 4 there are show to the Comparison of predictive data, GM(1, 1) and NGBM(1, 1). Finally we show in Figure 5 and Figure 6 to forecasting result of the Indian electricity production.

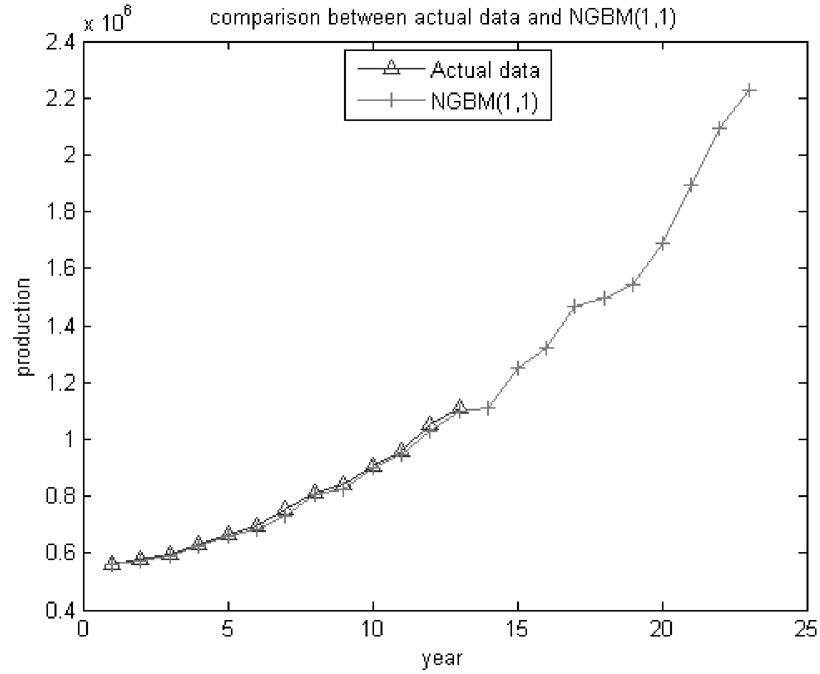

Figure 6: Model Forecast value by using NGM(1, 1)

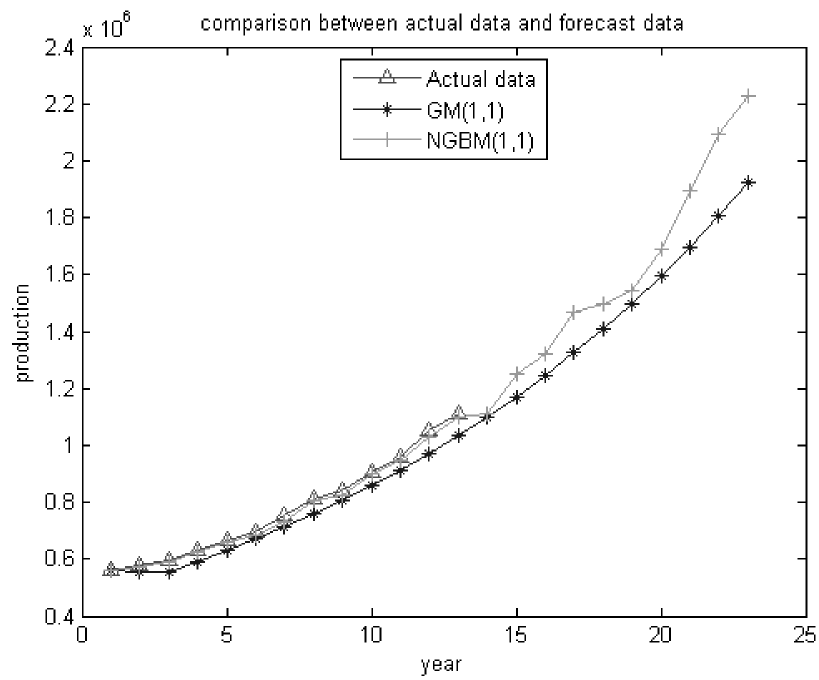

Figure 7: Comparison of actual ata, GM(1, 1) and NGBM(1, 1)

6. FUTURE WORK

To improve the accuracy and performance of NGBM (1, 1) model, we need to consider some more attributes like natural disasters, fuel resources, and chemical resources, so that the model will become more dynamic and robust for forecasting even with abrupt changes in production.

7. CONCLUSION

Based on the analysis of our experimented result, we have seen that the NGBM (1, 1) model performing over GM(1, 1) model with respect to our experimental dataset. Even using NGBM (1, 1) model we are not able to reach 100% accuracy, still this model is providing maximum accuracy than other existing model. So with some certain shortcomings we can conclude our experimental results are more convincing towards achieving the goal of forecasting.

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