Adapting Grey Energy Models for Demand Forecasting Across Diverse Datasets

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ABSTRACT

Energy consumption forecasting is a critical aspect of ensuring efficient allocation and utilisation of energy resources. Traditional forecasting methods are often limited in their ability to handle uncertainties, fuzziness, insufficient data, and high-volatility patterns. To address these limitations, significant research efforts have been dedicated to devising innovative mechanisms for forecasting time series data patterns. One such approach is the grey model theory, which has shown remarkable results in energy consumption prediction. In this research paper, we leverage the grey model theory to forecast electricity demand within power systems. Through the application of the grey theory model to diverse energy consumption datasets, we achieve remarkable results in terms of the grey model's performance, with an average error rate of **only 2.5%.** To underscore the practical relevance of our approach, we present a tangible example of energy consumption forecasting in a town with mechanical and metal processing enterprises, where we achieved an error rate of **only 1.8%**. Our results demonstrate that the grey model theory is highly accurate in energy forecasting, particularly in situations where data is limited or uncertain. This paper provides an overview of the grey model theory and its application in energy forecasting, highlighting its benefits and potential for future research. Our findings have significant implications for energy policy and planning, as accurate energy consumption forecasting is essential for ensuring efficient and sustainable energy use.

KEYWORDS

Grey model, Energy forecasting, Time Series Analysis, I-AGO, Production coefficient

1 Introduction

Energy utilization has always been one of the key factors in the energy sector when the world is trying to move forward towards green energy. This research paper aims to provide readers with an extensive exploration of Grey Models, delving deep into their principles, methodologies, and wide-ranging applications of predictive modelling in energy domain. Grey prediction models find widespread utility in various contexts, including economics, education, agriculture, transportation, meteorology, and military assessments, consolidating information to enhance decision-making and forecasting capabilities [1],[2],[3],[4]. In today's rapidly changing and increasingly complex world, accurate forecasting has become an indispensable asset across various domains. Precise predictions empower businesses to make informed decisions, while governments can strategically plan for the future. Our choice of the Grey model GM(1,1) for analysing energy consumption is rooted in its significance. Energy consumption analysis is critical for optimising resource management, combating climate change by reducing fossil fuel dependence, and addressing environmental concerns such as pollution and habitat destruction. Moreover, it helps identify opportunities for cost savings, fosters economic efficiency, and contributes to improved public health by reducing air pollution associated with energy production. For forecasting grey system theory which is fairly appropriate for prediction is used for the prediction task. Reducing data unpredictability is the main goal of the accumulated generating operation (AGO), which is the most significant feature of the grey system theory. The intermediate information for the construction of the grey prediction model is derived from the 1-AGO data of the original series. The systematic regularity may be rapidly and simply identified using the AGO approach. In other words, the grey prediction just requires a small amount of information to create a grey differential equation. Our energy consumption dataset has produced extremely encouraging findings when the grey model has been used. Datasets on power and energy consumption were employed in the experiment, and the outcomes properly predicted both the electricity load and future consumption. For the energy sector, predictive modeling-based solutions like forecasting and recommendation-based systems can offer valuable insights for effective management and better decision-making.

2 Literature Survey

The demand for electrical energy in homes and growing industries is strongly correlated with the growth in the world's population [5]. Researchers create forecasting models for efficient and cost-effective energy use in response to the requirement to balance the production and use of electrical energy [6]. A 1% increase in forecasting mistakes resulted in a 10-million-pound loss every year, according to UK electricity regulators in 1984 [7]. As a result, many prediction models have been put forth, the main goals of which are to optimize energy consumption and lower the prediction error rate to enhance the quality of power networks. Energy is the most important factor for any nation to prosper and achieve sustainable economic growth. It is essential to highlight that in 2022, the world's primary energy consumption reached 25,300 terawatt-hours (TWh), with India contributing 6.1% to this total. Consequently, the importance of predicting energy consumption patterns in India, especially the proportion of renewable energy sources in the overall energy consumption, cannot be overstated.

El Khantach et al. (2019) [4] employed five machine learning techniques (MLP, SVM, RBF regressor, REPTree, Gaussian process) for short-term load forecasting based on hourly data. Multi-layer perceptron (MLP) emerged as the most accurate, achieving a 0.96 MAPE, followed by SVM. This approach contrasts with González-Briones et al. (2019) [8], who utilised LR, SVR, RF, DT, k-NN, and incorporated one-day prior electricity consumption, with LR and SVR reaching an accuracy of 85.7%. In predicting load for various buildings using SVM, a 15.2% RMSE and 7.7% MBE were achieved. When predicting weekly power use, Tso et al. [8] compared the effectiveness of decision trees, neural networks, and regression analysis. The results showed that neural networks and decision trees outperform the regression method by a small margin, with a root average squared error (RASE) of 39.36.

Recognizing the limitations of conventional forecasting methods in effectively handling uncertainties, fuzziness, insufficient data, and high-volatility patterns, significant research efforts have been dedicated over recent decades to devising diverse mechanisms for forecasting time series data patterns [9]. A variety of applications are covered by these creative methods, such as the fuzzy logic application for short-term energy consumption forecasts at one retail complex in Cirebon City, A new modified artificial bee colony algorithm for the energy demand forecasting problem, an approach utilising fuzzy logic to forecast changes in energy consumption in a manufacturing system, a prediction of a building's electricity consumption using principal component analysis and optimised artificial neural networks, and so on.

The proposed work focuses on leveraging the grey model for load forecasting, a method well-suited for power system load's characteristics of limited and fluctuating data. Regression analysis, grey system theory, neural network analysis, SVM algorithm, machine learning, and prediction method are the techniques that are frequently utilised in load forecasting [10]. Autoregressive models are commonly used in energy consumption forecasting due to their ability to capture sequential patterns. The grey system theory, introduced by Deng Julong, has gained prominence among forecasting models [11]. Over the years, techniques such as residual sequence amendment and optimising whitening values have been developed to enhance the precision of grey models. The versatility of grey system theory is exemplified by its successful application across multiple domains. The five primary categories of grey prediction encompass: Time series forecasting, Calamity forecasting, Seasonal calamity forecasting, Topological forecasting, Systematic forecasting. A pivotal model within grey theory is the GM (1,1) model, which represents a first-order grey model for single-variable forecasting. This model has exhibited its efficiency by yielding high-precision outcomes even with a limited dataset comprising as few as four data points.

3 Dataset Description

In our research, we apply Grey Models to forecast energy consumption using diverse datasets. The first dataset focuses on China's tertiary industry energy consumption from 2005 to 2012, predicting 2013-2014 consumption. The second dataset tackles electricity consumption in a town with mechanical and metal processing enterprises, dealing with uncertainty in load factors .The third and fourth datasets, sourced from Tetuan City, help forecast energy consumption in Zone 1 and Zone 2, each with unique characteristics. Lastly, our fifth dataset, from southern Colombia, integrates socio-demographic features into electricity consumption forecasting, emphasizing the significance of socio-economic factors. Through these diverse datasets, our research aims to contribute to the field of energy consumption prediction, addressing various facets of the problem and shedding light on the potential applications of Grey Models in diverse contexts.

4 Methodology

4.1 Grey Model, GM (1, 1)

A single-variable grey prediction model based on a first-order difference equation, GM(1,1) was introduced by Professor Deng in **1982 [1].** When there are few accessible observations for modelling, this model is especially helpful. The GM(1,1) model is an effective tool for forecasting because it accurately represents the dynamics of the system under study and has a cybernetics-based predictive function. It has been widely utilized to tackle a variety of prediction problems in both life and production, such as assessing the risk of car fatalities and forecasting the output of the integrated circuit industry. With research concentrating on topics like parameter optimization, structure optimization, and the extension of modelling objects from real data to grey uncertain data, the theoretical system of GM(1,1) has been enhanced and refined throughout **time [2].**

Initial row data sequence with n entries:

$$a^{(0)} = (a^{(0)}(1), a^{(0)}(2), a^{(0)}(3), a^{(0)}(4), ..., a^{(0)}(n))$$

In this case, q(0)(k)>=0,k=1,2,…,n, and a(0) denotes non-negative original historical time series data

$$a^{(1)} = (a^{(1)}(1), a^{(1)}(2), a^{(1)}(3), a^{(1)}(4), ..., a^{(1)}(n))$$

where n represents all of the modelling data. A(1)'s 1-AGO creation is described as follows:

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

The created sequence of a(1)'s successive neighbors is denoted by Z(1).:

$$z^{(1)} = (z^{(1)}(1), z^{(1)}(2), z^{(1)}(3), z^{(1)}(4), ..., z^{(1)}(n))$$

The background value's production coefficient, denoted as p, lies within the closely spaced interval [0, 1]. In classic models, P is often fixed to ½.

$$z^{(1)}(k) = (p)a^{(1)}(k) + (1-p)a^{(1)}(k-1), k = 2,3,4,...,n$$

$$a^{(0)}(k) + wz^{(1)}(k) = y$$

The sequence that is formed in 1-AG0 is denoted as a(1), a non-negative sequence as a(0), and the sequence that follows a(1) is the sequence generated with mean z(1).

$$\frac{da^{(1)}(k)}{dk} + wa^{(1)}(k) = y$$

W and y represent the developing coefficient and the grey input, respectively. The coefficients w and y cannot be computed directly from the equation. Proceed to solve the equation and determine the respective values of w and y. Apply to the equation after determining the parameters w and y.

$$\begin{bmatrix} w \\ y \end{bmatrix} = (B^T B)^{-1} B^T C$$

Where, B and C is defined as:

$$B = \begin{bmatrix} -z^{(1)}(2) 1 \\ -z^{(1)}(3) 1 \\ -z^{(1)}(4) 1 \\ . \quad 1 \\ . \quad 1 \\ -z^{(1)}(n) 1 \end{bmatrix} C = \begin{bmatrix} a^{(0)}(2) \\ a^{(0)}(3) \\ . \\ . \\ . \\ a^{(0)}(n) \end{bmatrix}$$

The data vector is C, and the data matrix is B.
After the bleaching formula differential equation is resolved, the GM(1, 1) prediction model is produced:

$$a^{(1)}(k+1) = [a^{(0)}(1) - \frac{y}{w}]e^{-wk} + \frac{y}{w}, k = 1,3,...,n-1$$

Follow equation leads to forecasting result

$$a_p^{(0)}(k) = [a^{(0)}(1) - \frac{y}{w}]e^{-w(k-1)}(1-e^{w}), k = 2,3,...,n$$

MAPE is expressed as a percentage and provides a straightforward way to understand the average magnitude of errors between predicted and actual values.

$$MAPE = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{a_p^{(0)}(k) - a^{(0)}(k)}{a^{(0)}k}\right| \times 100\%$$

The posterior difference test examines the residuals (which are absolute errors) in a specific way. It involves analysing the absolute differences in residuals during each cycle. This analysis helps determine the likelihood of points having smaller residuals and explores the magnitude of the prediction error variance index. The procedure can be outlined as follows:
It is the average value of the original data a(0)(k),

$$\bar{a} = \frac{1}{n}\sum_{k=1}^{n} a^{(0)}(k)$$

It is the variance of the a(0)(k),

$$S_1^2 = \frac{1}{n}\sum_{k=1}^{n}(a^{(0)}(k) - \bar{a})^2$$

It is average value of the e(0)(k),

$$\bar{\varepsilon} = \frac{1}{n}\sum_{k=1}^{n}\varepsilon^{(0)}(k)$$

It is the variance of the e(0)(k),

$$S_2^2 = \frac{1}{n}\sum_{k=1}^{n}(\varepsilon^{(0)}(k) - \bar{\varepsilon})^2$$

It is the posterior difference ratio, where G is as small as possible at the time of prediction.

$$G = \frac{S_2}{S_1}$$

5 Results

The grey model has been experimented on different datasets from the energy domain where it mainly focuses on the power consumption and energy load forecasting. From the performance evaluation we got the value of grey model score (G) for dataset one is 0.066 with value of R2 is 99.5 percent which shows an excellent result same as performing better forecasting for other datasets**.** For second dataset we achieved grey model score and r2 score as 0.068 and 99.5 percentage respectively.

The following table explains the result obtain from experiment.

	Data 1[12]	Data 2 [13]	Data 3 [14]	Data 4 [14]	Data 5 [15]
Grey Score	0.0669	0.0687	0.0671	0.0917	0.3268
RMSE	38.4838	53.5376	211.825	137.095	0.8528
R2	0.9955	0.9951	0.9955	0.9916	0.8932
MAPE	1.3648	3.5394	0.7207	0.7205	0.8621

We attained remarkable results on datasets 3 and 4, achieving R2 scores of 99.6 percentage and 99.1 percentage, along with Grey model scores of 0.067 and 0.091, respectively. These outstanding performance demonstrate on the Tetuan city dataset. However, for dataset 5, we obtained an R2 score of 89.3 percentage and a Grey model score of 0.32.

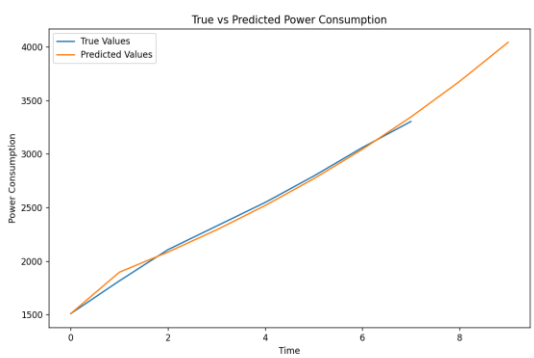

Figure 1. Energy consumption in China's tertiary industry

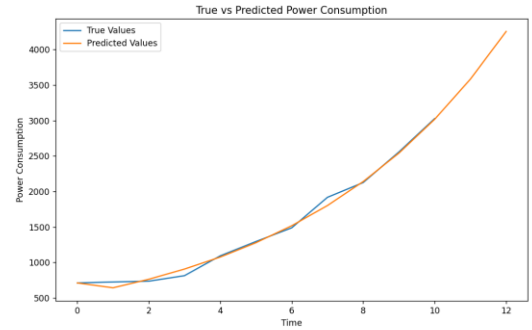

Figure 2. Energy usage in a town having mechanical and metal processing businesses.

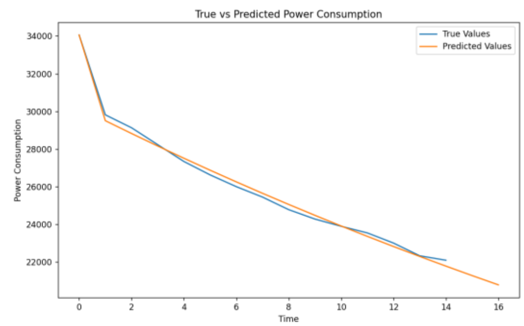

Figure 3. Energy usage within the first zone of Tetuan City.

In the field of energy-related datasets, we have conducted thorough experiments using the Grey model. Our main focus during these experiments has been on predicting power usage and forecasting energy load. Our performance assessments have yielded consistently impressive outcomes. For dataset one, the Grey model achieved a commendable performance, along with a high R2 score, similar to our success in forecasting for other datasets. Our forecasting capabilities are consistently demonstrated across all other datasets, as both the Grey model score and R2 score reinforce our performance.

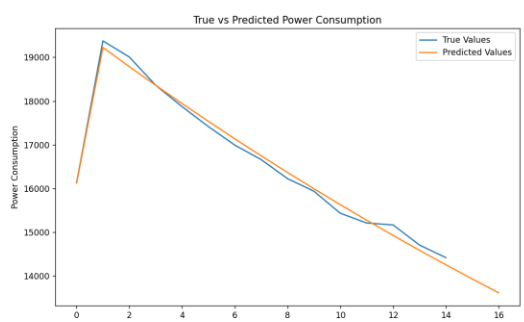

Figure 4. Energy usage within the second zone of Tetuan City.

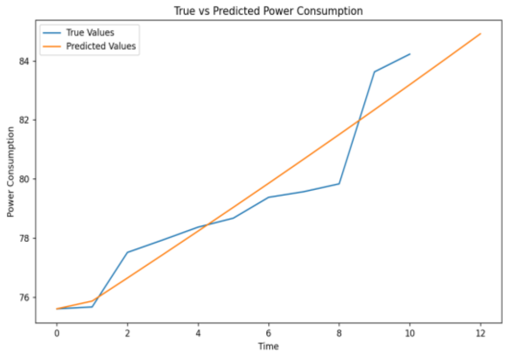

Figure 5. Analyzing energy usage in the southern region of Colombia while taking into account socio-demographic characteristics.

Conclusion and Future work

Grey model impacts in the predictive modeling in energy domain. The algorithm accurately follows the trends as well as seasonality of the data sequence. Results shows that the model predicts the electricity consumptions and power load in univariate method. Average r2 score is over 0.99 for all dataset and the grey model score G is above average accurate. Based on the analysis with different dataset, grey model is capable to predict the sequence and helps the energy sector with efficient management and collective decision making. In future we will work on multivariate grey models and comprehensive analysis with time series models in green energy.

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