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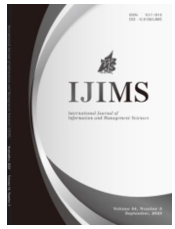

Empowering Tomorrow: Innovative Forecasting for UAE's Electricity Consumption

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Keywords

Non-Homogeneous Discrete Grey Modelling; Electricity; Forecasting; Mean absolute percentage error; Relative growth rate.

Abstract

In the dynamic landscape of the United Arab Emirates (UAE) electrical sector, accurately predicting long-term trends is paramount for sustainable energy planning. Owing to the consistently elevated temperatures experienced in the Gulf region during the summer months, there is a notable surge in demand for electricity in the UAE, leading to an increased energy consumption per capita. This heightened demand during the summer renders the power system particularly susceptible, posing a substantial risk of power outages, production shortfalls, and a subsequent escalation. This study delves into the realm of forecasting using Non-Homogeneous Discrete Grey Modeling (NDGM), a cutting-edge approach tailored to the unique challenges of the UAE's electrical domain. By leveraging NDGM, this research aims to provide a robust framework for anticipating electrical trends over an extended period. Precise load demand forecasting would impact energy-generating capacity scheduling and power grid management. The results promise valuable insights for policymakers, industry stakeholders, and energy planners, facilitating informed decision-making to meet the ever-evolving demands of the UAE's power sector. The findings of this study were unique in that it avoids increasing generation capacity in mid- and long-term plans, which will assist in avoiding load shedding and meeting energy demands in various sectors.

1. Introduction

The levels of energy consumption around the globe are rising annually due to the expansion of the economy and the rapid increase in the world's population. A solid energy demand model for various sectors is essential for every country's energy planning and strategy. This is because socio-economic variables such as population, urbanization, industrialization, net capital income, and technical improvements affect energy consumption (Al-Abri & Okedu, 2023). The majority

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of energy is still produced using fossil fuels, which harms the environment and hinders global economic and social sustainability. Due to the country's rising consumption, the issue of environmental pollution and the pursuit of sustainable development have taken on growing significance, making the urgent need to restructure and modernize the country's energy system (Kongkuah et al., 2022). United Arab Emirates (UAE) population expansion, economic activity, and high consumption rates that are unsustainable in the long run have made energy efficiency a major concern (Abual-foul, 2013). The UAE-UK Business Council's Energy Working Group recently convened a conference as part of Abu Dhabi's annual Sustainability Week to examine potential solutions to this problem. (Friedrich & Afshari, 2015). The discussion concentrated on three distinct energy efficiency topics: smart cities, which use building efficiency, which makes use of cutting-edge new materials, technologies, and designs to optimize energy usage in buildings; technology used in urban planning to minimize energy consumption; as well as water desalination, which employs a combination of hard and soft measures to reduce water demand and the associated energy required to desalinate and increase production through more saline water storage (Zhang et al., 2022). The UAE is putting in place ground-breaking programs for renewable energy and energy efficiency (Bayomi & Fernandez, 2018). Because it is conscious of the implications of climate change, the UAE is looking into alternative ways to provide the energy needed to run its economy. The first initiative of its type in the Middle East, the UAE's Net Zero by 2050 Strategic Initiative, aligns with the goals of the Paris Agreement and the nation's growth plan, which calls for the development of new knowledge, green industries, skills, and employment opportunities. The UAE has actively tried to diversify its economy and energy mix despite having the seventh-largest verified oil reserves and the seventh-largest reserves of natural gas. Sustainable development will be severely hampered if a balance between energy use, economic expansion, and environmental preservation cannot be established (Suganthi & Samuel, 2012). The government needs a precise estimate of the patterns of energy use and its intensity in each area of the United Arab Emirates (UAE).

Forecasting demand yields useful information for better supply chain management (Petropoulos et al., 2022). Creating an appropriate model to calculate the electricity demand predictions demanded by decision-makers is critical(Nepal et al., 2020). Utilities typically rely on long-term prediction models to develop appropriate strategies that take into account the economy, environment, demographics, and other relevant drivers (Filippov et al., 2021). However, the load system's size and data availability are crucial considerations when deciding on forecasting methodologies. Based on these needs,the key objective of this study is to propose a long-term forecasting approach for evaluating electricity demand and performance(Sharma, 2018). This study innovatively utilizes a non-homogeneous index sequence (NDGM) combined with MAPE for the long-term projection of electricity consumption, marking a distinctive approach in this field (Pessanha & Leon, 2015) and compare it with electricity production and country population. The significance of this study lies in its innovative approach to electricity consumption forecasting in the UAE using a Non-Homogeneous Discrete Grey Model (NDGM). It addresses the critical need for sustainable energy planning in a region with high demand fluctuations due to temperature variations. By proposing a long-term, weather-independent forecasting model that integrates past power data and data mining techniques, the study aims to enhance energy generation scheduling and grid management. This approach provides valuable insights for policymakers and energy planners, helping to avoid load shedding and meet the evolving energy demands efficiently. Even though a number of the UAE's constituent emirates have already started projects in these fields, the scale of the problem necessitates a more comprehensive strategy that connects all of the components into a unified energy-efficiency plan. To encourage people, developers, and other stakeholders to minimize their energy use, a specialized regulatory framework, a communications and information campaign, and a research and development (R&D) element should all be included in this strategy to ensure that the UAE is maximizing the potential of emerging technology to increase efficiency.

Precise load demand forecasting would impact energy-generating capacity scheduling and power grid management (Nti et al., 2020). This is because a successful projection would not only result in significant savings in operating and maintenance expenses but would also result in the right decisions for future expansion. Accurate energy demand forecasting is critical in a demand-side economic dispatch to maximize renewables while minimizing operating costs(Gabrielli et al., 2022). The model will aid economic development, and it also aids in determining the best time to trade electrical energy.

The main purpose of our study is to introduce and validate an innovative long-term forecasting approach for assessing electricity demand and performance in the UAE, utilizing a Non-Homogeneous Discrete Grey Model (NDGM) that operates independently of weather data. This approach is designed to enhance the accuracy and reliability of electricity consumption forecasts in regions where weather data may be scarce or unreliable, thereby supporting more effective energy management and policy planning.

Unlike traditional forecasting models that heavily rely on weather data and face challenges in accuracy due to weather variability, our NDGM-based approach minimizes these issues by excluding weather parameters from its forecasting process. This methodological shift represents a significant departure from the norm, offering a novel solution to a common problem in energy forecasting.

This study specifically targets the UAE, a region characterized by rapid economic growth and significant fluctuations in energy consumption due to its unique climate and developmental activities. Previous research has often adopted a more generalized approach, lacking the specificity needed to address the nuances of energy forecasting in the UAE. By focusing on this region, our study fills a critical gap in understanding and predicting energy demand within a context of rapid urbanization and economic expansion.

The projected period of our study (2023-2040) extends significantly beyond the temporal scope of most existing studies, which typically focus on shorter-term forecasts. This long-term perspective is crucial for strategic planning and infrastructure development, offering valuable insights for policymakers, energy companies, and stakeholders involved in long-term energy planning.

This study addresses several research gaps, including the need for forecasting models that can operate effectively without weather data, the lack of specific focus on the rapidly changing energy landscape of the UAE, and the absence of long-term energy forecasting studies that span over two decades. By tackling these gaps, our research contributes valuable new knowledge to the field of energy forecasting, offering a methodology that can be adapted and applied to other regions facing similar forecasting challenges.

Due to relatively high temperatures in the region throughout the summer, there is a rise in load demand in the UAE, resulting in high demand for energy per capita. Because of the increased demand throughout the summer, the power system is extremely vulnerable, with a significant risk of power failure, resulting in power shortfall production and a rise in electricity bills. It is important to know that an accurate electric load forecast enhances the initial steps in developing facilities for future generation, transmission, and distribution (Weron, 2014). The current analysis is unique in that it avoids increasing generation capacity in mid- and long-term plans, which will assist in avoiding load shedding and meeting energy demands in various sectors.

2. Literature Review

Long-term forecasting of electrical energy consumption has emerged as one of the most important disciplines in the electricity industry. The electricity sector has grown to such an extent that significant investments in new generation capacity are needed to boost the growing economy and meet demand (Al-Abri & Okedu, 2023). It is critical to develop an appropriate model for calculating the electricity demand prediction required by decision-makers. The MLR (multiple linear regression) model is developed for the Gulf Cooperation Council (GCC) as a function of population and GDP. Following that, the Neuro-Fuzzy is trained using earlier data sets. It forecasts yearly electricity demand in the future(AL-Hamad & Qamber, 2019). Energy planning models (EPMs) are critical in policy formation and the energy sector's growth. An EPM (energy portfolio management) is built on anticipating energy demand and supply. Various past forecasting methods have been employed, ranging from statistical to machine learning. The availability of data, as well as the aims of the tool and planning process, heavily influence the selection of a forecasting approach (Debnath & Mourshed, 2018). Load forecasting has always played a significant role in planning and managing electric utilities, including transmission and distribution businesses. Load forecasting is increasingly essential as technology advances, the economy changes, and a variety of other issues. The forecast influences and is influenced by load-influencing variables and activities conducted across different periods. However, because of its stochastic and uncertain nature, it has been difficult for electrical utilities to reliably anticipate future load demand (Khuntia et al., 2016). It is critical to anticipate consumer electricity consumption at all times precisely. Various forecasting methodologies, ranging from statistical to machine learning, have been used in the past. The availability of data, as well as the goals of the tool and the planning process, all significantly impact the choice of a forecasting strategy (Kim et al., 2022). These projections are critical inputsfor integrated resource planning (IRP) procedures that involve utilities, regulators, and other stakeholders. Despite their relevance, there has been little research on the accuracy of long-term utility load forecasts (Carvallo et al., 2018). The power plants have used various energy-producing units to fulfill the various electrical demands/load kinds. Peak load units have the lowest efficiency and the highest cost of all the units (Esteves et al., 2015). To make this a reality, power plants must be able to accurately forecast the volume and timing of peak load/demand. This provides for adequate start-up time to avoid grid congestion and is crucial in ensuring the power grid's economic benefits, security, and stability. With the rising penetration of large-scale intermittent energy sources such as wind and solar, as well as energy storage power plants (Ghods & Kalantar, 2011). The significant number of publications over the last decade reflects a growing interest in peak demand forecasting. This might be explained by the fact that as the economy grows, so does power consumption(Almuhaini & Sultana, 2023) . As a result, electricity load forecasting is becoming increasingly critical for energy networks' safe and reliable functioning by improving the integration of new and sustainable energy technology (Nti et al., 2020). An overestimation of long-term electrical load will result in significant wasted investment in surplus power facility development, whereas an underestimation of future load would result in insufficient generation and demand (Seyedan & Mafakheri, 2020). Due to relatively high temperatures in the region throughout the summer, there is a rise in demand for electricity in the UAE, resulting in high demand for energy per capita. Because of the increased demand throughout the summer, the UAE power system is extremely vulnerable, with a significant risk of power failure, resulting in power shortfall production and a rise in electricity bills. It is important to know that an accurate electric load forecast enhances the initial steps in developing facilities for future generation, transmission, and distribution (Hong et al., 2020). In this context, the importance of accurate energy demand forecasting cannot be overstated since it is a critical component in the planning of electrical businesses (Zhang et al., 2021) and plays a significant part in any electric power network (Mohammed & Al-Bazi, 2022). Demand forecasting would become more complex, and studies on the subject would expand in the future(Çunkaş & Altun, 2010).

3. Research Methodology

In the current work, a pragmatic method was utilized as a guide to develop a forecasting model for the UAE. Weather conditions, industrial development, population expansion, and social events in the country are all exogenous factors for long-term forecasting (Esteves et al., 2015). A unique grey forecasting model (NDGM) is suggested which is based on a non-homogeneous index sequence (Li & Zhang, 2018). It is shown that models based on homogeneous index sequences are all special cases of models based on non-homogeneous index sequences (Shodiq, 2019). Historical load data will be acquired from the National Center for Statistics and Information, Regional Transmission Operators, World Statistics, CEIC data, countryeconomy.com, and Energy Report Recession Data (Enerdata). Mean absolute percentage error (MAPE) is used to account for future volatility, whereas implied volatility is estimated using past volatility.

3.1. Grey forecasting model

Deng introduced the grey system theory in 1982, and grey prediction models play an essential part in it. These models are sometimes referred to as grey models (GM) since they are based on the grey system theory (Xie et al., 2013). Grey models have proven useful in dealing with uncertain circumstances with few samples and little information (Javed & Liu, 2018). The main advantage of grey theory is that it can deal with both limited and unclear information with remarkable precision (Tao et al., 2022). The precision of the grey forecasting model is crucial while creating the model (Balochian & Baloochian, 2021). Even though numerous researchers have undertaken extensive studies to increase the precision of grey forecasting models and achieved significant progress, their conclusions are far from sufficient (Xie et al., 2013). Because Liu assessed the accuracy of the GM (1, 1) model with pure index sequence, the NDGM model with pure non-homogeneous index sequence was used in this study.

3.2 Non-homogeneous discrete grey model (NDGM)

The NDGM model assumes that the actual/original data sequence follows the law of approximation non-homogenous exponential development (Ikram et al., 2019). Because the NDGM model is newer than other grey models, it has applications in many fields (Wang et al., 2020).

If $x^{(0)}$ represents the preliminary stream of data and $x^{(1)}$ the collected data stream in the NDGM model so:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots x^{(0)}(n)\}, \tag{1}$$

is the preliminary stream of data, and the sequence.

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots x^{(1)}(n)\}, \tag{2}$$

is the collected data stream of $X^{(0)}$ in NDGM model, where

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

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 k + \beta_3 \tag{4}$$

$$x^{(1)}(1) = x^{(1)}(1) + \beta_4 \tag{5}$$

is known as a discrete non-homogeneous grey model (NDGM) where, $x^{(1)}(k)$, is the simulative value and $x^{(1)}(1)$ is the iterative value of the NDGM model along with parameters β_1 , β_2 , β_3, and β_4. The NDGM model's parameters are equivalent to those of the GM (1,1) and DGM models (Ikram et al., 2019). This is the least squares method. So we may obtain parameter expressions in matrix form: If k=1,2,3....n-1

$$\begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix} = (B^T B)^{-1} B^T Y, \tag{6}$$

Where

$$Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ . \\ . \\ . \\ x^{(1)}(n) \end{bmatrix}$$

(7)

$$B = \begin{bmatrix} x^{(1)}(1) & 1 & 1 \\ x^{(1)}(2) & 2 & 1 \\ . & . & . \\ . & . & . \\ x^{(1)}(n-1) & k-1 & 1 \end{bmatrix} \tag{8}$$

NDGM parameters $\beta 1, \beta 2, \beta 3, \beta 4$ are determined via the least square approach, we can get the following relation:

$$\hat{\beta} = (B^T B)^{-1} B^T Y = [\beta_1, \quad \beta_2, \quad \beta_3]^T \tag{9}$$

The recursive function of the NDGM model is

$$\hat{x}(k+1) = \beta_1^k \hat{x}^{(1)}(1) + \beta_2 \sum_{j=1}^{k} j\, \beta_1^{k-j} + \frac{1-\beta_1^k}{1-\beta_1} \cdot \beta_3; k = 1,2, \ldots n-1 \tag{10}$$

The parameter β_4 can be calculated by the least square method. Minimizing the error of $\hat{x}^{(1)}(k)$ and $x^{(1)}(k)$, we can solve the optimized formula

$$\min_{\beta_4} \sum_{k=1}^{n} [\hat{x}^{(1)}(k) - x^{(1)}(k)]^2$$

We can get-

$$\beta_4 = \frac{\sum_{k=1}^{n-1} [x^1(k+1) - \beta_1^k x^{(1)}(1) - \beta_2 \sum_{j=1}^{k} j \beta_1^{k-j} - \frac{1-\beta_1^k}{1-\beta_1} \cdot \beta_3]}{1 + \sum_{k=1}^{n-1} (\beta_1^k)^2} \tag{11}$$

3.3 Performance Criteria

Mean Absolute Percentage Error used as the model comparison's performance criteria ,which is Mean absolute percentage error (MAPE), given by the following formula

$$\text{MAPE}(\%) = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{x^0(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \text{ x } 100\% \tag{12}$$

Here $x^0(k)$ and $\hat{x}^{(0)}(k)$ are representing real and simulated data values.

Relative growth rate

This model was developed to assess the relative growth of electricity demand, population growth, and electricity consumption in the UAE. Using the NDGM model, two factors Relative growth rate (RGR) and doubling time (Dt) were utilized to anticipate the rise in demand and consumption of electricity(Guefano et al., 2021) as per population growth in the UAE. The relative growth rate (RGR) is given by:

$$\text{RGR} = (\ln N_2 - \ln N_1) / (t_2 - t_1) \tag{13}$$

Where N_1 and N_2 are the cumulative number of growths in the years t_2 and t_1. When t_2-t_1 is one year then the equation reduces to

$$\text{RGR} = \ln(\frac{N_2}{N_1}) \tag{14}$$

D_t is the time to double the growth and it is as:

$$D_t = (t_2 - t_1) \ln[\frac{2}{\ln N_2 - \ln N_1}] \tag{15}$$

Or,

$$D_t = \ln(\frac{2}{RGR}), \tag{16}$$

Applied Relative growth rate (RGR) and doubling time (D_t) equations to find the population growth, electricity production, and consumption in the UAE.

4. Results

4.1 Analysis through NDGM models

The NDGM model was used to anticipate the relative increase in population growth, electricity production, and electricity consumption in the UAE. Simulated values were estimated using GM(1,1) and NDGM (1,1) utilizing available data from 2010 to 2022, and the results are shown in Tables 1,2 and 3. The accuracy level of the Mean absolute percentage error (MAPE) value of NDGM turned out to be 98.29%, 98.18%, and 97.36% (Table 5) for population growth, electricity production, and consumption respectively, demonstrating NDGM best-fit grey model to anticipate the amount of growth. The NDGM simulation values revealed an increasing consumption of electricity as compared to population growth and electricity production in the future (Figures 1,2 and 3).

Table 1 *Predicting Population Growth in UAE*

Years	Original data	NDGM	Cumulative	RGR	RGR Mean	D_t	Mean D_t
2010	8481771.000	8379772.000	8379772.000				
2011	8575205.000	8463102.000	16842874.000	0.50	0.80	1.72	1.20
2012	8664969.000	8634289.000	25477163.000	0.66		1.37	
2013	8751847.000	9674988.000	35152151.000	0.72		1.27	
2014	8835951.000	8798321.000	43950472.000	0.80		1.18	
2015	8916899.000	8817869.000	52768341.000	0.83		1.14	
2016	8994263.000	8976654.000	61744995.000	0.85		1.12	
2017	9068296.000	8913466.000	70658461.000	0.87		1.10	
2018	9140169.000	9032469.000	79690930.000	0.89		1.09	
2019	9211657.000	9123456.000	88814386.000	0.90		1.08	
2020	9287289.000	9178623.000	97993009.000	0.91		1.07	
2021	9365145.000	9255731.000	107248740.000	0.91		1.07	
2022	9441129.000	9441129.000	116689869.000				
2023		9517283.879	126207152.879	0.92	0.95	1.06	1.04
2024		9593435.543	135800588.422	0.93		1.05	
2025		9669587.206	145470175.628	0.93		1.05	
2026		9745738.870	155215914.498	0.94		1.05	
2027		9821890.534	165037805.032	0.94		1.05	
2028		9898042.197	174935847.229	0.94		1.04	
2029		9974193.861	184910041.091	0.95		1.04	
2030		10050345.525	194960386.616	0.95		1.04	
2031		10126497.189	205086883.804	0.95		1.04	
2032		10202648.852	215289532.656	0.95		1.04	
2033		10278800.516	225568333.172	0.95		1.03	
2034		10354952.180	235923285.352	0.96		1.03	
2035		10431103.843	246354389.195	0.96		1.03	
2036		10507255.507	256861644.703	0.96		1.03	
2037		10583407.171	267445051.873	0.96		1.03	
2038		10659558.834	278104610.708	0.96		1.03	
2039		10735710.498	288840321.206	0.96		1.03	
2040		10811862.162	299652183.368	0.96		1.03	
MAPE %		4.32%					

Table 1 shows the prediction of population growth in the UAE. The MAPE% data demonstrate an efficacy level of 98.13% (Table 5), demonstrating the ability of the NDGM best-fit-grey model to anticipate the population growth in UAE. The MAPE% of 4.32% mentioned in Table 1 refers to the accuracy of the predictions made by the Non-Homogeneous Discrete Grey Model (NDGM) regarding population growth in the UAE. .The specific value of 4.32% suggests that, on average, the predictions made by the NDGM model deviate from the actual observed values by 4.32%, indicating a high level of precision in the model's ability to forecast population growth without being heavily influenced by anomalies or outliers. This level of accuracy is significant for planning and decision-making processes related to energy policy, infrastructure development, and economic planning in the UAE.

Table 2 *Predicting Electricity Production in UAE*

Years	Original data	NDGM	Cumulative	RGR	RGR Mean	D_t	Mean D_t
2010	93949.000	92867.000	92867.000				
2011	99137.000	98856.000	191723.000	0.48	0.78	1.75	1.24
2012	106222.000	98767.000	290490.000	0.66		1.37	
2013	109978.700	197987.697	488477.697	0.59		1.49	
2014	116528.000	105276.000	593753.697	0.82		1.15	
2015	127366.000	112756.000	706509.697	0.84		1.14	
2016	129596.250	118596.210	825105.907	0.86		1.12	
2017	134553.076	123576.051	948681.958	0.87		1.11	
2018	135996.711	132896.611	1081578.569	0.88		1.10	
2019	138454.058	127432.057	1209010.626	0.89		1.08	
2020	137310.365	137310.365	1346320.991				
2021		136531.133	1482852.124	0.90	0.91	1.08	1.02
2022		135744.850	1618596.974	0.92		1.07	
2023		134958.568	1753555.542	0.92		1.06	
2024		134172.285	1887727.827	0.93		1.06	
2025		133386.002	2021113.829	0.93		1.05	
2026		132599.719	2153713.548	0.94		1.05	
2027		131813.437	2285526.985	0.94		1.04	
2028		131027.154	2416554.138	0.95		1.04	
2029		130240.871	2546795.009	0.95		1.04	
2030		129454.588	2676249.598	0.95		1.04	
2031		128668.305	2804917.903	0.95		1.03	
2032		127882.023	2932799.926	0.96		1.03	
2033		127095.740	3059895.666	0.96		1.03	
2034		126309.457	3186205.123	0.96		1.03	
2035		125523.174	3311728.297	0.96		1.03	
2036		124736.892	3436465.189	0.96		1.03	
2037		123950.609	3560415.797	0.97		1.03	
2038		123164.326	3683580.123	0.97		1.02	
2039		122378.043	3805958.167	0.97		1.02	
2040		121591.760	3927549.927	0.97		1.02	
Mape%		2.87%					

Table 2 shows the prediction of electricity production in the UAE. The MAPE% data demonstrate an efficacy level of 97.25% (Table 5), demonstrating the ability of the NDGM best-fit-grey model to anticipate the amount of electricity production in the UAE.

Table 3 *Predicting Electricity Consumption in UAE*

Years	Original data	NDGM	Cumulative	RGR	RGR Mean	D_t	Mean D_t
2010	82517.000	82517.000	82517.000				
2011	87067.000	86157.000	168674.000	0.489	0.82	1.74	1.25
2012	93242.000	92143.000	260817.000	0.647		1.39	
2013	96584.000	95477.000	356294.000	0.732		1.26	
2014	102326.000	99876.000	456170.000	0.781		1.20	
2015	111857.000	101768.000	557938.000	0.818		1.16	
2016	114463.000	103962.000	661900.000	0.843		1.13	
2017	118211.000	107921.000	769821.000	0.860		1.12	
2018	119987.000	101978.000	871799.000	0.883		1.10	
2019	122623.000	121621.000	993420.000	0.878		1.10	
2020	119516.000	109861.000	1103281.000	0.900		1.08	
2021	128610.000	128610.000	1231891.000				
2022		132707.927	1364598.927	0.896	0.93	1.08	1.05
2023		136805.853	1501404.780	0.909		1.07	
2024		140903.780	1642308.559	0.914		1.07	
2025		145001.706	1787310.266	0.919		1.06	
2026		149099.633	1936409.899	0.923		1.06	
2027		153197.559	2089607.458	0.927		1.06	
2028		157295.486	2246902.944	0.930		1.05	
2029		161393.413	2408296.357	0.933		1.05	
2030		165491.339	2573787.696	0.936		1.05	
2031		169589.266	2743376.962	0.938		1.05	
2032		173687.192	2917064.154	0.940		1.05	
2033		177785.119	3094849.273	0.943		1.04	
2034		181883.045	3276732.318	0.944		1.04	
2035		185980.972	3462713.290	0.946		1.04	
2036		190078.899	3652792.189	0.948		1.04	
2037		194176.825	3846969.014	0.950		1.04	
2038		198274.752	4045243.766	0.951		1.04	
2039		202372.678	4247616.444	0.952		1.04	
2040		206470.605	4454087.049	0.954		1.04	
MAPE%		3.12%					

Table 3 shows the prediction of electricity consumption in the UAE. The MAPE% data demonstrate an efficacy level of 98.23% (Table 5), demonstrating the ability of the NDGM best-fit-grey model to anticipate the amount of electricity consumption in the UAE.

Both Tables 2 and 3 are crucial for understanding the balance between electricity supply and demand in the UAE. They show the NDGM model's utility in guiding policymakers and energy sector stakeholders toward more informed decisions regarding energy production, distribution, and consumption planning. The accuracy reflected in the MAPE% values emphasizes the model's potential in contributing to the development of sustainable energy policies and infrastructure investments to meet future electricity needs efficiently.

All the factors experienced an increasing tendency. According to the results, the Mean absolute percentage error (MAPE) for NDGM in population growth is higher as compared to electricity production and consumption. The average Mean absolute percentage error (MAPE) accuracy level for NDGM showed a value of 97.94% (Table 5). The predicted trends in electricity consumption as compared to electricity production in UAE drive to emphasize the significance of increasing investment in electricity.

Population growth $_{(98.13\%)}$ > Electricity consumption ($_{98.23\%)}$ >Electricity production $_{(97.25\%)}$

4.2 Relative Growth rate (RGR) and doubling time (D_t) based on NDGM

Two additional indicators—the relative growth rate (RGR) and the doubling time (Dt)—were employed to supplement the analysis(Liu & Yang, 2011). The first was employed to shed light on the relative growth of population, electricity production, and consumption; the second was to find the time needed to double the number of the population, electricity production, and consumption(Ayvaz & Kusakci, 2017). Table 4 shows how the three factors rank in terms of projected RGR and doubling time (Dt) based on real and simulated data. The following ranking order was revealed by the RGR equation using the original data:

Electricity consumption $_{(0.82)}$ > Population growth $_{(0.80)}$ > $_{\text{Electricity}}$ production $_{(0.78)}$

As per the original data, the following process was observed to determine the required time for to rise in population growth, electricity production, and demand in the UAE.

Population growth $_{(1.20)}$ < Electricity production $_{(1.24)}$ < Electricity consumption $_{(1.25)}$

The statistics above show that the proportional increase in electricity consumption in the UAE is higher as compared to population growth and electricity production. Whereas the doubling time model suggests that the UAE produced more electricity compared to population growth and electricity consumption. As a result, the relative growth rate can serve as a source of balance between population growth and electricity consumption (AL-Hamad & Qamber, 2019). Similarly, from 2023 to 2040, NDGM-based simulated data was applied to estimate the amount of population growth, electricity production, and consumption (Yao et al., 2003). The following findings were obtained, as shown by the RGR sequence:

Population growth $_{(0.95)}$ > Electricity consumption $_{(0.93)}$ >Electricity production $_{(0.91)}$

Based on the simulated data, the same sequence was seen. For the period 2023–2040, all factors endure a progressive number in terms of RGR. The Dt model yields the following sequence of findings:

Electricity production $_{(1.02)}$ < Electricity consumption $_{(1.05)}$ < Population growth $_{(1.04)}$.

It was found that the population growth of UAE requires a significantly longer time to double the number as compared to electricity production and consumption in the UAE. Using NDGM (based on real and simulated data), estimated a rise in the amount of population growth, electricity production, and electricity consumption from 2010 to 2040.

4.3 Validity of the proposed model

To find which factor among population growth, electricity production, and electricity consumption has the maximum growth in the long run (Kaytez, 2020), original and forecasting values have been calculated. As per the indices, the sequence obtained for RGR and doubling time are as follows:

Population growth $_{(0.875)}$ >Electricity consumption $_{(0.863)}$ >Electricity production $_{(0.845)}$

and the doubling time (D_t) as follows:

Population growth $_{(1.12)}$ < Electricity production $_{(1.13)}$ <Electricity consumption $_{(1.15)}$

The results are in line with the actual data and the viability of the models has also successfully been evaluated because both sequences are practically identical to the sequences obtained against the actual data.

5. Discussion and Conclusions

The ability to predict an area's (country's) power usage is crucial for policymakers as well as the economy. Accurate forecasting outcomes might aid in the efficient application of power supply policies (Yao & Mao, 2023) following population demand and electricity production, assist prevent economic losses brought on by insufficient energy to some extent, and lower operational costs and hazards to the economy (Cai et al., 2020). The source database for generating electricity, however, is frequently constrained and varies greatly. As a result, the GM (1,1) model, one of the most popular grey prediction models, is a suitable tool for forecasting electricity consumption in relation to productivity and population growth (Li & Zhang, 2018). It only requires a small number of samples to create a prediction model with a relatively high prediction accuracy. The current study's findings provide important policy implications and guidance for industry stakeholders. After the pandemic, reliable tourist forecasting became crucial for policymakers in the tourism sector since tourism plays a significant economic role in many economies (Alhowaish, 2016). Using a forecasting framework like the grey forecasting method, the projected number of tourists in GCC countries is predicted. According to the results, the grey prediction model was successfully employed to anticipate the amount of electricity consumption and production growth from 2023 to 2040. Furthermore, using the doubling time (Dt) formula, this analysis provides a 2023 to 2040 for a rise in consumption. As per the doubling time, the population growth takes more time to double than electricity consumption and its production (Wu et al., 2023). The results confirmed that the proportional increase in electricity consumption and its production in UAE is higher as compared to the population growth pattern. In the long-term electricity production will result in significant wasted investment in surplus power facility development in UAE. The projection of electric power and the economy's evolution are inextricably linked (Lee & Tong, 2011). The UAE's energy consumption has climbed from 2010 to 2016 at an average annual rate of 4%, and forecasts show that it will reach 5% by 2020. Over the decade from 2010 to 2022, the global energy demand has more than quadrupled at a rate that will be challenging to sustain in the long run. One relatively easy strategy to reduce the growth of energy demand is to implement a sustained energy efficiency plan. Such a method might save a lot of money on consumption with very little time and expense. Reducing overall energy use has a number of advantages (Xie & Liu, 2009). It would protect the UAE's energy supplies, lower end-user energy costs, assist utilities in managing their infrastructure needs, and lessen the burden the UAE government would face from subsidies. This also has implications for national security and the day-to-day operations of any government. As a result, precise electricity demand forecasting would impact energy-generating capacity scheduling and power grid management. This is because a successful projection would not only result in significant savings in operating and maintenance expenses but would also result in the right decisions for future expansion (Li & Zhang, 2021).

Accurate energy demand forecasting is critical in a demand-side economic dispatch to maximize renewables while minimizing operating costs (Sui & Qian, 2022). This study will be tremendously helpful in developing a reliable and cost-effective network and forecasting electric utility resources to fulfill current demand cost-effectively. Looking forward, electricity is expected to play a key role in the energy consumption scenario as this research transition away from the residential use of fossil fuel-based heat pumps and toward the inclusion of electric vehicles (EVs) and other hybrid automobiles in the transportation sector (Murray et al., 2012). A change of this magnitude will significantly influence the overall electricity demand profile.

Table 4 *Ranking Order of Population Growth, Electricity Demand, and Electricity Consumption in UAE of Projected RGR and Doubling Time (Dt) Based on Real and Simulated Data*

Relative growth rate (RGR) / Doubling time (Dt)	Ranking
RGR (Original data)	Electricity consumption $_{(0.82)}$ > Population growth $_{(0.80)}$ > Electricity production $_{(0.78)}$
D_t (Original data)	Electricity production $_{(1.02)}$ < Electricity consumption $_{(1.05)}$ < Population growth $_{(1.04)}$.
RGR (Forecast data)	Population growth $_{(0.95)}$ > Electricity consumption $_{(0.93)}$ >Electricity production $_{(0.91)}$
D_t (Forecast data)	Electricity production $_{(1.02)}$ < Electricity consumption $_{(1.05)}$ < Population growth $_{(1.04)}$.

Table 5 *Mape % of Three Factors*

UAE	MAPE % (NDGM)
Population growth	4.32
Electricity production	2.87
Electricity consumption	3.12
Overall accuracy	97.94

As the MAPE is less than 5% it is considered as an indication that the forecast is acceptably accurate.

The overall accuracy of 97.94% mentioned in Table 5 is calculated based on the Mean Absolute Percentage Error (MAPE) values for three different factors: population growth, electricity production, and electricity consumption within the study. Here's a brief explanation of how this overall accuracy might have been derived:

MAPE Values: The document provided individual MAPE values for each of the three factors analyzed using the Non-Homogeneous Discrete Grey Model (NDGM):

Population Growth: 4.32%

Electricity Production: 2.87%

Electricity Consumption: 3.12%

Conversion to Accuracy: MAPE is a measure of prediction error. However, accuracy can be derived from MAPE by subtracting the MAPE value from 100%. This gives a measure of how accurate the predictions are, with higher percentages indicating higher accuracy. For instance, a MAPE of 4.32% for population growth translates to an accuracy of 95.68% (100% - 4.32%).

Overall Accuracy Calculation: The document does not provide explicit details on the mathematical operation used to combine these accuracies into an overall accuracy of 97.94%. However, an overall accuracy metric typically involves averaging the individual accuracies or using a weighted average if certain factors are considered more significant than others.

Given the MAPE values for the three factors, the calculation for individual accuracies would be as follows:

Population Growth Accuracy: 100% - 4.32% = 95.68%

Electricity Production Accuracy: 100% - 2.87% = 97.13%

Electricity Consumption Accuracy: 100% - 3.12% = 96.88%

An average of these three accuracies could approximate the overall model accuracy, depending on the specific method of averaging (simple or weighted) and the exact figures used. The reported overall accuracy of 97.94% suggests that the model performs very well across the different factors it predicts, indicating a high level of reliability and effectiveness of the NDGM in forecasting these aspects of UAE's electricity dynamics.

The academic and practical contributions of this research are manifold, reflecting its significance in both theoretical and practical realms based on the analysis results. Academically, this study introduces a novel approach to forecasting electricity consumption using the Non-Homogeneous Discrete Grey Model (NDGM). This model's application stands out as it deviates from traditional methods that heavily rely on weather data, presenting a new pathway for research in energy forecasting. The utilization of NDGM combined with MAPE for long-term forecasting has demonstrated high accuracy, as indicated by MAPE values being less than 5%. This level of precision is significant for academic circles looking to improve forecasting models' reliability and efficacy.

On a practical level, the study's findings aid in the strategic planning of energy production and consumption. By providing accurate forecasts, it enables policymakers and energy planners to make informed decisions, thus facilitating better management of energy resources and anticipation of future demands. The research contributes to the broader goal of sustainable energy management by forecasting the long-term electricity needs of the UAE. It supports the transition towards more sustainable energy systems by allowing for the effective integration of renewable energy sources into the grid, thus aligning with global sustainability goals. The study's outcomes have direct implications for economic development, as accurate energy demand forecasting is crucial for ensuring the stability and reliability of power supply. This reliability is essential for attracting investment, supporting industrial growth, and fostering overall economic stability in the UAE.

These contributions underscore the study's importance in advancing both the theoretical understanding and practical application of energy demand forecasting, particularly in the context of the UAE's dynamic and rapidly evolving energy landscape

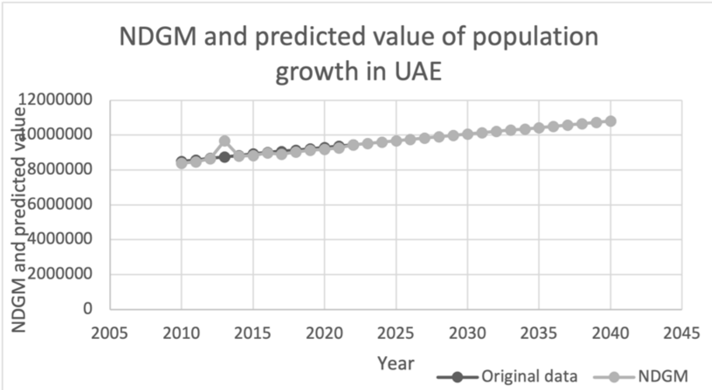

Figure 1 *NDGM and Predicted Value of Population Growth in UAE*

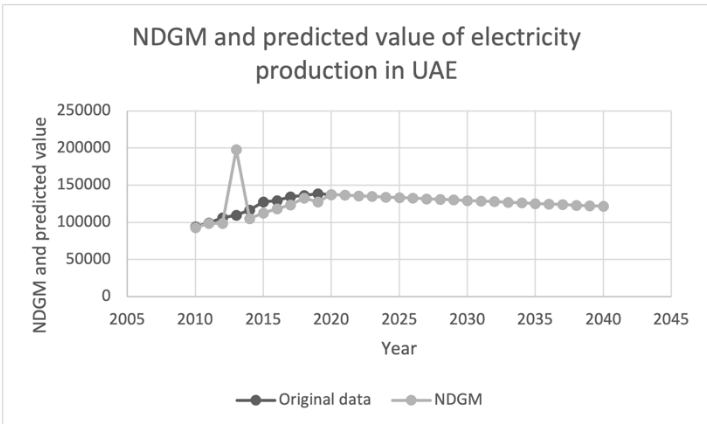

Figure 2 *NDGM and Predicted Value of Electricity Production in UAE*

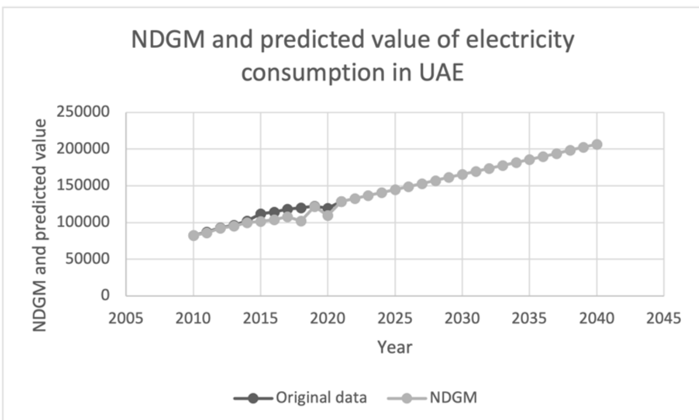

Figure 3 *NDGM and Predicted Value of Electricity Consumption in UAE*

6. Limitation and Future Research

Forecasts are projections. They have limits and are influenced by a variety of circumstances. It can be difficult to predict energy consumption since it depends on many different variables, such as weather patterns, economic trends, and consumer behavior. Demand forecasting is essential not just for day-to-day operations but also for short--, mid-, and long-term planning in the power industry. Due to changes in the economy, environment, or safety, the forecast cannot come true or will have dramatically different real-life numbers. However, in this case, the researcher attempted to minimize errors by using a sophisticated model. Other projection approaches, such as Future Research Lines, can also be utilized to generate a larger number of projections. Previous patterns in energy demand predictions may also be analyzed and utilized to estimate future more realistic and actual forecasts to gear up well in advance to meet the increasing demand. This study forecasted statistics over the next eighteen years. Future research recommendations from the study state that the country and the province must create and implement effective plans for proper utilization of electricity as per the population growth.

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