Energy demand forecasting of remote areas using linear regression and inverse matrix analysis

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ABSTRACT

Efficient energy demand forecasting is pivotal for addressing energy challenges in remote areas of Bangladesh, where reliable access to energy resources remains a concern. This study proposes an innovative approach that combines linear regression analysis (LRA) and inverse matrix calculation (IMC) to forecast energy demand accurately in these underserved regions. By leveraging historical energy consumption data and pertinent predictors, such as meteorological conditions, population dynamics, economic indicators, and seasonal patterns, the model provides reliable forecasts. The application of the proposed methodology is demonstrated through a case study focused on remote regions of Bangladesh. The results showcase the approach's effectiveness in capturing the intricate dynamics of energy demand and its potential to inform sustainable energy management strategies in these remote areas. This research contributes to the advancement of energy planning and resource allocation in regions facing energy scarcity, fostering a path towards improved energy efficiency and development. These techniques can be applied to estimate short-term electricity demand for any rural or isolated region worldwide.

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1. INTRODUCTION

In order to ensure the effective allocation and usage of energy resources, energy demand forecasting is of utmost importance, particularly in distant places where energy accessibility continues to be problematic. Accurate energy demand projection is sometimes made more difficult by remote places particular features, such as their poor infrastructure and remoteness from other areas. In Bangladesh, a nation that struggles with inequalities in its energy supplies, the need for exact forecasting in outlying areas is even more critical. The main objective of this work is to provide a unique method for predicting energy consumption in rural areas of Bangladesh utilizing inverse matrix computation and linear regression. This approach aims to provide a tailored solution for energy forecasting that can effectively address the complexities of remote energy consumption patterns by combining historical energy consumption data with pertinent influencing factors, such as meteorological parameters, demographic trends, economic indicators, and seasonal variations.

Although Bangladesh has made great strides in developing its energy infrastructure, the government still has issues providing fair access to power throughout the nation. Energy usage varies in remote areas because of geographical factors that are specific to particular regions. Due to data constraints, non-linear interactions, and seasonal dynamics, conventional forecasting techniques frequently find it difficult to take into account the complexity of such scenarios. This study proposes a methodology that not only considers these challenges but also utilizes the interplay of linear regression and inverse matrix analysis to provide accurate energy demand forecasts.

In Bangladesh, the per-person electricity consumption is one of the lowest in the world, standing at 136 kWh. This implies that almost half of the country's energy usage comes from non-commercial sources, such as wood fuel, animal waste, and crop residues. The nation has a significant abundance of natural gas, while its coal and oil reserves are meager [1]. Commercial energy usage is predominantly reliant on natural gas, making up 66%, with oil, hydropower, and coal following suit. Electricity powers most of the country's financial activities. However, with an annual usage of just 321 kWh per person, only 70% of Bangladesh's population has access to electricity, with the government setting a 20 GW target in 2019, expected to increase to 61 GW by 2041. Regrettably, Bangladesh's power sector is grappling with various issues, such as corruption in administration, high system losses, and project delays in constructing new power plants. These issues must be dealt with to improve the countries electricity infrastructure [2]. The countries power generation capability hasn't been able to keep up with demand for the last ten years now. Even so, the government of Bangladesh has made long-standing arrangements to address the countries energy problems, and it has begun to put those arrangements into action. Planned increases in electricity generation from 2021 to 2041 are shown in Figure 1. This study forecasts reactive demand at every transmission substation in light of a power factor of 90% for the transmission enquiry study for the years 2013, 2015, 2020, 2025, and 2030, based on a survey of 2016 information and interactions with Bangladesh power development board (BPDB) and power grid company of Bangladesh (PGCB) [3].

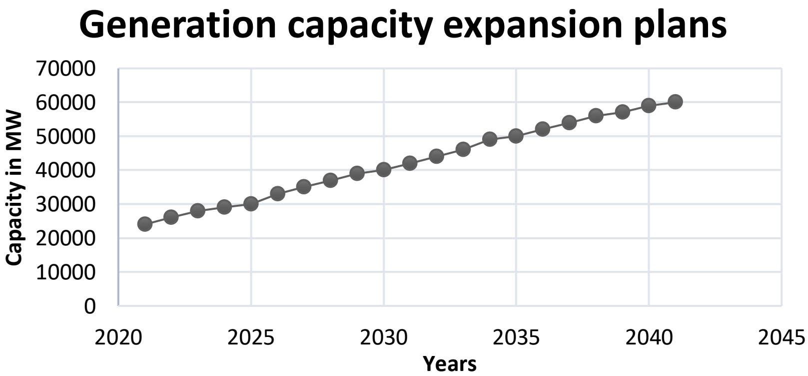


Figure 1. Power plant generation capacity expansion plans

Approximately 10% of the population has used petroleum natural gas, mainly in rural areas where it is not readily available [4]. People in rural areas use biomass energy sources like firewood, cow feces, and farming leftovers to heat their homes and cook their food. The most common form of lighting in rural areas is the lamp oil-based illumination. It was decided to continue the installation of new gas connections in manufacturing companies in April of this year, after they were originally scheduled to be completed in 2009 [5]. As a result, new gas connections in the residence house have been placed on hold "until further notice" because they were confined and expensive. So, in urban areas, individuals rely heavily on electric appliances in their homes. To maintain uninterrupted electrical supply across the country, there is not enough electricity generation and there is no way to estimate demand. Because of this, load shedding has been taking place. Currently, Bangladesh's government is planning to develop its power producing plant in order to ensure that there will be no interruptions in the supply of electricity [5].

There are numerous studies on how to predict the energy needs of a remote location [1], [6]. But the key limitation of these research papers is the energy demand histories are expected as known, which is not genuine. The use of solar panels in rural regions has recently been advocated using mixed-integer linear programming [7]. In comparison to traditional power generation, solar energy is more expensive and comes with a slew of drawbacks. In order to keep costs down, a remote location's energy demand must be accurately estimated before any new power lines or renewable microgrid systems can be built. The ones normally used by scientists are [8]: i) time series methods, ii) artificial intelligence (AI) based procedures [9], iii) regression-based analysis model, iv) bottom-up technique, v) top-down technique, vi) additive control methods, vii) matrix analysis, and viii) machine learning.

Kolapara and Kuakata, the locations under consideration, are two of Bangladesh's most important islands. The panoramic sea beach is another name for this location. Kolapara and Kuakata represent two distinct yet interconnected aspects of Bangladesh's coastal region. While Kolapara showcases the challenges and livelihoods of a coastal sub-district with an emphasis on agriculture, Kuakata shines as a picturesque tourist destination famous for its beach beauty and natural attractions. Both locations contribute to the diverse fabric of Bangladesh's coastal landscape, highlighting the importance of sustainable development and resilience in the face of environmental and economic changes.

The remainder of the paper is outlined as follows: linear regression analysis (LRA) [10], [11] and inverse matrix calculation (IMC) [11] for energy demand forecasting are briefly discussed in section 2 of this article. After that, a short description of the research location and the data collection are provided. According to section 4, it is explained how to use regression analysis and significant outcomes with graphical representation to forecast energy consumption in an off-grid location and displays the inverse matrices analysis approach. Lastly, in section 5, we offer some closing thoughts and ideas for further research.

2. LITERATURE REVIEW

2.1. Load forecasting

Load forecasting is a critical component of energy management and planning, encompassing the prediction of future electricity or energy demand based on historical data, external factors, and emerging trends. Accurate load forecasting is essential for ensuring reliable power supply, efficient resource allocation, and optimal operation of energy systems [12]. It plays a crucial role in addressing the challenges posed by fluctuating demand patterns, varying consumer behavior, and the integration of renewable energy sources into the grid. The complexity of modern energy systems, coupled with the increasing penetration of distributed energy resources and the advent of smart grid technologies, has amplified the significance of load forecasting. Accurate forecasts enable utilities and energy providers to make informed decisions regarding capacity expansion, infrastructure upgrades, and demand response strategies. Moreover, they facilitate cost-effective energy procurement and help prevent potential grid instability due to demand-supply imbalances.

The following are examples of load forecasting:

a. Short-term forecasts: For short-term load forecasting, a number of parameters, including time, weather data, and prospective client classifications, must be taken into account [13]. The day of the year, the week, and the time of day are all aspects to consider. The load is affected by the weather. In fact, short-term load projections rely heavily on the weather characteristics that have been predicted. The forecasting of loads can take into account a variety of weather variables. Predictors of demand, like temperature and humidity, are the most common. Daily operations and unit commitment are supported by this data, which is used to support system management. With short-term power load forecasting, utility company managers are provided with information about future electric load demand to help them run more efficient and reliable day-to-day operations.
b. Medium-term forecasts: A variety of elements go into the medium and long-term projections, including historical load and weather data, customer demographics, the types and ages of local appliances, and a variety of other variables, such as economic and demographic trends. Scheduled fuel deliveries and equipment maintenance are two of its primary functions [14].
c. Long-term forecasts: In most cases, it is utilized to provide electric utility company management with forecasts of upcoming requirements for expansion, equipment acquisitions, or staffing [15].

Load forecasting is a fundamental tool for ensuring the reliability, efficiency, and sustainability of energy systems. It makes it possible for customers, governments, and energy suppliers to prepare in advance, adjust to changing circumstances, and maximize resource use. Accurate load forecasting is a crucial facilitator of efficient energy management and a significant driver of the transition to a more resilient and sustainable energy future as the energy environment continues to change.

2.2. Linear regression analysis

A fundamental statistical method called LRA is used to represent the connection between one or more independent variables (predictors) and a dependent variable (response). Making forecasts, figuring out the strength and direction of their connections, and comprehending the linear link between variables are all things that may be done with it to great advantage. Due to its simplicity and interpretability, LRA is frequently used in a variety of disciplines, including economics, social sciences, engineering, and data science. Regression analysis is used to analyze the relationships between two or more variables [16]–[18]. Numerous modeling and analytic strategies are used to investigate the relationship between one dependent variable and several independent variables [19]. In this kind of study, off-grid regions are considered as dependent variables, whilst on-grid areas are handled as independent variables [20].

The simplest version of linear regression assumes that the independent variable(s) and dependent variable have a linear relationship. Finding the best-fitting model that reduces the discrepancies between the anticipated values. The actual observed value is the objective. The equation of a linear regression line is often represented as (1):

$$y = b_0 + b_1 x + \epsilon. \quad (1)$$

where y is the dependent variable. x is the independent variable, b_0 is the intercept. b_1 is the coefficient for the independent variable x. ϵ represents the error term or residual, accounting for unexplained variability. Linear regression analysis is a versatile and widely used technique for understanding the relationships between variables and making predictions based on historical data. Despite its simplicity, LRA remains a powerful tool in data analysis, hypothesis testing, and decision-making across diverse domains. A proper understanding of its assumptions, limitations, and appropriate usage is essential for obtaining meaningful insights from the data.

2.3. Inverse matrix calculation

There are many research conducting using inverse matrix calculation [21]–[23]. Four types of loads can be found in any given location, and they are all subdivided into one another: household loads, commercial loads, irrigation loads, and industrial loading. Factors like population, per capita revenue and adult literacy rate are also taken into consideration when determining the amount of work that must be done [11].

2.3.1. Local load demand

The local load may be affected by factors such as population density and living standards. Per capita income and the percentage of adults who are able to read are two factors that contribute to the disparity in the standard of living. All of these variables change throughout time. The local load, L_L may then be expressed as (2),

$$L_{LD}(t) = f_1\,(R_L\,(t), P_O\,(t), R_P(t)) \quad (2)$$

where, $R_L\,(t)$=Adult reading ability rate at time *t*, $P_O\,(t)$=Populace at time *t*, $R_P(t)$=Per capita revenue at time *t*.

2.3.2. Load demand of manufacturing

Per capita income, inland communication in total area, distance from the local town, reading ability rate, and farming land in total area may all affect manufacturing load in a given location. Communication across the sea may be the primary mode of communication in some distant regions. That is why it is important to include both land and water routes in the communication [11]. This manufacturing load M_L can be calculated as (3),

$$M_{LD}(t) \;=\; f_2\,(R_P\,(t), L_R\,(t), T_D(t), L_F(t)) \quad (3)$$

where, $R_P\,(t)$=per capita revenue, $L_R\,(t)$=inland communication length in per unit area at time t, $T_D(t)$=distance from local town, $L_F(t)$=farming land in percent of total area at time t.

2.3.3. Load demand of commercial

It typically refers to the demand for electrical power or energy that business buildings and establishments use. Offices, retail stores, restaurants, malls, and other non-residential buildings are examples of commercial buildings where business operations are conducted. In general, the commercial load is influenced by factors such as per capita income, inland communication per unit area, and distance from the next town. The commercial load, C_L may then be expressed as (4),

$$c_{LD}(t) \;=\; f_3\,(R_P\,(t), L_R\,(t), T_D(t)) \quad (4)$$

2.3.4. Load demand of farming

Per capita income and farming land area are the two most important factors affecting farming's burden. This industrial load F_L can be calculated as (5),

$$F_{LD}(t) \;=\; f_4\,(L_F\,(t), R_P\,(t)) \quad (5)$$

The total electrical load demand, $E_{LD}(t)$ in an isolated area is the sum of the above four loads. That is (6),

$$E_{LD}(t) = \; L_{LD}\,(t) + M_{LD}(t) + C_{LD}(t) + F_{LD}(t) \quad (6)$$

Therefore, the load demand of an isolated area can be expressed as (7),

$$T_{LD}(t) = f_4(R_L(t), P_0(t), R_p(t), L_R(t), T_D(t), L_F(t)) \tag{7}$$

There are six time-dependent variables in equation, however this does not mean that the load depends on them. To generate load, however, not all variables must be equal. Let Q_1, Q_2, Q_3, Q_4, Q_5, and Q_6 represent the weighting factors by which each time varying factor $R_L(t)$, $P_0(t), R_p(t), L_R(t), T_D(t)$ and $L_F(t)$ respectively contributes towards the load growth. The weighting factors, [Q] are also random in nature. It is possible that they'll differ depending on where you live.

It is now possible to represent the load as (8),

$$E_{LD}(t) = [Q] \times \begin{bmatrix} R_L(t) \\ P_O(t) \\ R_P(t) \\ L_R(t) \\ T_D(t) \\ L_F(t) \end{bmatrix} \tag{8}$$

From the equation, the weight factors [Q] can be calculated as (9).

$$[Q] = E_{LD\,T} \times P_{inv} \begin{bmatrix} R_L(t) \\ P_O(t) \\ R_P(t) \\ L_R(t) \\ T_D(t) \\ L_F(t) \end{bmatrix} \tag{9}$$

IMC is a fundamental mathematical operation with diverse applications in various fields. It plays a crucial role in solving systems of equations, transformations, and numerous other mathematical tasks that involve matrices. However, care must be taken to consider conditions, computational complexity, and numerical stability when dealing with inverse matrices in practical applications.

3. DATA COLLECTION

The data collection process is a systematic approach to gathering information for research, analysis, or decision-making purposes. It involves planning, designing, implementing, and managing strategies to acquire relevant and accurate data. An effective data collection process ensures the quality and integrity of the collected data. Collecting high-quality data is a crucial step in performing accurate and meaningful regression analysis. The data will directly impact the results and insights derived from analysis. Three stages of data collection are involved. In the first place, I went to the Kalapara Upazila Nirbahi Officer (UNO) office to collect the time-invariant data such as population (P_O), adult literacy rate (R_L), per capita income (R_P), land communication strength (L_R) and agricultural land (L_F), distance from main land (T_D), tourist visitor (T_v). After that, we headed to the Kalapara Bangladesh Rural Electrification Board (BREB) office to collect the town's maximum and average load. For more trustworthy data and an understanding of per-capita income, I then visited the Bangladesh Statistical Bureau. The Kalapara area is connected to the grid, while the Kuakata area is not. The following are the results of the data collection for time invariant variables shown in Table 1. The regression table of Kalapara (K_a) and Kuakata (K_u) is shown in Table 2. Tables 3 and 4 are the average demand/load and maximum demand/load of Kalapara town from 2019-2022 by month respectively.

Table 1. The data collected from UNO office of Kalapara

Data	Kalapara (on-grid)	Kuakata (off-grid)
P_O (1000)	19.92	10.51
R_L (%)	75.08	65.08
R_P (USD)	79.17	59.63
L_R (KM)	12.11	3.13
L_F (Hector)	1.6	1.45
T_D (KM)	3.1	20
T_v (1000)	0.5	1.2

Table 2. The regression table of Kalapara (K_a) and Kuakata (K_u)

K_a	K_u	K_a^2	K_aK_u
19.92	10.51	396.81	209.36
75.08	65.08	5037.01	4886.21
79.17	59.63	6267.89	4720.91
12.11	3.13	146.65	37.9043
1.6	1.45	2.56	2.32
3.1	20	9.61	62
0.5	1.2	0.25	0.6
$\sum K_a$=191.48	$\sum K_u$=161	$\sum K_a$^2=11860.78	$\sum K_aK_u$=9919.304

Table 3. The average demand/load of Kalapara town from 2019-2022 by month

Month	Average demand/load (KW)			
	2022	2021	2020	2019
January	101.9814	94.613	80.6192	72.4458
February	99.6904	92.8793	83.7771	78.6378
March	97.9567	91.0217	84.582	84.9536
April	102.3529	99.5666	84.8297	91.3932
May	96.7183	99.3189	90.031	90.774
June	107.3065	90.4025	96.2229	85.5728
July	103.9009	98.7616	97.5851	87.1207
August	102.7864	92.8793	87.9257	88.6068
September	86.6873	102.0433	90.2786	93.6842
October	104.5201	105.7585	90.5263	91.8266
November	96.4706	95.1084	88.2972	87.0588
December	97.2136	94.1176	81.0526	85.6966

Table 4. The maximum demand/load of Kalapara town from 2019-2022 by month

Month	Maximum demand/load (KW)			
	2022	2021	2020	2019
January	226.6254	210.2786	179.195	160.9907
February	221.4241	206.4396	186.192	174.8607
March	217.5851	202.291	188.0495	188.7926
April	227.4923	221.3003	188.5449	203.096
May	214.7988	220.805	200.1238	201.7337
June	238.5759	200.805	201.4241	190.2167
July	231.0217	219.5046	216.904	193.6842
August	228.4211	206.5015	195.4799	197.0279
September	192.5077	226.8111	200.743	208.2972
October	232.2601	235.0464	201.2384	204.0867
November	214.2415	211.4551	196.2229	193.4985
December	216.0991	209.2879	180.1238	190.4644

It is necessary to know the area's history in order to compute the weighted average value of these variables. Another alternative is to look at a location that has some of the isolated area's characteristics. This is the key contribution of this work. The practical execution of the proposed strategy will shed light on this issue.

4. RESULTS AND DISCUSSION

4.1. Load forecasting using LRA

In this section, we present the results of our load forecasting study using regression analysis. We focus on the key findings derived from the regression model and discuss their implications for accurate load prediction. The performance of the regression model was evaluated through the coefficient of determination, which quantifies the proportion of variability in the load data explained by the independent variables. The regression value obtained for our model was 0.83, indicating that approximately 83% of the load variation can be accounted for by the predictor variables integrated into the model. This suggests a substantial relationship between the predictors and the load in the short term.

Load forecasting using regression analysis of (10):

$$K_u = A + R\,K_a \tag{10}$$

where

$$R = \frac{\left(\sum KaKu - \frac{\sum \boldsymbol{Ka} \sum \boldsymbol{Ku}}{\boldsymbol{n}}\right)}{\left(\frac{\sum \boldsymbol{Ka^2} - (\sum \boldsymbol{Ka})^2}{\boldsymbol{n}}\right)} = \left(\frac{9919.304 - \frac{191.48*161}{7}}{11860.78 - \frac{191.48^2}{7}}\right) = 0.8327 \tag{11}$$

$$A = \sum K_u/n - \sum \frac{K_a}{n} = 23 - 0.83 * 27.3 = 30 \tag{12}$$

$$K_u = A + R\,K_a \rightarrow= 0.30 + 0.8327\,K_a$$

when

$$\begin{aligned} K_a = {} & 101.9814\,KW\ (Average\ load\ of\ January\ 2022\ of\ Kalapara). \\ & = 0.30 + 0.8327 * 101.9814 \\ & = 85.22\,KW\ (Average\ load\ of\ January\ 2022\ of\ Kuakata) \end{aligned}$$

Table 5 summarizes the average and maximum demand of Kuakata for 2022 based on Kalapara's 2022 load using regression analysis and shown in Figure 2. In this study, we employed regression analysis to forecast short-term load patterns, and the results have provided valuable insights into the dynamic behavior of energy demand. Our analysis underscores the significance of considering key predictor variables to achieve accurate short-term load predictions.

Table 5. The estimated average and maximum load of Kuakata

Month	Average demand/load (KW) 2022	Maximum demand/load (KW) 2022
January	85.2199	189.011
February	83.3122	184.6798
March	81.8685	181.4831
April	85.5293	189.7328
May	80.8373	179.163
June	89.6541	198.9622
July	86.8183	192.6718
August	85.8902	190.5062
September	72.4845	160.6012
October	87.3339	193.703
November	80.6311	178.6989
December	81.2498	180.2457

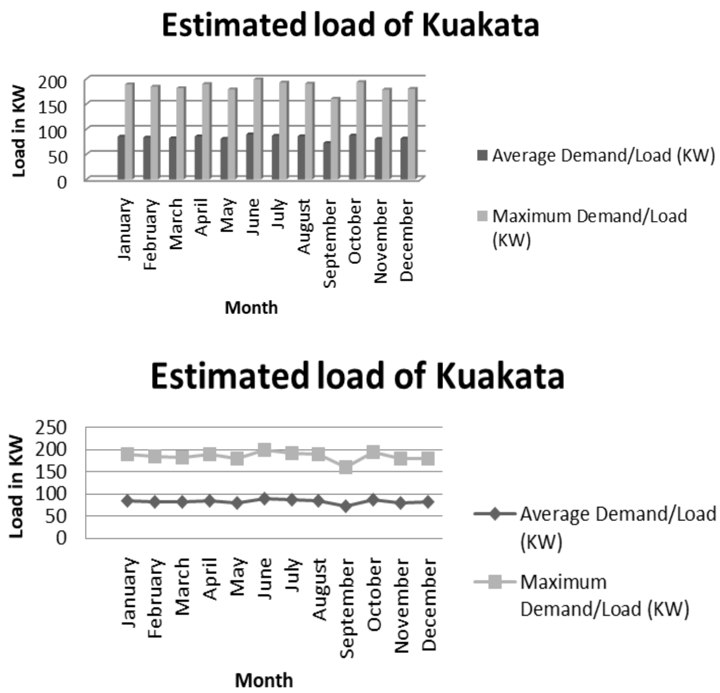


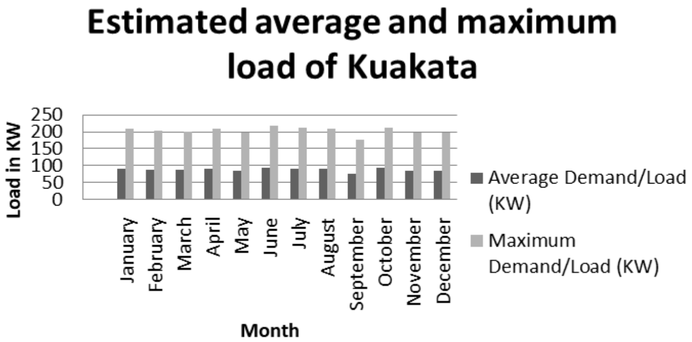
Figure 2. The graphical diagram of estimated average and maximum load of Kuakata, left: bar, right: line

4.2. Load forecasting using IMC

It is customary to utilize the Moore–Penrose pseudoinverse (henceforth, just pseudoinverse) to compute a "best fit" (least squares) solution to a non-unique set of linear equations [24]–[26]. Finding the smallest (Euclidean) norm solution to a linear equation system with many solutions is another use [11], [27]. In linear algebra, the pseudoinverse makes it easier to state and prove results [9], [28], [29]. The IMC-based load forecasting method was evaluated based on its ability to accurately predict load values for a specified time period. The calculated root mean squared error (RMSE) between the forecasted load values and the actual load data was found to be very small units. This indicates a relatively small deviation between the forecasted values and the actual load, suggesting that the IMC approach effectively captures load trends. Matrix study estimates the average and maximum load for Kuakata, with Kalapara representing the on-grid area and Kuakata representing the off-grid territory. Table 6 shows the estimated average and maximum load of Kuakata using inverse matrix analysis and shown in Figure 3.

Table 6. The estimated average and maximum load of Kuakata

Month	Average demand/load (KW) 2022	Maximum demand/load (KW) 2022
January	90.3331	207.9121
February	88.3109	203.1478
March	86.7806	199.6314
April	90.6611	208.7061
May	85.6875	197.0793
June	95.0333	218.8584
July	92.0274	211.939
August	91.0436	209.5568
September	76.8336	176.6613
October	92.5739	213.0733
November	85.469	196.5688
December	86.1248	198.2703



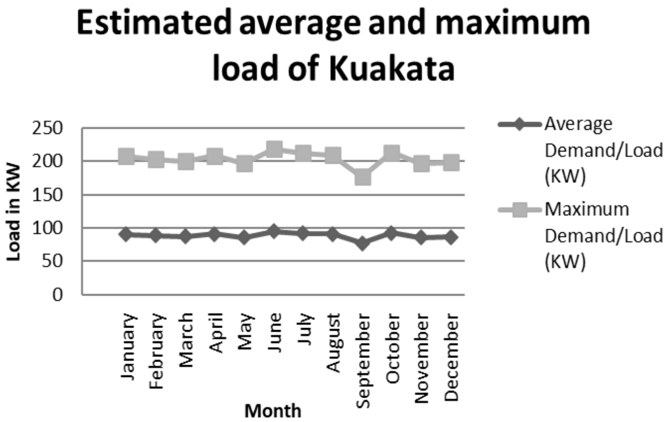


Figure 3. The graphical diagram of estimated average and maximum load of Kuakata. Left: bar, right: line

In conclusion, our load forecasting approach utilizing IMC offers a practical and accurate method for predicting load variations. By effectively incorporating external factors such as temperature and day of the month, our approach contributes to the arsenal of tools available for enhancing energy management and ensuring a stable and reliable energy supply. As the energy landscape evolves, accurate load forecasting remains pivotal, and our study contributes to advancing this critical facet of modern energy systems.

4.3. Load forecasting comparison between LRA and IMC

Two separate approaches are used to forecast the amount of traffic in this particular patch of work. The results of the comparison demonstrate that the two methods yielded roughly the same estimates of electricity consumption. Figure 4 shows the comparison of estimated average load of Kuakata using two methods. Short-term forecasting was used in this case. The results would be more exact and precise if more aspects such as time, temperature, area, peak and off-peak time, lifestyle of the people, etc. were taken into consideration. However, this research anticipated demand is rather realistic because it is based on on-load data. Electric utility companies will be able to use this information to help with purchasing and generation of electric power [30], [31], load switching and infrastructure development. Above all, the mathematical model can be used in any off-grid or isolated island setting.

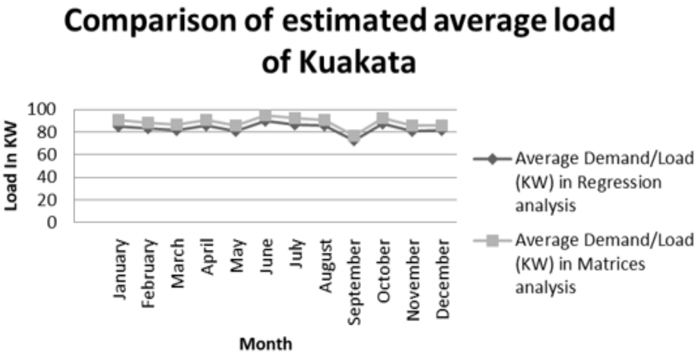


Figure 4. The comparison of estimated average load of Kuakata using two methods

5. CONCLUSION

In this study, we embarked on a comprehensive exploration of energy demand forecasting for remote areas through the combined application of linear regression and inverse matrix analysis. The amalgamation of these techniques offered valuable insights into the intricacies of energy consumption patterns in regions where access to reliable energy sources is crucial. The purpose of this research methodology is to determine the average and maximum load of a remote location to aid the government in estimating the potential load requirements for constructing a power plant in the future. The study team successfully applied a regression analysis strategy to this end. The efficiency of the approach utilized was demonstrated by a comparison of the regression analysis findings with those using matrices. Both methods provided results that were almost similar. Energy consumption for remote places has been predicted thanks to the interaction between linear regression and inverse matrix analysis. Our research emphasizes the significance of taking into account a variety of influencing elements, enabling precise forecasts that serve as the basis for energy planning and resource management. Our study significantly contributes to the energy independence and resilience of distant regions as they grow and work toward sustainable development, promoting a better future for these neglected places.

The study recommends the use of artificial intelligence (AI) and machine learning algorithms for future load forecasting work. The researcher can look into how combining smart grid and internet of things (IoT) devices might deliver real time data for demand forecasts. These approaches have the potential to provide more accurate and reliable predictions, which can help in planning and constructing power plants in isolated regions.

REFERENCES

[1] S. M. Hossain and S. Biswas, "Reinforcing renewable resources for sustainable future of Bangladesh," in *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, Apr. 2023, pp. 1–7, doi: 10.1109/I2CT57861.2023.10126224.
[2] N. K. Das, J. Chakrabartty, M. Dey, A. K. Sen Gupta, and M. A. Matin, "Present energy scenario and future energy mix of Bangladesh," *Energy Strategy Reviews*, vol. 32, Nov. 2020, doi: 10.1016/j.esr.2020.100576.
[3] Bangladesh National Portal, "Power system master plan-2016," *Power Division*. 2016, Accessed: Mar. 11, 2021. [Online]. Available: http://www.powerdivision.gov.bd/site/page/f68eb32d-cc0b-483e-b047-13eb81da6820/Power-System-Master-Plan-2016.
[4] World Bank, "Country profile data: Bangladesh," *World Bank*. Accessed: Feb. 17, 2021. [Online]. Available: https://data.worldbank.org/country/bangladesh?view=chart.
[5] Bangladesh National Portal, "Bangladesh power development board," *Bangladesh National Portal*, Accessed: Mar. 11, 2021. [Online]. Available: www.bpdb.gov.bd.
[6] S. Bin Amin and S. Rahman, "Renewable energy practices in Bangladesh," in *Energy Resources in Bangladesh*, Cham: Springer International Publishing, 2019, pp. 93–96.
[7] A. Maroufmashat, M. Fowler, S. S. Khavas, A. Elkamel, R. Roshandel, and A. Hajimiragha, "Mixed integer linear programing based approach for optimal planning and operation of a smart urban energy network to support the hydrogen economy," *International Journal of Hydrogen Energy*, vol. 41, no. 19, pp. 7700–7716, May 2016, doi: 10.1016/j.ijhydene.2015.08.038.
[8] A. A. Mir, M. Alghassab, K. Ullah, Z. A. Khan, Y. Lu, and M. Imran, "A review of electricity demand forecasting in low and middle income countries: the demand determinants and horizons," *Sustainability*, vol. 12, no. 15, Jul. 2020, doi: 10.3390/su12155931.
[9] U. K. Rout, A. Vo$β$, A. Singh, U. Fahl, M. Blesl, and B. P. Ó. Gallachóir, "Energy and emissions forecast of China over a long-time horizon," *Energy*, vol. 36, no. 1, pp. 1–11, Jan. 2011, doi: 10.1016/j.energy.2010.10.050.
[10] C. B. Robledo, L. B. van Leeuwen, and A. J. M. van Wijk, "Hydrogen fuel cell scooter with plug-out features for combined transport and residential power generation," *International Journal of Hydrogen Energy*, vol. 44, no. 56, pp. 29648–29657, Nov. 2019, doi: 10.1016/j.ijhydene.2019.04.103.
[11] M. Sarker, M. A. Rahman, and P. D. Z. Mahmud, "Electricity demand load forecasting for a remote area of Bangladesh," *International Journal of Scientific & Engineering Research*, vol. 8, no. 1, pp. 265–277, 2017.
[12] T. Hong and S. Fan, "Probabilistic electric load forecasting: a tutorial review," *International Journal of Forecasting*, vol. 32, no. 3, pp. 914–938, Jul. 2016, doi: 10.1016/j.ijforecast.2015.11.011.

[13] G. Chitalia, M. Pipattanasomporn, V. Garg, and S. Rahman, "Robust short-term electrical load forecasting framework for commercial buildings using deep recurrent neural networks," *Applied Energy*, vol. 278, Nov. 2020, doi: 10.1016/j.apenergy.2020.115410.
[14] F. M. Butt, L. Hussain, A. Mahmood, and K. Javed Lone, "Artificial intelligence based accurately load forecasting system to forecast short and medium-term load demands," *Mathematical Biosciences and Engineering*, vol. 18, no. 1, pp. 400–425, 2021, doi: 10.3934/mbe.2021022.
[15] A. I. Almazrouee, A. M. Almeshal, A. S. Almutairi, M. R. Alenezi, and S. N. Alhajeri, "Long-term forecasting of electrical loads in Kuwait using prophet and holt–winters models," *Applied Sciences*, vol. 10, no. 16, Aug. 2020, doi: 10.3390/app10165627.
[16] M. A. Zapala and N. J. Schork, "Multivariate regression analysis of distance matrices for testing associations between gene expression patterns and related variables," *Proceedings of the National Academy of Sciences*, vol. 103, no. 51, pp. 19430–19435, Dec. 2006, doi: 10.1073/pnas.0609333103.
[17] S. Sannigrahi, F. Pilla, B. Basu, A. S. Basu, and A. Molter, "Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach," *Sustainable Cities and Society*, vol. 62, Nov. 2020, doi: 10.1016/j.scs.2020.102418.
[18] B. L. Welch and R. L. Plackett, "Principles of regression analysis," *Journal of the Royal Statistical Society. Series A (General)*, vol. 124, no. 2, 1961, doi: 10.2307/2984136.
[19] M. Talaat, M. A. Farahat, N. Mansour, and A. Y. Hatata, "Load forecasting based on grasshopper optimization and a multilayer feed-forward neural network using regressive approach," *Energy*, vol. 196, Apr. 2020, doi: 10.1016/j.energy.2020.117087.
[20] M. T. Sarker and M. A. Rahman, "Electricity load calculative method of an inaccessible area of Bangladesh," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 5, no. 5, 2016.
[21] L. Salvati, "The dark side of the crisis: disparities in per capita income (2000–12) and the urban-rural gradient in greece," *Tijdschrift voor Economische en Sociale Geografie*, vol. 107, no. 5, pp. 628–641, Dec. 2016, doi: 10.1111/tesg.12203.
[22] P. R. Israilevich, G. J. D. Hewings, M. Sonis, and G. R. Schindler, "Forecasting structural change with a regional econometric input-output model," *Journal of Regional Science*, vol. 37, no. 4, pp. 565–590, Nov. 1997, doi: 10.1111/0022-4146.00070.
[23] G. Miladinov, "Socioeconomic development and life expectancy relationship: evidence from the EU accession candidate countries," *Genus*, vol. 76, no. 1, Dec. 2020, doi: 10.1186/s41118-019-0071-0.
[24] K. Hinkelmann, *Experimental design: statistical models, and genetic statistics: Essays in honor of Oscar kempthorne*. CRC Press, 1984.
[25] D. Zheng, B. Zhang, and R. Chalaturnyk, "Uncertainty quantification of in situ horizontal stress with pressuremeter using a statistical inverse analysis method," *Canadian Geotechnical Journal*, vol. 59, no. 3, pp. 397–409, Mar. 2022, doi: 10.1139/cgj-2021-0004.
[26] A. Wiesel, Y. C. Eldar, and S. Shamai, "Zero-forcing precoding and generalized inverses," *IEEE Transactions on Signal Processing*, vol. 56, no. 9, pp. 4409–4418, Sep. 2008, doi: 10.1109/TSP.2008.924638.
[27] L. Wang, Z. Su, J. Qiao, and F. Deng, "A pseudo-inverse decomposition-based self-organizing modular echo state network for time series prediction," *Applied Soft Computing*, vol. 116, Feb. 2022, doi: 10.1016/j.asoc.2021.108317.
[28] R. Fox, S. McAleer, W. Overman, and I. Panageas, "Independent natural policy gradient always converges in markov potential games," *Proceedings of Machine Learning Research*, vol. 151, pp. 4414–4425, Oct. 2021.
[29] M. T. Sarker, M. J. Alam, and M. N. Uddin, "Auto intensity control technology for solar street lights and feasibility study with traditional system in Bangladesh," *International Journal of Engineering and Techniques*, vol. 9, no. 1, pp. 36–44, 2023.
[30] M. A. Rahman, M. Khan, M. T. Sarker, and Z. H. Mahmood, "Design , inspection and implementation of solar PV driven smart and automated irrigation systems," *International Journal of Science and Engineering Invention*, vol. 2, no. 4, 2016, doi: 10.13140/RG.2.2.17180.16002.
[31] M. T. Sarker *et al.*, "GSM & microcontroller based three phase fault analysis system," *International Journal of Advancements in Research & Technology*, vol. 6, no. 1, pp. 1–8, 2017.

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