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Forecasting Electricity Consumption Trends in India Using ARIMA-Based Regression Analysis: A Focus on Historical Lags

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ABSTRACT
The ability to forecast electricity generation is crucial for effective energy management and policy planning. This study investigates the use of historical electricity generation data as a predictor for future generation trends using an autoregressive integrated moving average (ARIMA)-based regression model. Focusing on lagged values of electricity generation, we assess the predictive accuracy and statistical significance of the lagged variable (LAG1) for forecasting. The results indicate a strong positive relationship between past and future electricity generation, with the LAG1 coefficient being statistically significant at the 1% level. The regression model explains 97% of the variation in electricity generation, demonstrating its high utility for future forecasting. This analysis provides valuable insights for energy policymakers and stakeholders in preparing for future electricity demand.

Keywords: Electricity consumption, ARIMA, regression analysis, forecasting, lagged values, energy policy, predictive modeling.

Introduction

Accurate forecasting of electricity generation is essential for policymakers, utilities, and energy planners. The demand for electricity is constantly evolving due to factors like population growth, industrial development, and technological advances. In this context, historical data becomes a powerful tool for predicting future trends. One of the most effective forecasting techniques is based on time series models, particularly those using autoregressive integrated moving average (ARIMA) methodologies. By analyzing lagged values of electricity generation, ARIMA models can offer valuable insights into future generation requirements. This paper explores the application of ARIMA-based regression analysis using lagged electricity generation values (LAG1) to forecast future electricity generation in India, providing a statistical framework for decision-making in energy production and policy.

Methodology

This study utilizes a regression-based approach with the inclusion of lagged values (LAG1) to forecast electricity generation trends. Data from 2009-10 to 2023-24 are analyzed, and the regression model is built to examine the relationship between current electricity generation and the previous year's generation (LAG1). The model incorporates the following time series formula

$$\text{Electricity Consumption Forecast}_t = \alpha + \beta_1 \text{LAG}_{t-1} + \beta_2 \text{LAG}_{t-2} + \beta_3 \text{LAG}_{t-3} + \varepsilon$$

Where ,
LAG_{t-1} - Electricity Consuption for one prior period
LAG_{t-2} - Electricity Consuption for two prior period
LAG_{t-3} – Electricity Consuption for three Prior Period
α - Intrepect Constant

β1, β2 and β3 are the coefficients for LAG1, LAG2, and LAG3, respectively,
ϵ is the error term (residual).

Literature Review

The forecasting of electricity generation has been a critical area of research due to the need for accurate planning to avoid power shortages and optimize energy supply. Several studies have examined time series forecasting models, including ARIMA, which is particularly effective in capturing patterns in historical data.

S.L. Ho [a], M. Xie (1988), ARIMA time series technique makes very few assumptions and is very flexible. It is theoretically and statistically sound in its foundation and no a priori postulation of models is required when analysing failure data. An illustrative example on a mechanical system failures is presented. Comparison is also made with the traditional Duane model. It is concluded that ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance.

Adebiyi A. Ariyo; Adewumi (2015),the autoregressive integrated moving average (ARIMA) models have been explored in literature for time series prediction. This paper presents extensive process of building stock price predictive model using the ARIMA model. Published stock data obtained from New York Stock Exchange (NYSE) and Nigeria Stock Exchange (NSE) are used with stock price predictive model developed. Results obtained revealed that the ARIMA model has a strong potential for short-term prediction and can compete favourably with existing techniques for stock price prediction

J. Contreras; R. Espinola (2003),price forecasting is becoming increasingly relevant to producers and consumers in the new competitive electric power markets. Both for spot markets and long-term contracts, price forecasts are necessary to develop bidding strategies or negotiation skills in order to maximize benefit. This paper provides a method to predict next-day electricity prices based on the ARIMA methodology. ARIMA techniques are used to analyze time series and, in the past, have been mainly used for load forecasting, due to their accuracy and mathematical soundness. A detailed explanation of the aforementioned ARIMA models and results from mainland Spain and Californian markets are presented.

Peter C. Reiss, Matthew W. White (2005),recent efforts to restructure electricity markets have renewed interest in assessing how consumers respond to price changes. This paper develops a model for evaluating the effects of alternative tariff designs on electricity use. The model concurrently addresses several interrelated difficulties posed by nonlinear pricing, heterogeneity in consumer price sensitivity, and consumption aggregation over appliances and time. We estimate the model using extensive data for a representative sample of 1300 California households. The results imply a strikingly skewed distribution of household electricity price elasticities in the population, with a small fraction of households accounting for most aggregate demand response. We then estimate the aggregate and distributional consequences of recent tariff structure changes in California, the consumption effects of which have been the subject of considerable debate

Arunesh Kumar Singh*, Ibraheem(2013),load forecasts are extremely important for energy suppliers and other participants in electric energy generation, transmission, distribution and markets. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasts are extremely important for energy suppliers and other participants in electric energy generation, transmission, distribution and markets. This paper presents a review of electricity demand forecasting techniques. The various types of methodologies and models are included in the literature. Load forecasting can be broadly divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. Based on the various types of studies presented in these papers, the load forecasting techniques may be presented in three major groups: Traditional Forecasting technique, Modified Traditional Technique and Soft Computing Technique.

Jatin Bedi, Durga Toshniwal (2009),research has focused on consumer segmentation and demand pattern analysis using smart metering data, with an emphasis on long-term electricity consumption prediction at the utility (UT) level. Simulation tools for energy use prediction are typically classified into engineering, AI, and hybrid methods. While engineering methods are clear, they are computationally intensive and less generalizable. Statistical machine learning techniques, such as linear regression, have been applied but often struggle with non-linearity in the data. Multi-Layer Perceptron (MLP) models have demonstrated better accuracy compared to linear regression and ARIMA, Support Vector Machines (SVM). Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) approaches have been developed for energy demand estimation across various sectors. Hybrid frameworks, which combine different models, have been proposed for short-term electricity demand forecasting, with machine learning techniques like SVM, ANN, and random forest showing effectiveness in these tasks. Recent studies suggest that Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models outperform other neural network architectures in price prediction. Additionally, ensemble strategies have been introduced to improve the generalization capabilities of deep learning models, further enhancing their predictive accuracy

Zauresh Atakhanova_, Peter Howie (2007),between 1990 and 2003, Kazakhstan's GDP structure underwent significant changes, with the service sector's share rising from 32% to 52%, while the agricultural sector's share fell from 35% to 8%. Total electricity consumption in the country decreased by 40% between 1990 and 1999 but began to rise again in 2000, reaching 62,000 GWh by 2003. The industrial sector accounted for 57% of total electricity consumption, while the service and residential sectors consumed 8.5% and 10%, respectively. Large industrial consumers and regional electricity companies (RECs) purchase electricity directly from generators in an unregulated wholesale market, while other consumers buy electricity from regulated RECs and pay additional distribution system access fees, alongside generation and transmission tariffs. The introduction of competition between large generating companies and the provision of open access to transmission facilities led to an 80% drop in wholesale prices from 1997 to 2002, with prices in 2004 ranging from 0.5 to 1 US cent per kWh. In 2000, residential electricity prices in Kazakhstan were about 30% of the long-run marginal cost, and although non-payment was a significant issue, collection levels improved after 1997, reaching an estimated 85% of billings in 2004.

Catia Cialani, Reza Mortazavi (2018) electricity consumption often employs a partial adjustment model, which assumes that the desired level of consumption is influenced by factors such as price, GDP, and other economic variables. A dynamic panel data approach is frequently used to analyze electricity consumption at both the aggregate household and industry levels, with particular attention given to the residential and industrial sectors. These models highlight the importance of past consumption in shaping current electricity usage, suggesting a habitual component in consumer behavior. Logarithmic regressors are commonly used in these models, as they allow for direct interpretation of the coefficients as demand elasticities. Studies examine both short- and long-run price elasticities to better understand how electricity demand responds to price changes over different time horizons. Additionally, the endogeneity problem posed by the inclusion of lagged consumption variables is a recognized challenge, with instrumental variable estimators often employed in the literature to address this issue and obtain unbiased estimates of the relationship between electricity consumption and its determinants.

Gareth Powells,Harriet Bulkeley (2014) ,on time-of-use (TOU) pricing explores its impact on the timing and rhythms of electricity consumption, with a particular focus on consumer behavior during peak and off-peak hours. A notable example of such research is the Customer Led Network Revolution (CLNR) project, a large interdisciplinary study that produces multiple types of data, including power system monitoring, electricity consumption data from smart meters, surveys on socio-technical context and attitudes, and qualitative research visits to investigate current and emerging practices related to energy use. This project is situated within the context of the UK's Low Carbon Network Fund (LCNF), which aims to explore demand shifting or 'flexibility' in energy consumption. The LCNF seeks to replicate incentives for innovation typically found in unregulated companies, fostering new approaches to managing electricity demand. The research investigates how TOU tariffs, which offer financial incentives to minimize electricity use during peak hours, influence consumer behavior, with detailed rate structures often provided for specific trials. The CLNR project, in particular, aims to advance the concept of 'flexibility' in energy users and systems, challenging the traditional view of electricity load as a purely physical property of networks and emphasizing the dynamic, adaptable nature of modern energy consumption patterns.

Himanshu A. Amarawickrama (2006), a comprehensive time-series analysis of electricity demand in Sri Lanka explored the application of six econometric methods—Static and Dynamic Engle-Granger, Fully Modified OLS (FMOLS), Johansen, Pesaran-Shin-Smith (PSS), and Structural Time Series Modeling (STSM)—to estimate and forecast demand up to 2025. The study revealed significant variability in elasticity estimates, with long-run income elasticity ranging from 1.0 to 2.0 and price elasticity remaining low, between 0 and -0.06. Despite methodological differences, forecasts among models showed reasonable consistency, with a maximum divergence of 452 MW in peak demand by 2025. Scenario analysis highlighted sensitivity to GDP growth rates, illustrating how high and low GDP assumptions could significantly impact demand projections. The findings underscore the importance of using multiple forecasting models to inform energy planning in Sri Lanka's capital-constrained electricity sector. Notably, the low price elasticity suggests that pricing reforms alone may have a limited effect on moderating demand. The study also emphasizes the challenges posed by Sri Lanka's restricted ability to import or export electricity, coupled with economic growth fluctuations, which amplify planning risks for the energy sector.

Source : Source:
https://powermin.gov.in/en/content/power-sector-glance-all-india

Year	Total Generation Electricity			
	(Including Renewable Sources) (Billion Units)	LAG1	LAG2	LAG3
2009-10	808.498			
2010-11	850.387	808.498		
2011-12	928.113	850.387	808.498	
2012-13	969.506	928.113	850.387	808.498
2013-14	1,020.20	969.506	928.113	850.387
2014-15	1,110.39	1,020.20	969.506	928.113
2015-16	1,173.60	1,110.39	1,020.20	969.506
2016-17	1,241.69	1,173.60	1,110.39	1,020.20
2017-18	1,308.15	1,241.69	1,173.60	1,110.39
2018-19	1,376.10	1,308.15	1,241.69	1,173.60
2019-20	1,389.10	1,376.10	1,308.15	1,241.69
2020-21	1,381.86	1,389.10	1,376.10	1,308.15
2021-22	1,491.86	1,381.86	1,389.10	1,376.10
2022-23	1,624.16	1,491.86	1,381.86	1,389.10
2023-24	1739.09	1,624.16	1,491.86	1,381.86
2024-25	?	1739.09	1,624.16	1,491.86
			1739.09	1,624.16
				1739.09

ACTUAL	LAG1	LAG2	LAG3
969.506	928.113	850.387	808.498
1,020.20	969.506	928.113	850.387
1,110.39	1,020.20	969.506	928.113
1,173.60	1,110.39	1,020.20	969.506
1,241.69	1,173.60	1,110.39	1,020.20
1,308.15	1,241.69	1,173.60	1,110.39
1,376.10	1,308.15	1,241.69	1,173.60
1,389.10	1,376.10	1,308.15	1,241.69
1,381.86	1,389.10	1,376.10	1,308.15
1,491.86	1,381.86	1,389.10	1,376.10
1,624.16	1,491.86	1,381.86	1,389.10
1739.09	1,624.16	1,491.86	1,381.86

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99

R Square	0.98
Adjusted R Square	0.97
Standard Error	37.65
Observations	12.00

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3.00	582438.87	194146.30	136.93	0.00
Residual	8.00	11342.69	1417.84		
Total	11.00	593781.57			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	17.93	68.89	0.26	0.80	-140.92	176.78	-140.92	176.78
LAG1	1.48	0.30	4.86	0.00	0.77	2.18	0.77	2.18
LAG2	-1.00	0.52	-1.91	0.09	-2.20	0.21	-2.20	0.21
LAG3	0.57	0.36	1.57	0.16	-0.27	1.40	-0.27	1.40

Interpretation of Regression Results Using Lag1, Lag2 and Lag3 Variables

The regression analysis conducted in this study aims to model the electricity generation in India, utilizing lag variables (LAG1, LAG2, and LAG3) as predictors. Below is the detailed interpretation of the results, which can be used for a journal article:

1. Regression Statistics Overview

- **Multiple R**: 0.99 — This indicates a very strong linear relationship between the actual and predicted values of electricity generation. A value close to 1 suggests that the model explains nearly all the variance in the data.
- **R-squared**: 0.98 — The model explains 98% of the variance in electricity generation. This is an excellent fit, showing that the lagged variables are highly predictive of future generation levels.
- **Adjusted R-squared**: 0.97 — After accounting for the number of predictors, the adjusted R-squared confirms that the model is robust and does not overfit the data. It supports the reliability of the findings.
- **Standard Error**: 37.65 — This is the standard deviation of the residuals (the difference between the actual and predicted values). A lower standard error indicates that the predictions are relatively close to the actual values.

2. ANOVA (Analysis of Variance)

- **F-statistic**: 136.93 — This statistic indicates that the overall regression model is highly significant. A high F-statistic, combined with a very low **Significance F** value (0.00), shows that at least one of the predictors (LAG1, LAG2, or LAG3) has a meaningful relationship with electricity generation.
- **Significance F**: 0.00 — This extremely low value suggests that the probability of obtaining this F-statistic by random chance is negligible. Therefore, the model as a whole is statistically significant.

3. Coefficients and Interpretation

- **Intercept (17.93)**: The intercept represents the baseline value of electricity generation when all lagged variables are zero. This value is not statistically significant (p-value = 0.80), indicating that it is not meaningful for predicting future values of generation by itself.
- **LAG1 (1.48)**: This is the coefficient for the lag of one year. The positive coefficient means that a 1-unit increase in the previous year's generation is associated with an increase of 1.48 units in the current year's generation. The **p-value** (0.00) is highly significant, suggesting a strong and statistically reliable relationship. LAG1 is the most important predictor of future electricity generation, and its influence is clear.
- **LAG2 (-1.00)**: The negative coefficient for LAG2 indicates that a 1-unit increase in generation from two years ago is associated with a decrease of 1.00 unit in the current year's generation. However, this relationship is only marginally statistically significant with a **p-value** of 0.09. This suggests that LAG2 may not be as reliable as LAG1 for predicting future values, but it could still have a slight influence on generation trends.
- **LAG3 (0.57)**: The coefficient for LAG3 is positive, suggesting that an increase in electricity generation from three years ago is associated with a modest increase in the current year's generation. However, this result is not statistically significant (p-value = 0.16), indicating that the impact of LAG3 is weaker and may be more incidental than predictive.

4. Statistical Significance and Practical Implications

- **Significant Variables**: LAG1 is highly statistically significant, with a p-value of 0.00, indicating that the previous year's generation has the most considerable predictive power for current generation. In contrast, LAG2 and LAG3 have relatively weaker or insignificant effects on future generation, as evidenced by their higher p-values (0.09 and 0.16, respectively).
- **Practical Implication**: Given that LAG1 is the most significant predictor, policymakers and energy planners can focus on recent trends in electricity generation to forecast future needs. The inclusion of lagged variables, especially LAG1, allows for more informed decision-making regarding infrastructure planning, energy policy, and resource allocation.

Calculating ARIMA using Only LAG1

ACTUAL	LAG1
969.506	928.113
1,020.20	969.506
1,110.39	1,020.20
1,173.60	1,110.39
1,241.69	1,173.60
1,308.15	1,241.69
1,376.10	1,308.15
1,389.10	1,376.10
1,381.86	1,389.10
1,491.86	1,381.86
1,624.16	1,491.86
1739.09	1,624.16

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99
R Square	0.97
Adjusted R Square	0.97
Standard Error	40.66
Observations	12.00

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1.00	577247.10	577247.10	349.12	0.00
Residual	10.00	16534.45	1653.45		
Total	11.00	593781.60			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	5.90	71.86	-0.08	0.94	-166.03	154.22	-166.03	154.22
LAG1	1.06	0.06	18.68	0.00	0.93	1.18	0.93	1.18

Electricity Consumption $_{2024\text{-}25}$ = 5.90 + 1.06 (LAG1)
= 5.90 + 1.06 (1739.09)
= 1847.16 BU (Billion Units)

So, the forecasted electricity generation for 2024-25 is **1,847.16 billion units (BU)** using the provided formula.

Interpretation of Regression Results for Electricity Generation Using LAG1 Variable

This regression analysis aims to examine the relationship between electricity generation (dependent variable) and its lagged value (LAG1) from the previous year, in order to forecast future generation. The results of the regression analysis are summarized below, along with an interpretation for a journal article.

1. Regression Statistics Overview

- **Multiple R**: 0.99 — The correlation coefficient of 0.99 indicates a very strong positive linear relationship between the actual and predicted values of electricity generation. This suggests that LAG1 is an excellent predictor of future generation levels.
- **R-squared**: 0.97 — This means that 97% of the variance in electricity generation can be explained by the lagged value from the previous year (LAG1). The high R-squared value indicates a strong model fit.
- **Adjusted R-squared**: 0.97 — The adjusted R-squared value confirms that the model does not overfit the data. Even after accounting for the number of predictors, the lagged variable remains a reliable predictor.
- **Standard Error**: 40.66 — The standard error represents the average distance that the observed values fall from the regression line. A relatively low standard error indicates that the model's predictions are very close to the actual data.

2. ANOVA (Analysis of Variance)

- **F-statistic**: 349.12 — The F-statistic assesses the overall significance of the model. A value this high, along with a **Significance F** value of 0.00, strongly suggests that the model is highly statistically significant. It indicates that LAG1 has a meaningful impact on predicting electricity generation, and the model is not due to chance.
- **Significance F**: 0.00 — This extremely low p-value indicates that the regression model is statistically significant at any conventional level of significance, such as 0.05 or 0.01. The probability of obtaining this F-statistic by random chance is negligible.

3. Coefficients and Interpretation

- **Intercept (5.90)**: The intercept represents the expected value of electricity generation when LAG1 is zero. Since the intercept is not statistically significant (p-value = 0.94), it does not have much predictive power. In this context, the intercept is not crucial for interpreting the results but serves as a baseline when LAG1 is zero.
- **LAG1 (1.06)**: The coefficient for LAG1 indicates that for every 1-unit increase in the previous year's electricity generation, the current year's generation is expected to increase by 1.06 units. This positive coefficient suggests that past generation is a strong predictor of future generation. The **p-value** for LAG1 is 0.00, which is highly statistically significant. This result shows that the lagged value of electricity generation is a reliable predictor and confirms the importance of using LAG1 in forecasting future generation levels.

The **Standard Error** of LAG1 (0.06) is relatively small, indicating that the estimate of the coefficient is precise. The **t-statistic** of 18.68, which is much greater than 2, indicates a very strong relationship between the independent variable (LAG1) and the dependent variable (current generation).

4. Statistical Significance and Practical Implications

- **Significant Variable**: LAG1 is highly statistically significant (p-value = 0.00), demonstrating that it is a crucial factor in predicting future electricity generation. Given that the coefficient for LAG1 is positive (1.06), the model suggests that electricity generation follows a strong positive trend year over year, meaning that the previous year's generation has a clear influence on the next year's level.
- **Practical Implications**: The high R-squared and significance of LAG1 make this model an effective tool for forecasting future electricity generation. For policymakers, energy producers, and planners, the analysis emphasizes the importance of recent trends in electricity generation for anticipating future demand and ensuring that sufficient resources are available.

Results

Regression Analysis Output

The regression results indicate a highly significant relationship between the lagged value (LAG1) and current electricity generation. The **Multiple R** of 0.99 and **R-squared** value of 0.97 suggest a very strong fit of the model. The **F-statistic** of 349.12 (p-value = 0.00) confirms that the regression model is statistically significant. The coefficient for LAG1 is 1.06, indicating that for each unit increase in electricity generation from the previous year, there is a corresponding increase of 1.06 units in the current year's generation. The **p-value** for LAG1 is 0.00, confirming that LAG1 is a highly significant predictor. The forecasted electricity generation for 2024-25 is **1,847.16 billion units (BU)** using the provided formula

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