Abstract

This study analysis Bangladesh's national electricity generation and consumption dynamics using two time-series forecasting methods — Autoregressive Integrated Moving Average (ARIMA) model and Vector Error Correction Model (VECM, a type of VAR), along with a Long Short Term Memory (LSTM) artificial neural network. Data on annual generation and consumption of net electricity from 1971 to 2023 were utilized to train and test the predictions for Bangladesh, extracted from Bangladesh Power Development Board (BPDB) and Bangladesh Bureau of Statistics (BBS). We thus include macroeconomic covariates (GDP per capita and Urbanization rate) into the VECM framework to describe long run equilibrium relationships, whereas the LSTM model takes advantage of multiple lagged inputs to learn complex nonlinear dependencies. Determination of the accuracy of the forecasts was through Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). ARIMA(2,2,2) had the lowest errors for generation forecasting (RMSE = 912.26 GWh; MAE = 596.19 GWh) exceeding VECM (RMSE = 1,193.72 GWh; MAE = 263.88 GWh) and LSTM (RMSE=4,815.03 Gwh;MAE=4,308.44). On the other hand to consumption forecasting VECM performed well (RMSE = 450.08 GWh; MAE = 263.88 GWh) even better than ARIMA (RMSE = 719.77 GWh; MAE = 502.36 GWh) and LSTM (RMSE = 1,256.88 GWh; MAE=932.96 Gwh). Generation was projected to rise 24%, with consumption up even more, by 32% in the three previous estimates for 2024–2028, illustrating growing demand pressures. The results also validate ARIMA for univariate, supply-driven forecasting and VECM for modeling IVAR dependence among demand-side variables, thereby assisting policy makers in matching specific sectoral planning needs with the right set of forecasting tools.

Table of Contents

Chapter One

Introduction

1.1 Background of the study

Electricity demand and supply forecast is a challenge to energy planners and policymakers in many developing countries. As population is increasing, economy is expanding and states are undergoing rapid economic transition, the necessity to forecast load patterns becomes very crucial for ensuring energy security as well as sustainable development (Bangladesh Power Development Board [BPDB], 2024; World Bank, 2023) in Bangladesh. Electricity is the lifeline for modern economic activities, affecting productivity of factories, educational access and healthcare system (Ahmed & Rahman 2021; Islam 2020).

Since the last one decade, electricity sector goes through a tremendous change in Bangladesh. Penetration electrification nationwide hit 99.5% in the year 2023 (IEA, 2023; UNDP, 2022), compared to merely 47% in 2009. Installed capacity grew from 5,493 MW in the year 2009 to now over 28,000 MW by the year 2024 (IEA, 2023; Rahman, 2022), yet it has faced periods of overcapacity with utilization rates as low as about 40%. The system is facing over capacity, generation costs are on the rise and continued heavy dependence on imported fossil fuel imports pose a persistent challenge for the sector, despite the steps taken by Bangladesh so far (IEEFA 2023: CPD 2021).

That can lead to real consequences when forecasts are off. Underestimating demand leads to supply shortages and forced outages, reducing productivity and economic growth, while overestimating demand results in excessive investment, financial pressures, and increased electricity prices (CPD 2021; World Bank 2023). In 2021–22, Bangladeshi power sector subsidies totalling around USD 2.82 billion provide a stark reminder of the stakes involved in forecasting (Bangladesh Energy Regulatory Commission [BERC], 2022; Ministry of Finance, 2022).

The relation between electricity consumption and economic development has signified crucial implications. Research shows the consumption-led growth model, establishing a unidirectional from electricity to GDP in Bangladesh (Hossain and Mamun, 2021; Sarker, 2020) Industries & agriculture, the source of over 50% of GDP, consume almost 45% of total electricity (BBS, 2023; Hossain and Mamun, 2021). This interdependency demonstrates the need for a dependable supply of reliable to ensure continued economic development.

A number of generic reasons for current demand driven by developing economies Driven by rapid urbanization (projected to represent 56% of the population by 2050) alongside industrialization and increasing living standards, growth is facilitated. (Asian Development Bank [ADB], 2021; UNDP, 2022). Footnote 7 The ready-made garments industry is the largest industrial export sector, contributing more than 10% to GDP and over 80% to exports (BGMEA, 2023; ADB, 2021) Demand patterns have been exacerbated by population growth, agricultural modernization, and rising appliance ownership (BBS, 2023; Sarker, 2020).

Forecasting methodologies have evolved considerably. Traditional statistical methods such as ARMA (AutoRegressive Integrated Moving Average) models are popularly applied during the process of forecasting in developing countries, but prove to be incompetent when objectively addressing non-linear or complex demand patterns (Box et al., 2015; Chatfield, 2000). Interdependences among variables such as GDP and population can be modeled by using Vector AutoRegression (VAR) models (Lütkepohl, 2005; Hendry & Doornik, 2014). Nevertheless, Long Short-Term Memory (LSTM) neural networks have emerged using a recurrent architecture that is better capable of capturing complex long range temporal dependencies and non-linear relationships (Hochreiter & Schmidhuber, 1997; Greff et al., 2017)

Comparative studies yield mixed results. The practical recommendation is thus to pit an LSTM model against ARIMA and see for yourself — some authors report that LSTM models lead to error rate reductions of 84–87% compared to ARIMA (Zhu et al., 2022; Kumar & Singh, 2021), and others findings that linear stationary series are definitely something ARIMA can do better than an

LSTM: a good rule of thumb hereis possibly that if your process is so linear and readily predictable by up/down behaviour, there might be no need to design really powerful NNs (Tashman, 2000; Hyndman & Athanasopoulos,2018). This observation underscores the urgent need for context-specific assessments.

In the case of Bangladesh, where the goal is 20% renewable electricity by 2030 and the ambition increases to 30% by 2040, good forecasting will be in high demand to support policy decisions and infrastructure investment (Government of Bangladesh, 2021; IEEFA, 2023). We compare three forecasting models, ARIMA, VAR and LSTM using annual time series data over the period of 1971–2023 with respect to their prediction power and general applicability for policy purpose or planning.

1.2 Objective of the Study

1.To explore historical trends in electricity generation and consumption in Bangladesh.

2. To develop and validate time series forecasting models using ARIMA, VAR, and LSTM.

3. To compare the performance and accuracy of classical and deep learning approaches.

4. To generate short-term (2024–2028) forecasts of electricity generation and consumption.

Chapter Two

Literature Review

2.1 Literature Review

AutoRegressive Integrated Moving Average (ARIMA) models have long been applied to electricity forecasting. Ali, Chowdhury, and Karim (2021) used ARIMA to predict per-capita consumption in Bangladesh, reporting a mean absolute percentage error (MAPE) of 4.50% over 43 years of data. Saha and Rahman (2019) compared ARIMA(1,1,1) with Grey Model (GM(1,1)) and Exponentially Weighted Moving Average (EWMA) for annual demand forecasts from 2010 to 2018; ARIMA outperformed alternatives, demonstrating robustness for national projections.

Vector models incorporate macroeconomic variables. Guefano, Singh, and Patel (2021) developed a hybrid GM(1,1)–VAR(1) model, achieving a MAPE of 1.63% by integrating demographic and economic factors. In Bangladesh, Rahman, Islam, and Hossain (2021) implemented an ARIMAX(0,1,1) model with exogenous GDP per capita and population series, validating forecasts for 2014–2018 with a MAPE of 5.43%.

Long Short-Term Memory (LSTM) networks capture non-linearities and long-term dependencies. An IRJET case study separated generator load data and trained individual LSTM models over 2018–2021, achieving precise short-term and peak load forecasts suitable for unit-commitment decisions (IRJET, 2022). Heliyon (2024) demonstrated an LSTM-RNN approach with hourly forecast MAPE of 1.5% and yearly MAPE of 1.77%. Hybrid architectures combining convolutional layers with LSTM (LSTM-SC) have also been proposed; Ullah, Khan, and Ahmed (2023) applied LSTM-SC to Pakistan's grid data, attaining a multi-step MAPE of 3.72%.

Comparative analyses indicate that ARIMA performs well for univariate, linear series, VAR and ARIMAX capture economic influences, and LSTM-based methods excel in modeling complex, non-linear patterns. However, few studies compare these models on a unified dataset for Bangladesh, and hybrid models remain underexplored. This study addresses these gaps by systematically evaluating ARIMA, VAR, and LSTM approaches on Bangladesh's historical data (1971–2023), offering insights for policymakers and planners

Chapter Three

Research Methodology

3.1 Data collection

The data for this research was gathered from secondary sources, including the Bangladesh Power Development Board (BPDB) and the Bangladesh Bureau of Statistics (BBS). The dataset consists of historical records on electricity generation and consumption in Bangladesh, as well as key socio-economic factors such as Net Generation electricity, Net Consumption electricity, Installed Capacity, Maximum Generation electricity, Per Capita Consumption, Per Capita Production, Population, and GDP. These variables are essential for accurately forecasting electricity trends and understanding the demand-supply dynamics of the energy sector. The data spans the period from 1971 to 2023, formatted as annual time series data. To ensure a comprehensive analysis, socio-economic variables like GDP and population were also included in the dataset, as they significantly influence electricity consumption. The data comprises 53 years of records, each representing annual values for electricity generation, consumption, and the socio-economic variables mentioned above.

Software and Tools

The data analysis and modeling were performed using the Python programming language (version Python 3.11.13)

3.2 Methods

3.2.1 Time Series Analysis

Time series is a set of observations, each one recorded at a specific time interval (Brockwell and Davis, 2016). The could be hourly, daily, or even weekly (Fagerholm, 2019). The various techniques used to analyse such data fall under time-series analysis (Box et al., 2015). Time series forecasting involves using historical observations and these analytical techniques to develop models that predict future values. By understanding past patterns, trends, and seasonality, forecasting models generate future estimates that inform planning and decision-making. Various sectors worldwide employ time series methods to anticipate demand and supply dynamics, so models must be selected carefully for each application. Common examples include the Autoregressive Moving Average (ARMA) model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, and the Autoregressive Integrated Moving Average (ARIMA) model. Multivariate extensions, such as the Vector Autoregression (VAR) model, capture interdependencies among multiple series by modeling each variable as a function of its own and others' lags.

To develop robust forecasting tools tailored to Bangladesh's electricity sector and to move beyond purely univariate approaches , this study adopts ARIMA, VAR, and Long Short-Term Memory (LSTM) models. ARIMA and VAR have long histories of accurate performance in energy forecasting, while LSTM offers enhanced capacity for learning nonlinear temporal relationships. In subsequent sections, we discuss the theoretical foundations, implementation details, and comparative performance of each modeling approach for forecasting electricity generation and consumption in Bangladesh.

3.2.2 Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average The Autoregressive Integrated Moving Average (ARIMA) model is a popular statistical method used to analyze and predict time series data (Box, Jenkins, & Reinsel, 2015). It works well for different kinds of forecasting problems and is especially good at making short-term predictions when the data shows linear patterns. ARIMA predicts future values by combining past values and past errors in a linear way. However, it has some limitations: it performs better for short-term forecasts and is not suitable for data with non-linear patterns (Arumugam & Natarajan, 2023; Ediger & Akar, 2007).

The ARIMA model can be written as:

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \cdots + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t$$

In this model:

y'_t represents the differenced electricity time series data of (stationary series obtained after differencing d times).

c is a constant.

$\phi_1, \phi_2, ..., \phi_p$ are the autoregressive coefficients (AR).

$\theta_1, \theta_2, ..., \theta_q$ are the moving average coefficients (MA).

ϵ_t is the random noise or error at time t.

p: the number of past observations used (autoregressive term),

d: the number of differences applied to make the series stationary (integration term),

q: the number of past errors considered in the moving average part of the model.

Autoregressive AR(p)

In the ARIMA model, the Autoregressive (AR) component indicates that the current value of the variable YtY_t is regressed on its past values. The term lags refers to how a current time period's value is influenced by previous periods. The order of the AR model is denoted by **p**.

For example, an AR model of order 1, written as AR(1)**,** is a first-order autoregressive process. In this case, at time tt, the value of the outcome variable is only influenced by the value from the previous period, Yt−1Y_{t-1}. As **p** increases, the model incorporates more past values to predict the current value.

Moving Average MA(q)

In the ARIMA model, the Moving Average (MA) component assumes that the forecast error at a given time is a linear combination of past forecast errors. Rather than using past values of the variable for prediction, the model uses the residuals (errors) from previous forecasts to adjust the current prediction. The order of the MA model is denoted by **q**, which indicates the number of past forecast errors used in the model to predict the current value

Differencing (d):

In ARIMA models, the data used for forecasting must be stationary. A stationary series has statistical properties, such as mean and variance, that remain constant over time. To check for stationarity, the data is often plotted graphically. If the data is non-stationary, differencing is applied to make it stationary by removing trends and patterns. Differencing involves subtracting the current observation from the previous observation.

First differencing involves subtracting each observation from the one preceding it, while Second differencing involves applying the differencing process twice.

Differencing helps eliminate any trends in the dataset and is an effective method for transforming a non-stationary series into a stationary one.

Stage of ARIMA model building

The flowchart in Figure 1 summarizes the ARIMA modeling procedure. First, the data is visualized to identify key time series components such as seasonality and trends. Next, the Augmented Dickey-Fuller (ADF) test is used to check for stationarity in each column, and AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) plots are analyzed. The model order is determined using a trial-and-error approach, with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) used to select the best model order. Finally, the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) is calculated to assess the model's accuracy, as shown in Equation 1 and 2:

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{t}=1}^{\mathrm{n}} \left| \mathrm{Y_t} - \widehat{\mathrm{Y}}_{\mathrm{t}} \right| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Root Mean Squared Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where,

$\mathrm{Y_t}$ = Actual values.

$\widehat{Y}_t$= Predicted values.

n = Number of forecast points.

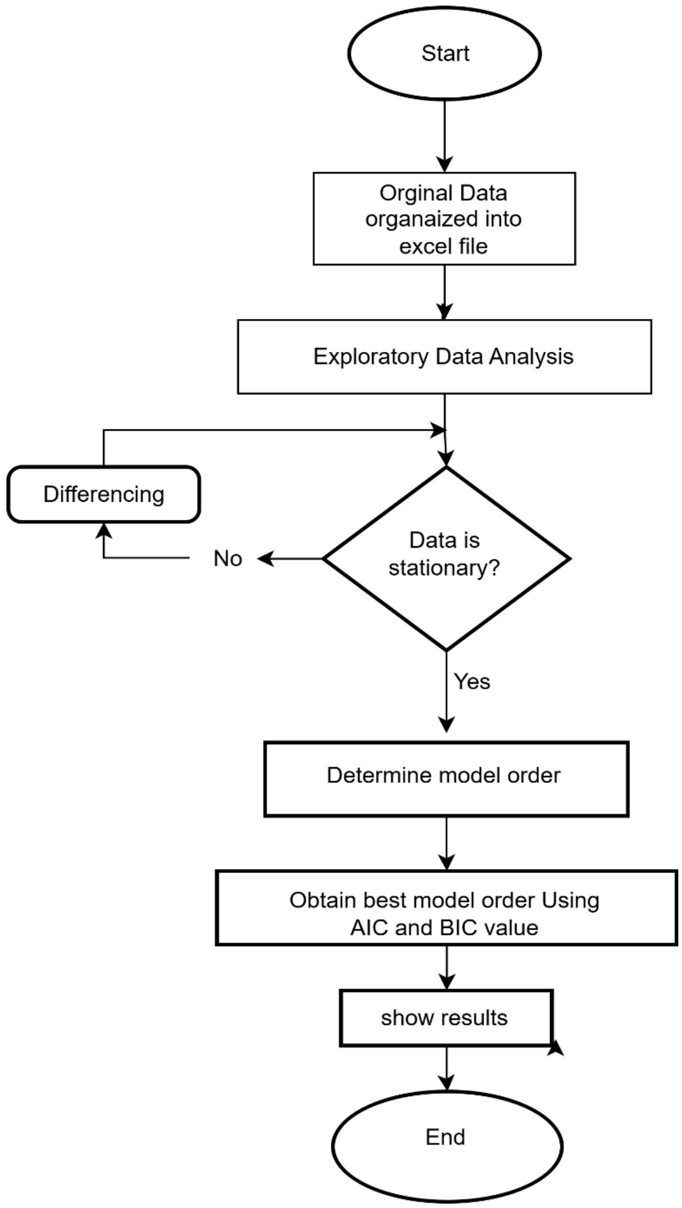

Figure 1 (flow chat of ARIMA model)

Stationarity Check

In checking whether the electricity consumption and generation data is stationary or not (unit root), the Augmented Dicky-Fuller (ADF) test as well as the plots of the Autocorrelation and Partial Autocorrelation Functions are used. ADF test: The ADF test is a statistical test used to determine if there are trends present in a dataset. The presence of trends indicate non-stationarity and absence indicates stationarity. In the implementation ADF test, a test statistic and a p-value are estimated. The more negative the test statistic value is, the time series is considered to be stationarity; this theory is known as the null hypothesis. If a p-value less than 0.05 is obtained, the null hypothesis is ignored and the time-series data is considered to be stationary, if otherwise, it is non stationary indicating the presence of trends in the dataset. Differencing must be applied to make the dataset stationary.

ACF and PACF Plots

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots help identify the presence of trends. For stationary data, the ACF will typically show a quick decay or cut off after a few lags. However, if the ACF or PACF shows significant autocorrelations over many lags, this suggests non-stationarity in the data.

Differencing

When the data is found to be non-stationary, differencing is often used to make the data stationary. First differencing involves subtracting each observation from the previous one, which can remove trends. If there are seasonal patterns, seasonal differencing can be applied to remove those effects.

Model Identification

To select the most suitable ARIMA (p, d, q) model for forecasting electricity consumption and generation, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are utilized. Both AIC and BIC are statistical tools used for model selection. Generally, lower values of AIC and BIC indicate a better-fitting model. When the AIC and BIC values of two models are similar, AIC is preferred for predictive models, while BIC is favored for explanatory models.

3.2.3 Vector Autoregressive (VAR)

The Vector Autoregression (VAR) model is a statistical model used to capture the linear interdependencies among multiple time series variables. Unlike univariate models (like ARIMA), which focus on a single time series, VAR models analyze how several variables evolve together over time, allowing each variable to be influenced by both its own past values and the past values of all other variables in the system.

For a VAR model of order p (denoted as VAR(p)), the mathematical form for a system with k variables is-

Yt=c+A1Yt−1+A2Yt−2+⋯+ApYt−p+ϵt

Where,

- Yt is a (k x 1) vector of observable variables at time t (for example, electricity consumption,generation, GDP, etc.).
- c is a (k x 1) vector of constants (intercepts).
- A1,A2,... are (k x k) matrices of coefficients for each lag.
- ϵt is a (k x 1) vector of error terms, representing shocks or innovations at time t.

For example, for two variables (y_1 and y_2) and lag 1:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$$

And the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) is calculated to assess the model's accuracy, as shown in Equation 3 and 4:

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{t}=1}^{\mathrm{n}} \left| \mathrm{Y_t} - \widehat{\mathrm{Y}}_{\mathrm{t}} \right| \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(3)$$

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Steps for Building a Vector Autoregression (VAR) Model

Constructing a Vector Autoregression (VAR) model involves a sequence of methodical steps designed to ensure that the resulting model reliably captures the dynamic interrelationships among multiple time series variables. The procedure can be outlined as follows:

1. Data Preparation and Stationarity Assessment

Prior to model estimation, it is imperative to examine the time series data for stationarity. Stationarity implies that the statistical properties of the series, such as mean and variance, do not vary over time. Nonstationary data can yield spurious regressions and misleading inference. To assess stationarity, unit root tests such as the Augmented Dickey-Fuller (ADF) or Phillips-Perron (PP) tests are typically employed. If any series is found to be nonstationary, appropriate transformations , commonly first differencing , should be applied to render the series stationary.

2. Lag Order Selection

The choice of lag length p is a crucial modeling decision in VAR analysis. The lag length determines how many past time points are included to explain the current values of the variables. Too few lags may omit relevant dynamics, while too many can introduce unnecessary complexity and reduce estimation efficiency.

Lag order selection is generally performed using information criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or the Hannan-Quinn Criterion (HQC). These criteria balance goodness-of-fit with model parsimony and help identify an optimal lag structure.

3. Model Estimation

Once the lag order is determined, the VAR model is estimated by expressing each endogenous variable as a linear function of its own lagged values and the lagged values of all other variables in the system. The estimation is commonly performed using ordinary least squares (OLS) applied individually to each equation, as the VAR system is recursive in nature.

4. Diagnostic Checking

Following estimation, diagnostic procedures are necessary to validate the adequacy of the fitted VAR model. This includes:

Stability Analysis: Verifying that the inverse roots of the characteristic polynomial lie within the unit circle, ensuring that the VAR process is stable and stationary.

Residual Diagnostics: Examining the residuals for autocorrelation, heteroscedasticity, and normality. Autocorrelation tests (e.g., Portmanteau test) help detect if model residuals exhibit temporal dependence, which would indicate model misspecification.

These diagnostic checks confirm that the model complies with the assumptions underlying VAR estimation and inference.

5. Forecasting

Finally, the validated VAR model can be employed to generate forecasts for the endogenous variables. Multivariate forecasts account for the interdependencies modeled by the VAR, offering a comprehensive temporal outlook for all series concurrently. Evaluate out-of-sample forecasts using metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE).

3.2.3 Long Short-Term Memory (LSTM) model

The Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) designed specifically to learn and forecast patterns in **sequential data**, such as electricity consumption and generation over time. LSTMs have a unique architecture that helps them remember long-range dependencies by using three critical components called gates: the input gate, forget gate, and output gate.

LSTM Architecture

LSTM architecture has a chain structure that contains four neural networks and different memory blocks called cells.

Cells store information, and the gates control how that information is updated or used.

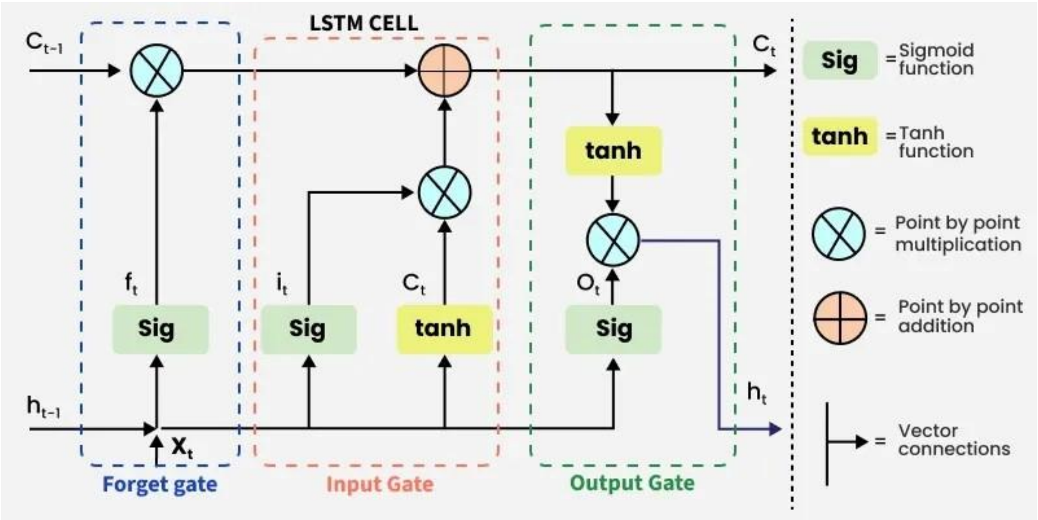

Figure 2(LSTM Architecture)

Input Gate

The addition of useful information to the cell state is done by the input gate. First the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs ht−1 and xt. Then, a vector is created using tanh function that gives an output from -1 to +1 which contains all the possible values from ht−1 and xt. At last the values of the vector and the regulated values are multiplied to obtain the useful information. The equation for the input gate is:

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)$$

$C\hat{}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$

We multiply the previous state by ftft effectively filtering out the information we had decided to ignore earlier. Then we add it $\odot$ $C\hat{}_t$ which represents the new candidate values scaled by how much we decided to update each state value.

$C_t = f_t \odot C_{t-1} + i_t \odot C\hat{}_t$

Where,

$\odot$ denotes element-wise multiplication.

tanh is activation function.

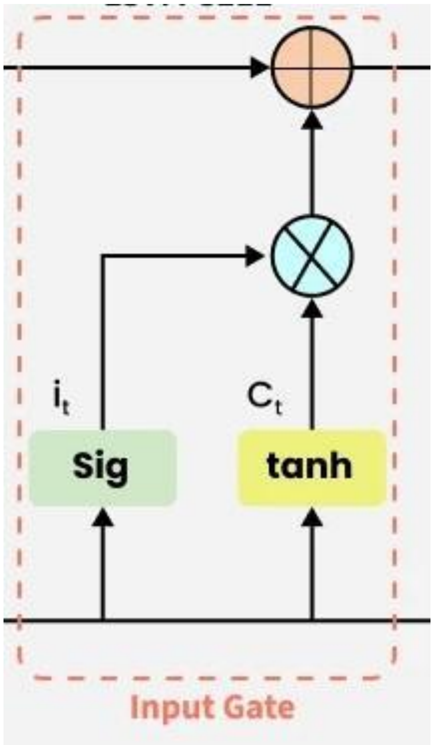

Figure 3 (Input Gate)

Output Gate

The task of extracting useful information from the current cell state to be presented as output is done by the output gate. First, a vector is generated by applying tanh function on the cell. Then, the information is regulated using the sigmoid function and filter by the values to be remembered using inputs ht−1 and xt. At last the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell. The equation for the output gate is:

$o_t=\sigma(W_o \cdot [h_{t-1},x_t]+b_o)$

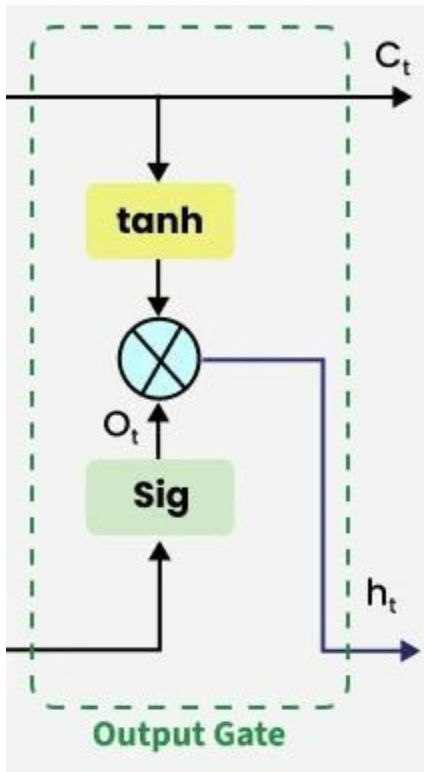

Figure 4 (Output Gate)

Forget Gate

The information that is no longer useful in the cell state is removed with the forget gate. Two inputs xt (input at the particular time) and ht−1 (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through sigmoid activation function which gives output in range of [0,1]. If for a particular cell state the output is 0 or near to 0, the piece of information is forgotten and for output of 1 or near to 1, the information is retained for future use.

The equation for the forget gate is:

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f)$$

Where,

W_f represents the weight matrix associated with the forget gate.

$[h_{t-1},x_t]$ denotes the concatenation of the current input and the previous hidden state.

b_f is the bias with the forget gate.

σ is the sigmoid activation function.

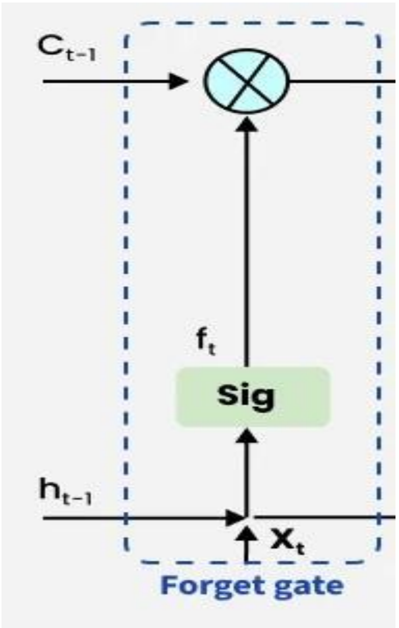

Figure 5 (Forget Gate)

Stage of LSTM model

Input Preparation

Gather historical time series of electricity consumption and/or generation from reliable sources (e.g., smart meters, grid operations logs). Clean the data by handling missing values or anomalies, then normalize or scale each series (for instance using min–max normalization) to ensure uniform feature ranges. Finally, segment the continuous series into overlapping input windows (e.g., the previous 24 hours) and corresponding forecast targets (e.g., next-hour consumption), reshaping into a three-dimensional tensor of shape (samples, timesteps, features).

Input Combination

At each time step *t*, the LSTM cell concatenates the current input vector $\mathbf{x_t}$ (e.g., normalized consumption at hour *t*) with the previous hidden state $\mathbf{h_{t-1}}$. These combined values form the basis for all gate computations, allowing the network to leverage both new observations and prior learned context.

Forget Gate Activation

A sigmoid-activated layer computes

$$f_t = \sigma(W_{(f)}\cdot[h_{t-1}, x_t] + b_{(f)})$$

where each element of $\mathbf{f_t}$ lies between 0 and 1, indicating the proportion of the corresponding cell-state component to retain from $\mathbf{C_{t-1}}$. In electricity forecasting, this mechanism filters out outdated patterns (e.g., irregular events) and focuses on relevant seasonal or daily trends.

Input Gate Activation and Candidate Generation

A second sigmoid gate determines which portions of the new information to write into the cell,

$$i_t = \sigma(W_{(i)}\cdot[h_{t-1}, x_t] + b_{(i)})$$

while a tanh layer generates candidate values,

$$\hat{c}_t = tanh(W_{(C)}\cdot[h_{t-1}, x_t] + b_{(C)})$$

These combined outputs allow the LSTM to selectively incorporate fresh consumption or generation signals, such as sudden demand spikes, into its internal memory.

Cell State Update

The new cell state $\mathbf{C_t}$ is calculated by merging retained past memory with new candidate information:

$$C_t = f_t * C_{t-1} + i_t * \hat{c}_t$$

This blend dynamically balances long-term trends (e.g., seasonality) and short-term fluctuations (e.g., weather-induced load changes), ensuring the model's memory is both stable and adaptable.

Output Gate Activation

A third sigmoid gate decides which parts of the updated memory should influence the output:

$$o_t = \sigma(W_{(o)} \cdot [h_{t-1}, x_t] + b_{(o)})$$

This filtering ensures only the most pertinent signal—reflecting both historical patterns and new observations—propagates to the next layer or time step.

New Hidden State and Forecast Generation

Finally, the hidden state $\mathbf{h_t}$, which serves as the model's output at time t, is derived by applying the output gate to the activated cell state:

$$h_t = o_t * tanh(C_t)$$

In a forecasting setup, $\mathbf{h_t}$ is fed through one or more dense layers to produce the predicted electricity consumption or generation for the next interval, closing the loop for sequential forecasting.

Table 1 Model Evaluation Criteria for Time Series Forecasting Methods

Model	**Statistical Fit**	**Residual Checks**	**Forecast Accuracy**	**Other Tests**
ARIMA	AIC, BIC	White noise, Ljung-Box	RMSE, MAE	Normality plots
LSTM	(N/A)	Residual trend/correlation	MAE, RMSE	Loss curves, Cross-validation
VAR	AIC, BIC	Residual correlation	RMSE, MAE	Stability, Impulse Response

Chapter Four

Data Analysis and Results

4.1 Electricity consumption

4.1.1 ARIMA

Before using the ARIMA model to forecast electrical consumption, we needed to ensure that the dataset was stationary. To do this, we first ran the Augmented Dickey-Fuller (ADF) test and checked the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.

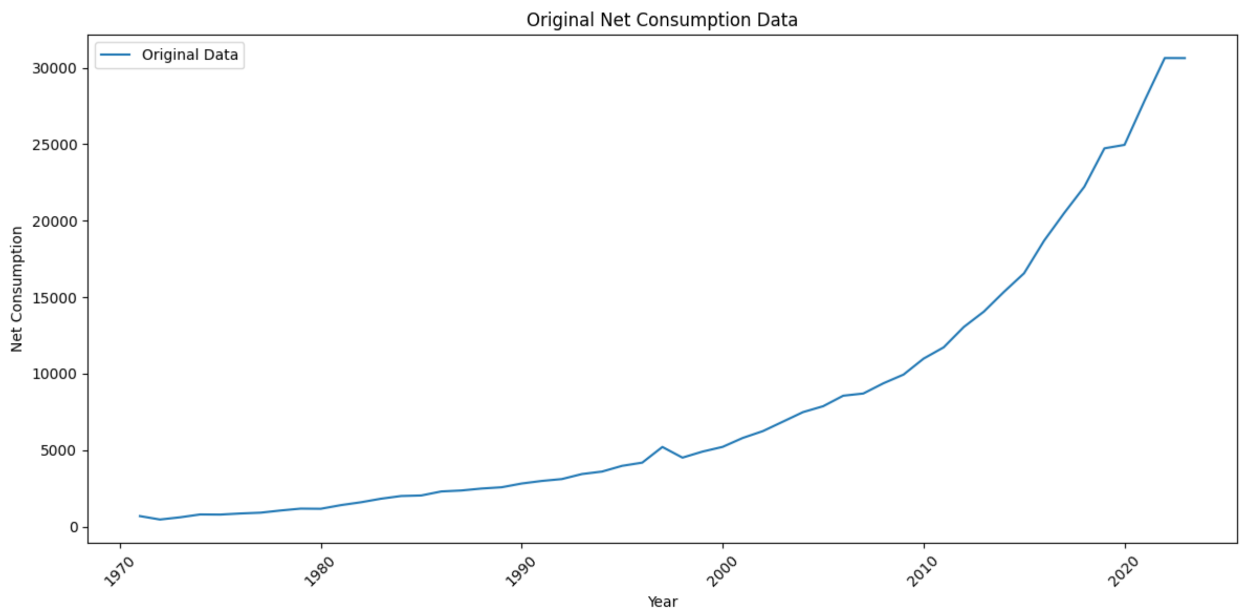

Figure 6 (Yearly Net Electricity consumption Graph)

Figure 6, shows the original time series of electrical consumption, which reveals a clear upward trend. This pattern indicates that the data is non-stationary. When we first ran the ADF test, it gave us a p-value of 1.0, confirming the presence of a unit root and non-stationarity.

To make the data stationary, we applied second-order differencing. After transforming the series, we ran the ADF test again, and this time the p-value dropped to 0.000000 (well below 0.05), confirming that the differenced series was now stationary. Which is shown as figure 7**.**

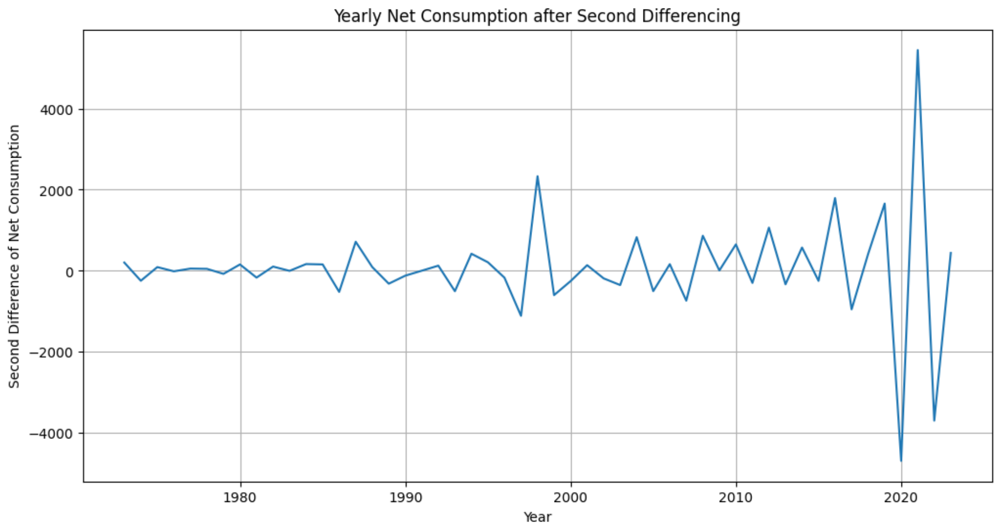

Figure 7 (Yearly Net Consumption plot after 2^{nd} Differencing)

Next, we looked at the **ACF** and **PACF** plots in Figures 8 and 9. After differencing, the lags in both plots dropped sharply after lag 2 and stayed within the confidence bounds (the shaded area). This was a clear indication that the data had become stationary, which was in line with the results of the ADF test.

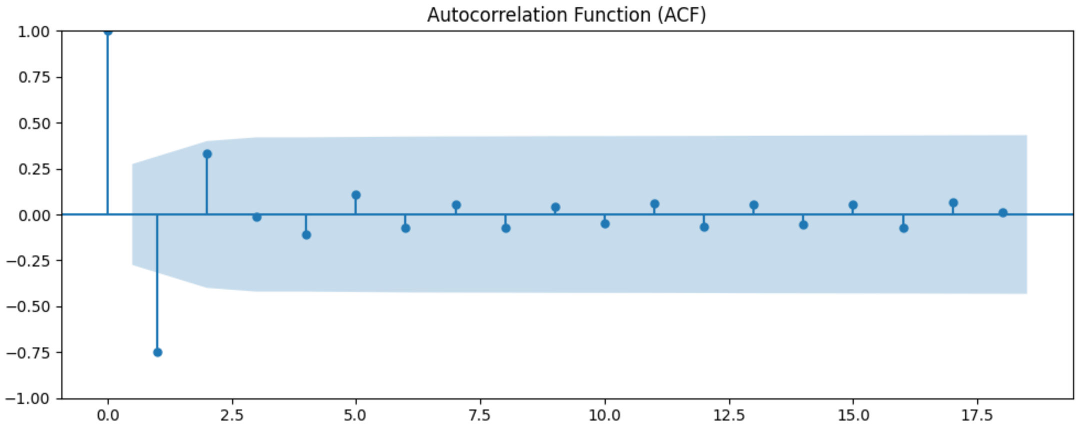

Figure 8 (Autocorrelation Function plot)

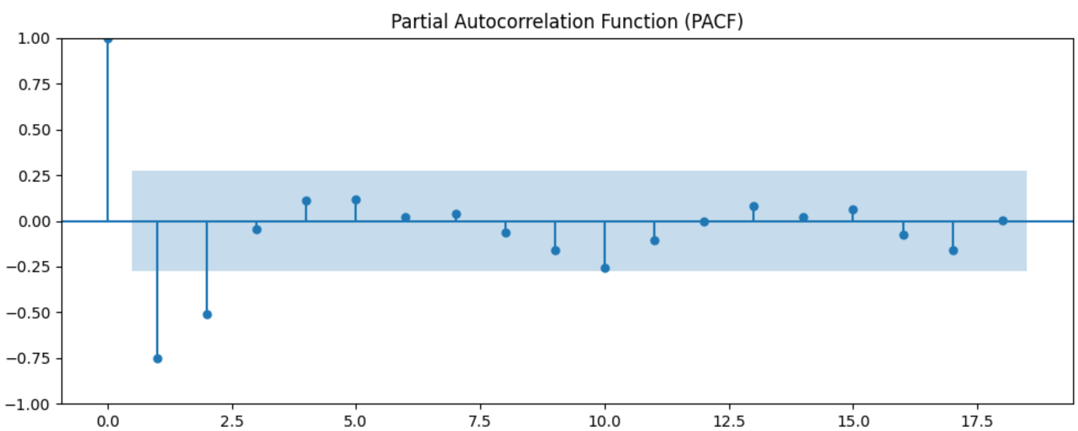

Figure 9 (PACF plot)

Finally, in **Table 2**, we examined the AIC and BIC values for different ARIMA model configurations. The ARIMA(2, 2, 0) model had the lowest AIC and BIC values, making it the best choice as it provided a good balance between model accuracy and complexity for the differenced series.

Table 2 (configurations of ARIMA model)

Order	**AIC**	**BIC**	**RMSE**	**MAE**
(0, 2, 1)	844.821453	848.685104	917.081843	547.447531
(1, 2, 2)	822.458387	830.185690	686.154788	464.315420
(2, 2, 1)	823.379857	831.107160	708.202310	484.961892
(1, 2, 1)	831.509225	837.304702	787.559750	507.006943
(2, 2, 0)	**822.745930**	**828.541407**	719.774800	502.355216
(3, 2, 0)	822.984205	830.711507	705.347921	478.048708
(3, 2, 1)	823.775000	833.434128	697.254294	472.839691

The Ljung-Box test in residuals analysis is used to determine the presence of any residual autocorrelation not yet considered by the ARIMA model. Since the p-value is drastically larger than the common significance threshold at 0.05, we do not reject the null hypothesis (p = 0.8231). This indicates that no further significant autocorrelation remains in the residuals at the selected lags. This indicates that the ARIMA (2,2,0) model has been effective in accounting for the underlying patterns within the data and the residuals(figure 9) are now random noise without any obvious autocorrelation. Thus implying that the model is likely to be fitted by the data; We can say this as we have a Lag order of 1 with a very high p-value, which is rejected.

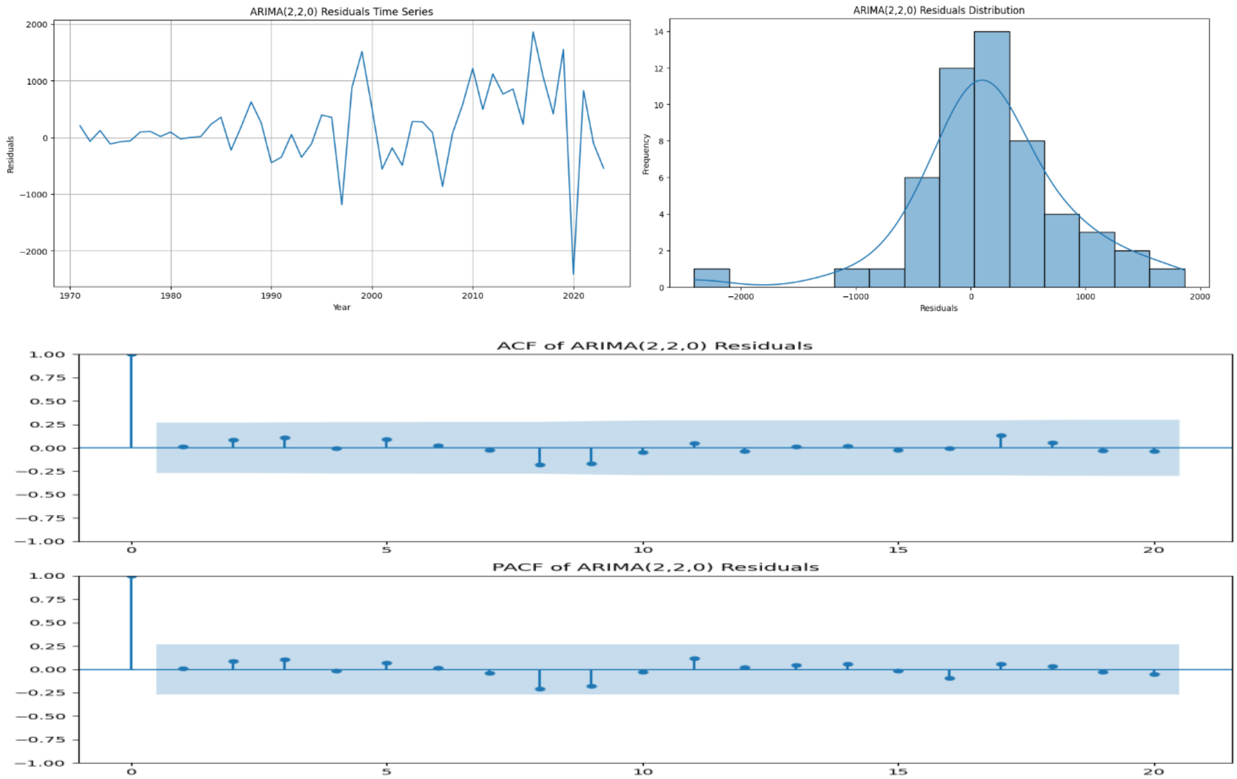

Figure 10 (Residuals Plots)

Figure 11, further shows that the fitted and forecasted values from the ARIMA(2,2,0) model closely follow the trend of the original data, which enhances our confidence in using this model to predict future net consumption.

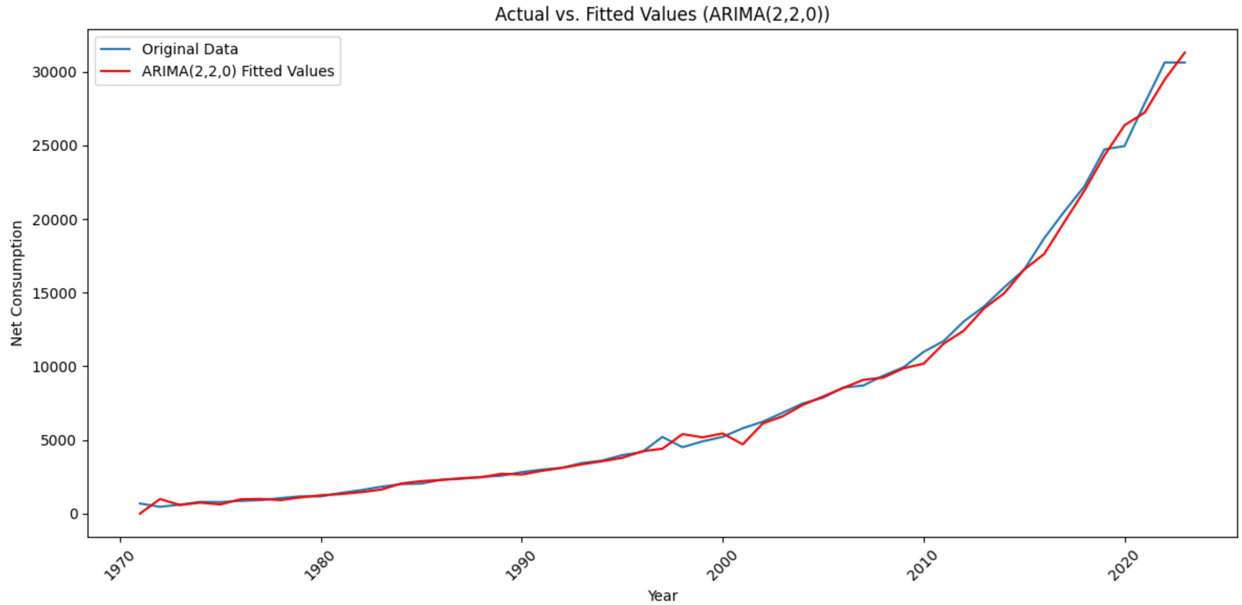

Figure 11 (Actual vs fitted Net consumption Plot)

4.1.2 Vector autoregressive Model

In this analysis, a Vector Autoregressive (VAR) model was employed to examine the dynamic relationships among three key macroeconomic variables: net generation**,** net consumption, and GDP (current US$)**.** since economic time series such as net generation, net consumption, and GDP often exhibit non-stationarity, we first conduct unit root tests to determine their order of integration. Upon confirming that the variables are integrated of the same order (typically I(1)), we proceed to test for cointegration using Johansen's method.

The cointegration test results indicate the presence of one or more cointegrating relationships, signifying that although the series are individually non-stationary, a linear combination of them is stationary, implying a long-run equilibrium relationship.

Given the presence of cointegration, the VAR model in levels would be miss specified due to non-stationarity, and differencing the data would omit valuable long-run information. Therefore, we shift to estimating a Vector Error Correction Model (VECM), which appropriately captures both the short-run dynamics through differenced variables and the long-run equilibrium through error-correction terms.

Table 3(Johansen Cointegration Test Results)

Statistic Type	Rank = 0	Rank = 1	Rank = 2
lambda_trace	47.08	13.35	0.04
lambda_max	33.73	13.31	0.04
Critical Value Level (90%)	18.89	12.3	2.71
Critical Value Level(95%)	21.13	14.26	3.84
Critical Value Level (99%)	25.87	18.52	6.63

Interpretation based on Trace statistic -

Trace statistic (47.08) > 95% Critical Value (21.13) for rank <= 0. Reject H0: cointegrating rank is 0 or less.

Trace statistic (13.35) <= 95% Critical Value (14.26) for rank <= 1. Fail to reject H0: cointegrating rank is 1 or less.

Trace statistic (0.04) <= 95% Critical Value (3.84) for rank <= 2. Fail to reject H0: cointegrating rank is 2 or less.

The optimal lag order for the VECM

Optimal lag order based on AIC: 5

Optimal lag order based on BIC: 3

The optimal lag order for the VECM, based on fitting VAR models and using information criteria, is 5 according to AIC and 3 according to BIC. A VECM model was successfully fitted to the log-transformed data with a cointegration rank of 1 and an optimal lag order of 3 (based on BIC).

Table 4 (VECM Model)

Variable	Coefficient	Std. Error	z-value	P-value	95% Confidence Interval
L1.log_net consumption	-0.4838	0.194	-2.495	0.013	(-0.864, -0.104)
L1.log_net generation	0.4718	0.203	2.322	0.02	(0.073, 0.870)
L1.log_GDP (current US$)	0.0819	0.063	1.308	0.191	(-0.041, 0.204)
L2.log_net consumption	-0.1723	0.183	-0.939	0.348	(-0.532, 0.187)
L2.log_net generation	0.2058	0.181	1.139	0.255	(-0.148, 0.560)
L2.log_GDP (current US$)	-0.0524	0.056	-0.937	0.349	(-0.162, 0.057)
L3.log_net consumption	-0.0701	0.156	-0.449	0.653	(-0.376, 0.236)
L3.log_net generation	0.1663	0.153	1.084	0.278	(-0.134, 0.467)
L3.log_GDP (current US$)	0.0844	0.056	1.511	0.131	(-0.025, 0.194)

Table 3 shows only for consumption. Based on this results in table 4 , VECM Model are written as

$$\begin{aligned}\Delta \log(net\ consumption)\ t &= \alpha_1 + \gamma_1 \cdot \{cointegration\} + (-0.4838) \cdot \Delta log(\{net\ consumption\})_{\{t-1\}} \\ &+ (0.4718) \cdot \Delta log(\{net\ generation\})_{\{t-1\}} + (0.0819) \cdot \Delta log(\{GDP\})_{\{t-1\}} \\ &+ (-0.1723) \cdot \Delta log(\{net\ consumption\})_{\{t-2\}} + (0.2058) \\ &\cdot \Delta log(\{net\ generation\})_{\{t-2\}} + (-0.0524) \cdot \Delta log(\{GDP\})_{\{t-2\}} + (-0.0701) \\ &\cdot \Delta log(\{net\ consumption\})_{\{t-3\}} + (0.1663) \cdot \Delta log(\{net\ generation\})_{\{t-3\}} \\ &+ (0.0844) \cdot \Delta log(\{GDP\})_{\{t-3\}} + \epsilon_t\end{aligned}$$

The results reveal that log_net consumption is significantly influenced by its own past value (lag 1), showing a negative relationship (p-value = 0.013). This means that when consumption was higher in the past, it tends to decrease in the current period. On the other hand**,** log_net generation (lag 1) has a significant positive impact (p-value = 0.020), indicating that when past generation was higher, it leads to increased consumption now. However, log_GDP (lag 1) doesn't have a strong effect on consumption, as its p-value is 0.191, suggesting it doesn't play a significant role in the short term. The past values of log_net consumption and log_net generation at lags 2 and 3, along with log_GDP at any lag, do not significantly affect consumption, as their p-values are all above 0.05.

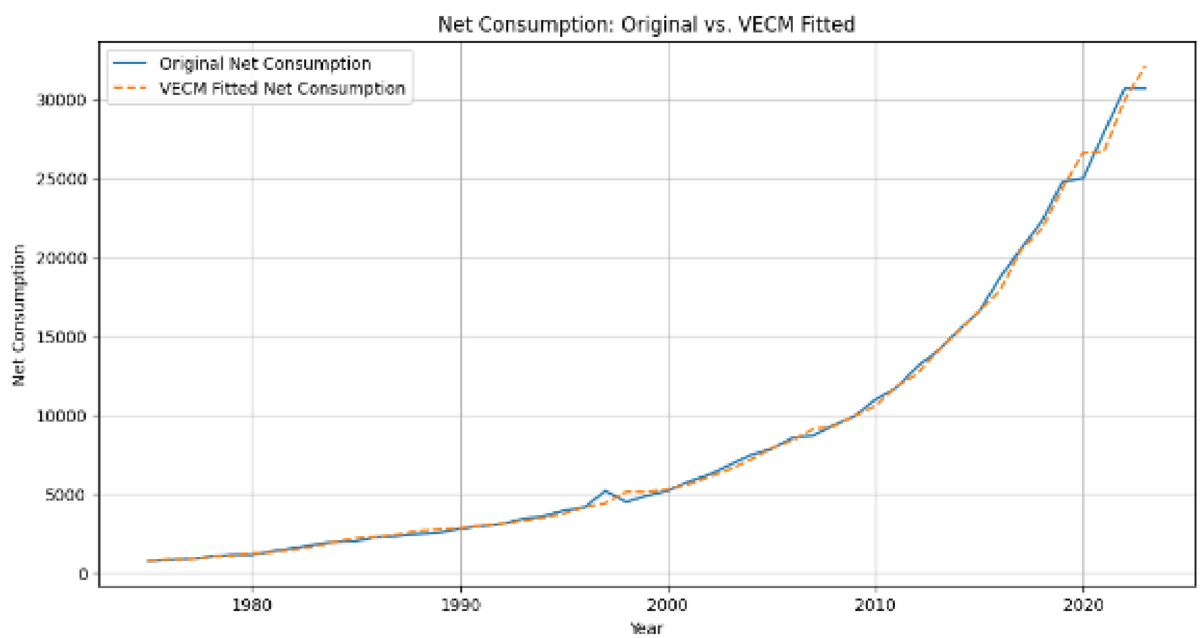

Figure 12 (Original Data vs VECM fitted plot)

Figure 12,   presents a comparative plot of the original net consumption series (solid blue line) and the values fitted by the VECM model (dashed orange line). The VECM demonstrated excellent fit to the historical data, closely tracking the observed trajectory across the entire period. Both the original and fitted series reveal a consistent upward trend in net consumption, with the VECM effectively modeling fluctuations and growth phases over time. This strong performance is further supported by quantitative error metrics: the Root Mean Square Error (RMSE) of 450.08 and the Mean Absolute Error (MAE) of 263.88 indicate that the model's predictions closely approximate the actual values, reflecting a high degree of accuracy in capturing the net consumption dynamics.

4.1.3 Long Short-Term Memory (LSTM)

From table 3 ,The combination of n_steps = 4 and 100 epochs in this LSTM model turns out to be the sweet spot for predicting electricity consumption. The results speak for themselves, with impressively low MAE and RMSE. By giving the model a broader historical context with 4 time steps, it gets a clearer picture of the data, which helps it make better predictions. The 100 epochs provide ample training time, allowing the model to really fine-tune its understanding of the data. In the end, this setup delivers the most accurate results, with predictions that closely match the actual values. It's like the model has found its groove, understanding the trends and patterns perfectly.

Table 5(The combination of n_steps and epochs)

n_steps	epochs	MAE	RMSE
1	50	15157.007273	15870.707519
1	70	13934.140529	14581.079219
1	100	12200.002523	12723.492346
2	50	12075.979308	12594.014855
2	70	11020.601112	11502.862264
2	100	5239.918139	5591.255565
3	50	11229.207723	11691.712261
3	70	1989.271004	2169.239538
3	100	2945.758586	4062.724960
4	50	2855.254793	2996.913943
4	70	2614.541121	2864.413630

4	**100**	**932.969035**	**1256.888878**
5	50	5268.434969	5397.345083
5	70	2105.426375	2324.640924
5	100	1426.111711	2085.996474

Figure 13, The graph shows the comparison between the **actual net consumption** and the **fitted net consumption** over time, using the best LSTM model configuration with **n_steps = 4** and **epochs = 100**. The blue line represents the actual net consumption data from the training set, while the orange line shows the fitted values, or the model's predicted consumption, during the training period. The fitted values closely follow the actual values, indicating that the LSTM model has done a good job of capturing the underlying patterns in the training data. You can see that the model's predictions are almost parallel to the actual data, with very little deviation. This suggests that the model has learned the trend of the time-series data well.

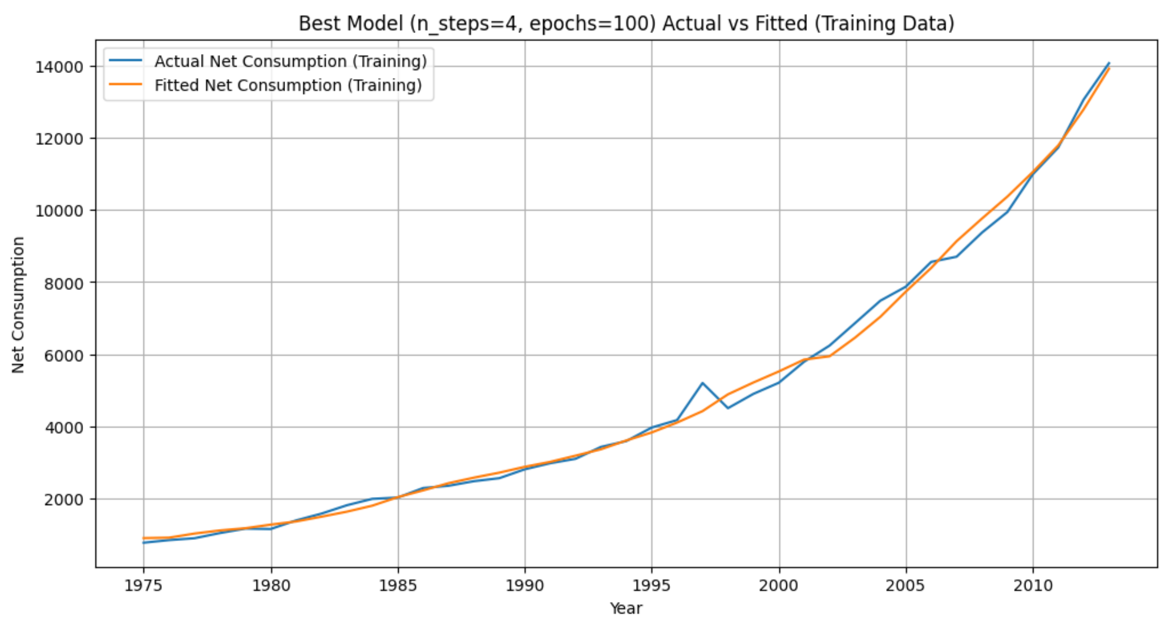

Figure 13 (actual net consumption and fitted net consumption)

The model successfully captured the overall upward trend in net consumption. As illustrated in Figure 14 , the predicted values closely follow the actual values throughout the majority of the time period. The model accurately reflects the growth between 2014 and 2021, with only minor underestimation visible in some intermediate years (e.g., 2016–2018), where predicted values are slightly lower than actuals. Notably, in the final years (2022–2023), the model slightly overpredicts net consumption, diverging above the actual measured values. This may suggest a tendency of the model to extrapolate ongoing growth from recent data, potentially overlooking subtle saturation or leveling effects in the observed data.

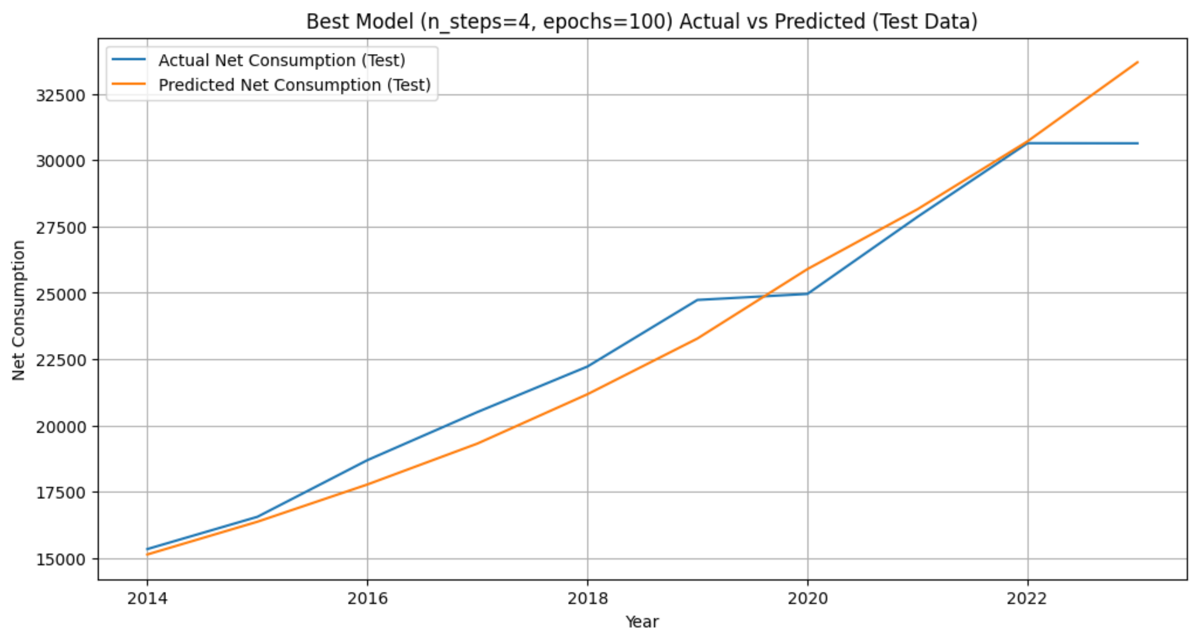

Figure 14 (Actual vs fitted (test data))

4.1.4 Model comparison

In the table 6 ,VAR/VECM outperforms the other models with the lowest RMSE and MAE, highlighting its ability to make the most accurate and reliable predictions. This model is particularly strong in handling time-series data and effectively capturing the relationships between multiple variables, which makes it an excellent choice for forecasting.

Table 6 (Model comparison for Net consumption data)

MODEL	RMSE	MAE
ARIMA	719.77	502.36
VAR/VECM	450.08	263.88
LSTM	1256.88	932.96

So, VECM is a great choice for forecasting net electricity consumption.

The figure 15 highlights an observed, steady increase in net consumption over time, followed by a projected sharp rise in the coming years according to the VECM model.

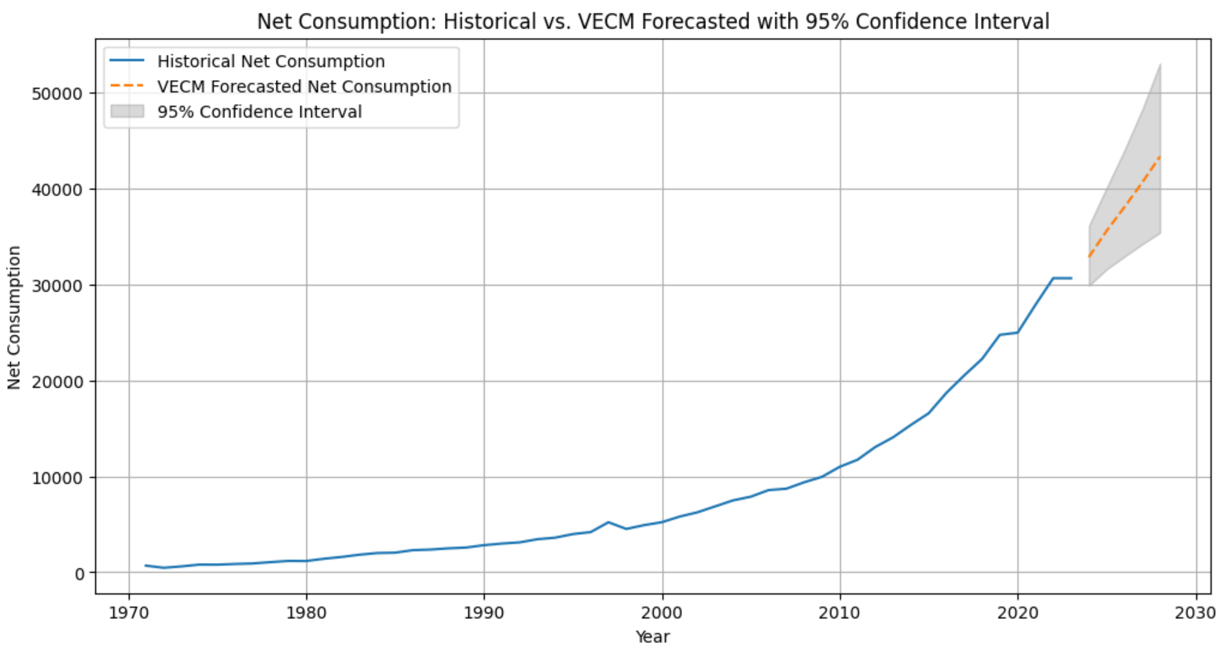

Figure 15 (forecast Net electricity consumption plot)

Table 7 (forecasted value for Net consumption)

Forecasted year	Forecasted Net consumption
2024	**32832.853040**

2025	**35566.423906**
2026	**38034.082270**
2027	**40592.685522**
2028	**43312.870325**

Here table 7 shows forecasted net electricity consumption for 5 year.

4.2 Electricity Generation

4.2.1 ARIMA

Before applying the ARIMA model to forecast net generation, we first ensured that the dataset was stationary. To do this, we conducted the Augmented Dickey-Fuller (ADF) test and examined the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.

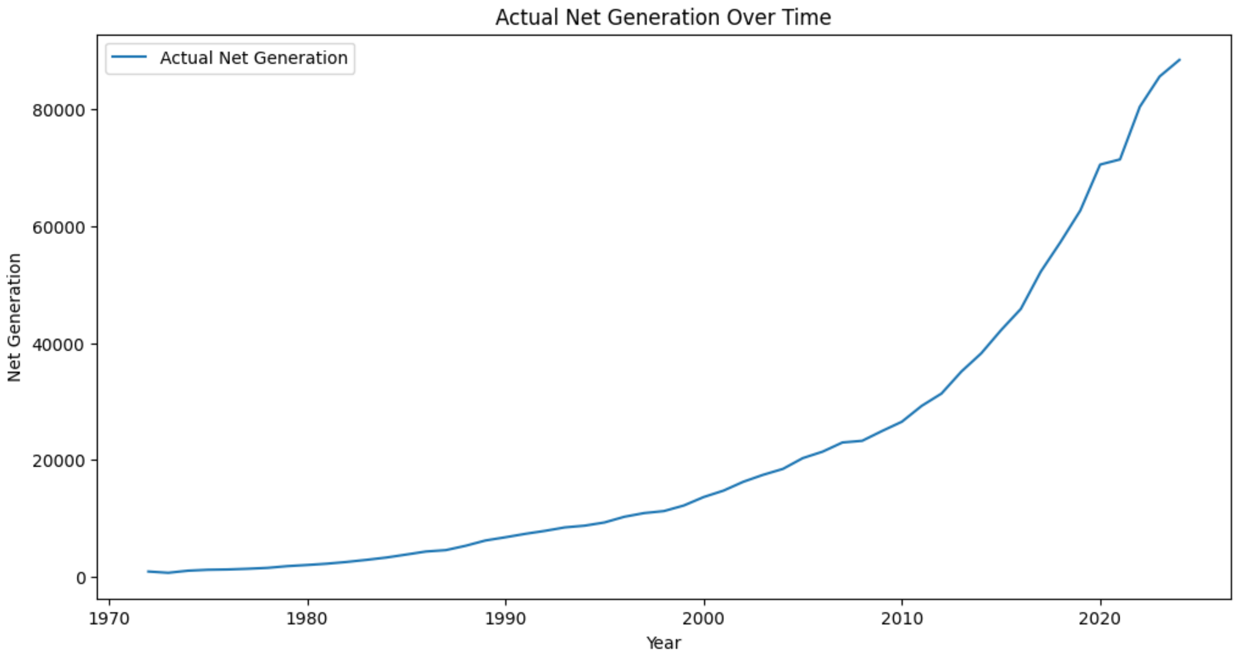

Figure 16 (Actual Net generation plot)

Figure 16 shows the electrical generation time series with an upward trend, indicating non-stationarity. The ADF test gave a p-value of 1.0, confirming the presence of a unit root.To make the data stationary, we applied second-order differencing. After transformation, the ADF test yielded a p-value of 0.001054, confirming that the differenced series was stationary, as shown in Figure 17.

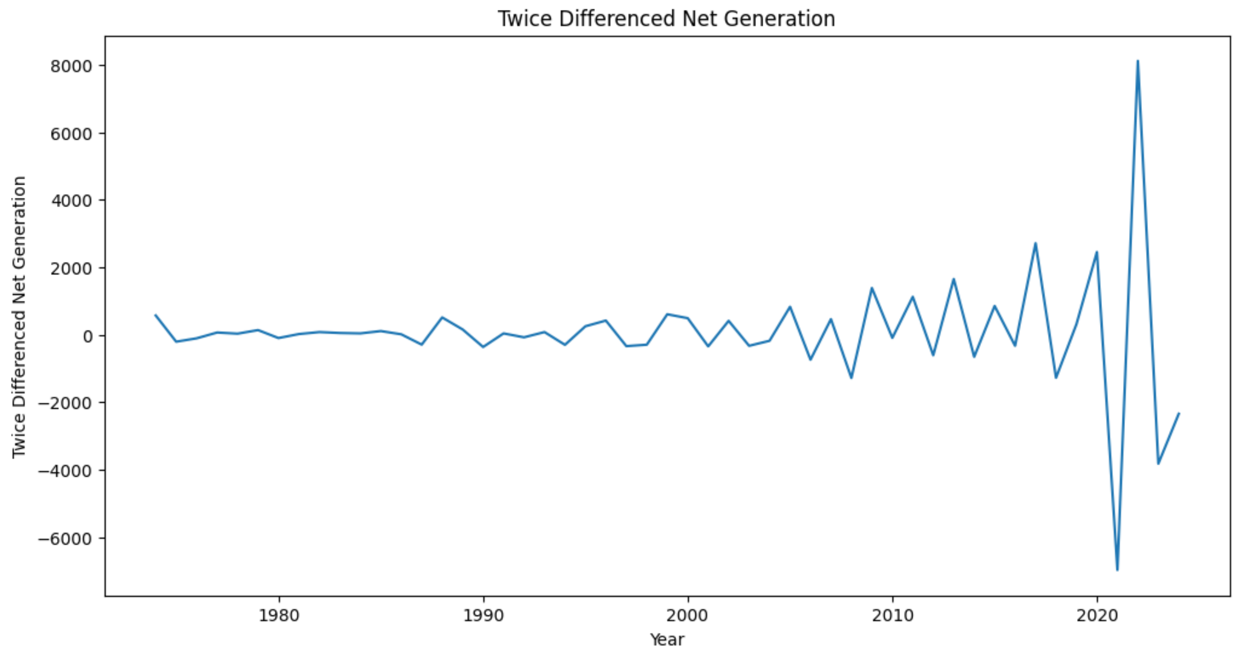

Figure 17 (2nd differenced Net generation plot)

Finally, in Table 4, we compared the AIC and BIC values for different ARIMA model configurations. The ARIMA(2, 2, 2) model had the lowest AIC and BIC, making it the optimal choice for balancing accuracy and complexity in the differenced series.

Table 8 (the AIC and BIC values for different ARIMA)

ARIMA	**ORDER**	**AIC**	BIC
1	**(2, 2, 2)**	**852.404326**	**862.063454**
2	(2, 2, 1)	852.617189	860.344492
3	(0, 2, 2)	858.544870	864.340347

4	(1, 2, 2)	860.505681	868.232984

Figure 18 shows the actual net generation (in blue) alongside the fitted values (in green), and we can see that the two lines align closely. This means the ARIMA model has done a great job of capturing the trend in net generation from 1970 to 2020. With an RMSE of 912.26 and an MAE of 596.19, the model's predictions are quite accurate, with only a small difference from the actual values. These results show that the ARIMA model is reliable for forecasting net generation.

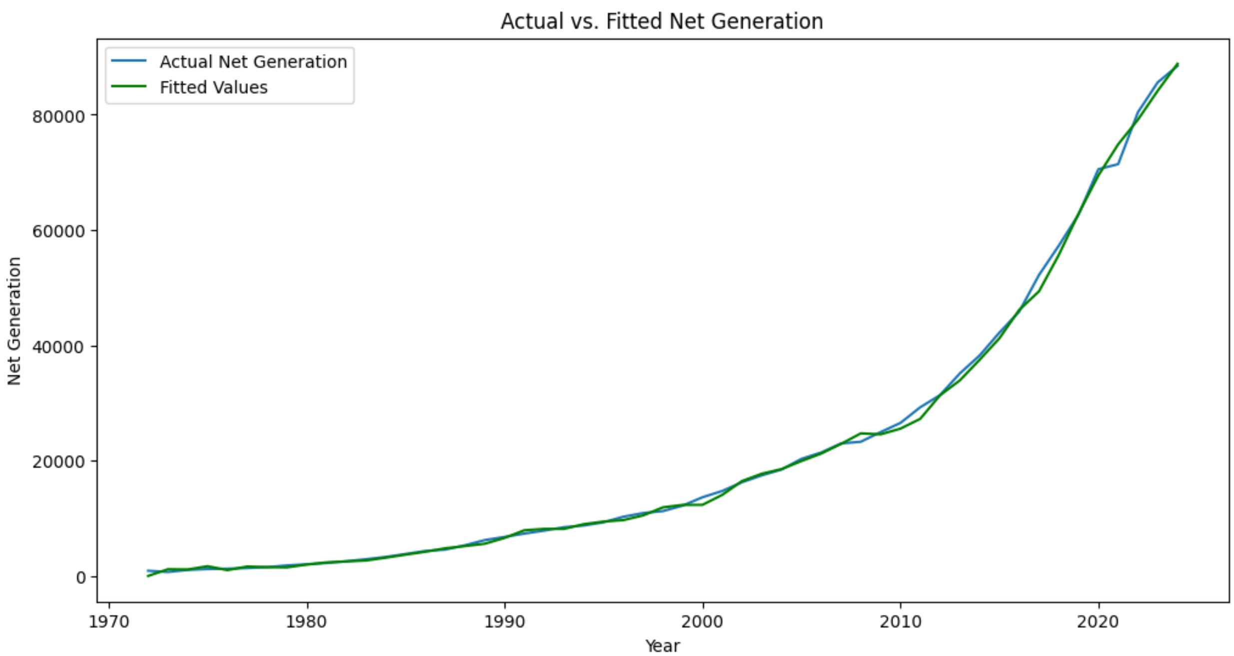

Figure 18 (Actual vs fitted Net generation plot)

The residuals plot (figure 19) for the ARIMA model shows a symmetric distribution centered around zero, with most residuals clustered near the center. This indicates that the model's predictions are generally accurate, with only a few larger errors (outliers). The residuals' relatively narrow spread suggests the model fits the data well overall.

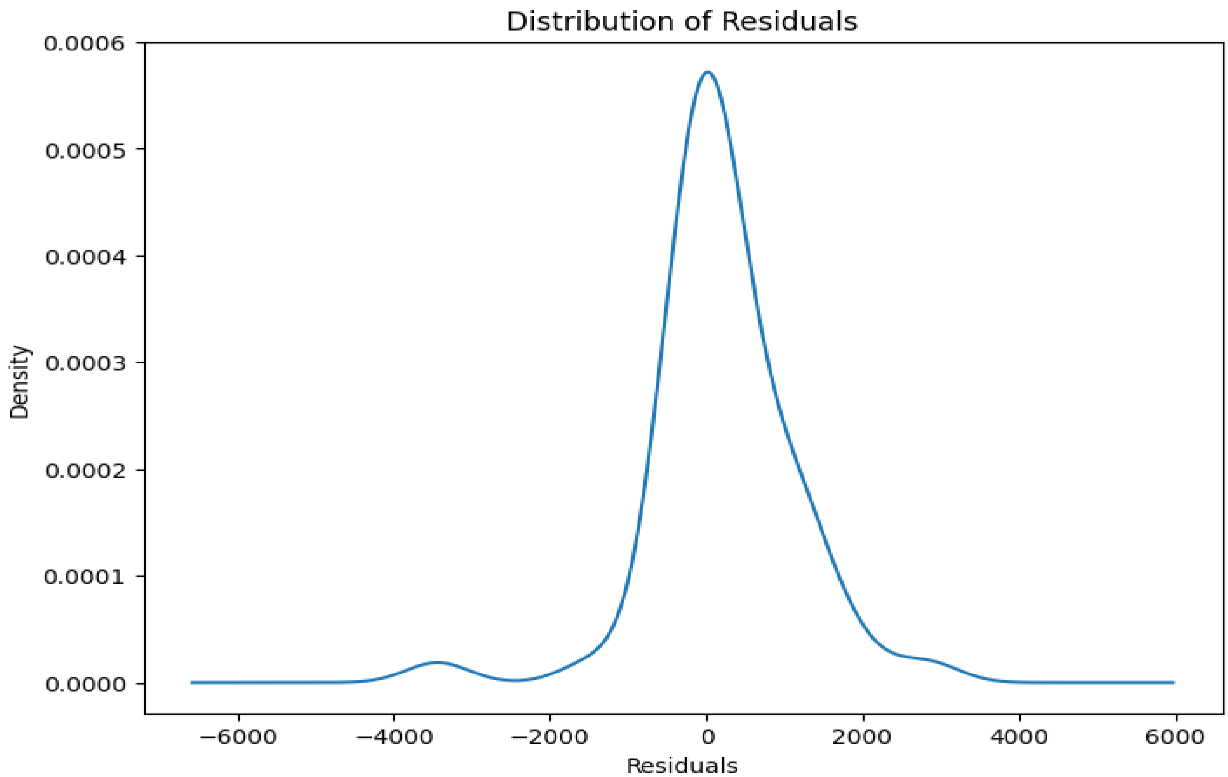

Figure 19 (Distribution of residuals)

4.2.2 VAR (vector autoregressive model)

I fitted a VAR model using net consumption, net generation, and GDP to forecast net consumption. Now, I use the same model to forecast net generation.

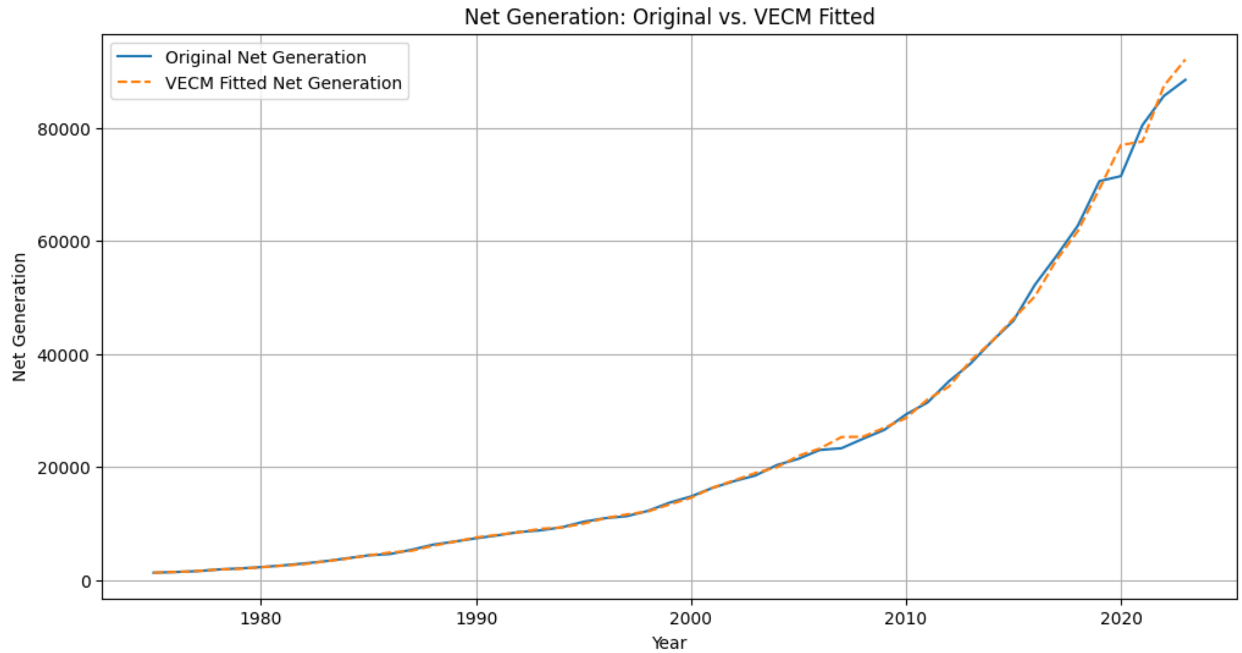

Figure 20 (Original vs VECM fitted Net Generation data)

Figure 20 compares the original net generation series (blue) with the VECM fitted values (orange). The VECM closely follows the actual trend, accurately capturing fluctuations and growth. The model's accuracy is further supported by the error metrics: the RMSE of 1193.72 and MAE of 598.63. The RMSE of 1193.72 and MAE of 598.63 indicate a strong fit and high accuracy in modeling net generation.

4.2.3 Long Short-Term Memory (LSTM)

From Table 9, the LSTM model with n_steps = 5 and 100 epochs delivers optimal results for predicting electricity generation, with an MAE of 4308.44 and RMSE of 4815.03. The 5 time steps offer better historical context, and 100 epochs allow for thorough training, resulting in accurate predictions closely matching actual values.

Table 9 (LSTM with different steps and epochs)

n_steps	**epochs**	**MAE**	**RMSE**
1	50	41377.186080	43469.179083
1	100	37088.783026	38917.190621
2	50	32304.356001	34169.781619
2	100	9179.792259	10004.760407
3	50	27635.938477	28697.638895
3	100	7104.106250	7642.117862
4	50	15014.904688	15583.746499
4	100	11895.850391	12903.949476
5	50	5643.515625	6279.016889
5	**100**	**4308.441406**	**4815.030937**

Figure 21 shows the comparison between the actual net generation and the fitted net generation over time, using the best LSTM model configuration with n_steps = 5 and epochs = 100. The blue line represents the actual net generation data from the training set, while the orange line shows the fitted values, or the model's predicted generation, during the training period. The fitted values closely align with the actual values, indicating that the LSTM model has effectively captured the underlying patterns in the training data. The predictions follow the actual data almost perfectly, with minimal deviation, suggesting the model has learned the trend of the time-series data well.

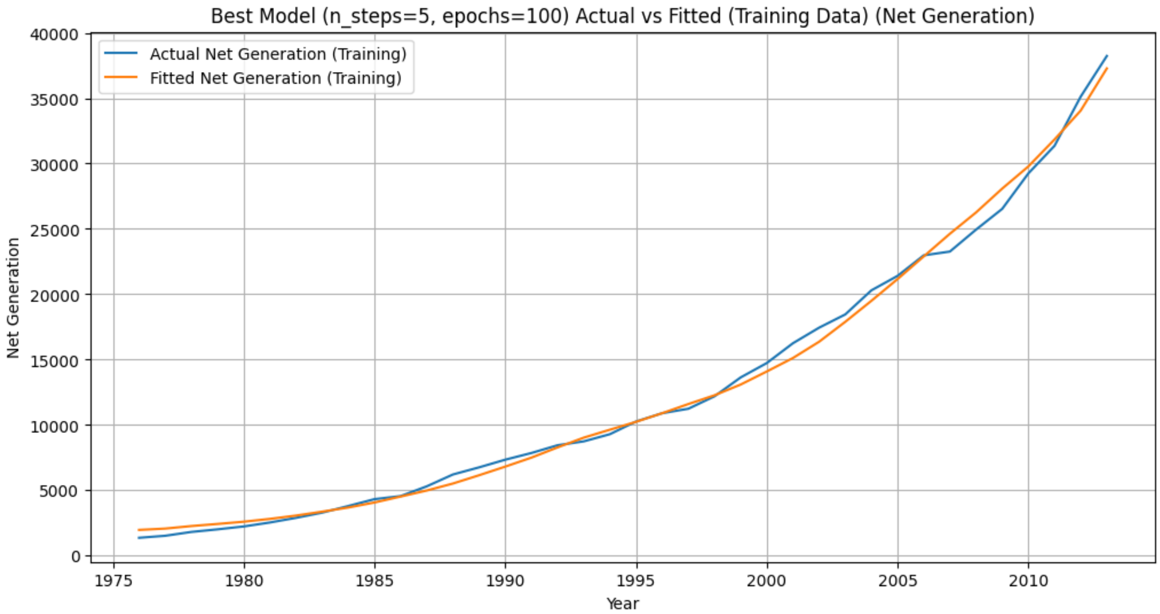

Figure 21 (Actual vs fitted Net generation data for training data)

The graph (figure 22) compares the actual net generation (blue line) with the predicted net generation (orange line) for the test data, based on the best LSTM model with n_steps = 5 and 100 epochs. While the predicted values closely follow the actual values throughout the period, there is a noticeable divergence starting in the later years. The predicted values grow at a slightly faster rate, suggesting the model might be extrapolating the trend, possibly overlooking subtle changes in growth patterns towards the end of the test period.

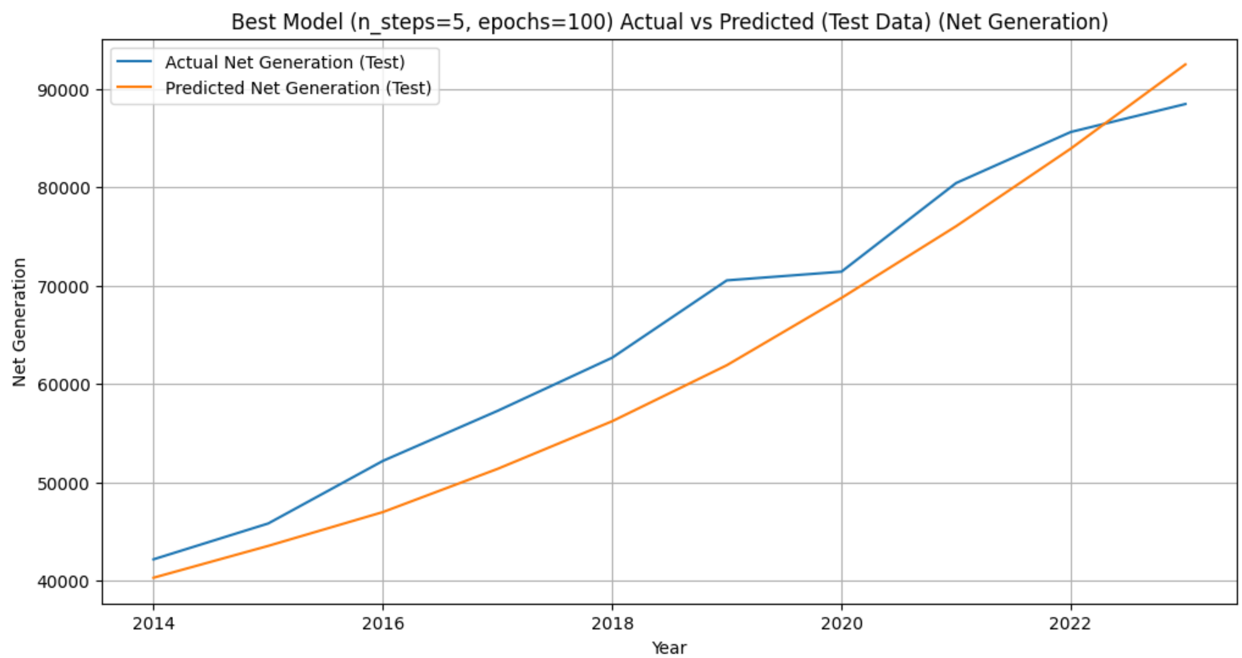

Figure 22 (Actual vs fitted plots for testing data)

4.2.4 Model comparison

In Table 10 ,ARIMA seems to strike the best balance among the models, with a moderate RMSE and MAE. This makes it a more reliable option compared to VAR/VECM and LSTM, which either have higher error rates or struggle with larger discrepancies. If i looking for a solid and consistent model, ARIMA is likely your best bet.

Table 10 (Model comparison)

MODEL	**RMSE**	**MAE**
ARIMA	912.26	596.19,
VAR/VECM	1193.72	263.88
LSTM	4815.03	4308.44

So, ARIMA is a great choice for forecasting net electricity Generation.

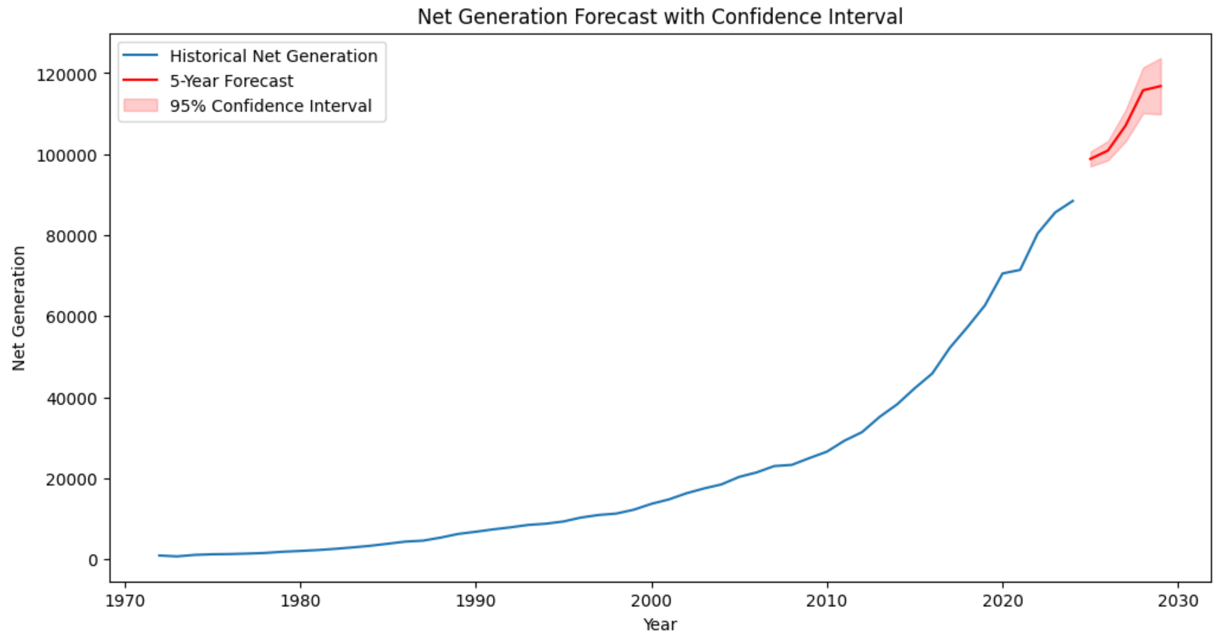

Figure 23 (forecasted value for net generation)

This figure 23, illustrates the historical trend of net generation over the years, with a five-year forecast extending into 2030. The blue line tracks the actual data, while the red line represents the forecasted values. The shaded area around the forecast indicates the 95% confidence interval, giving us a sense of the range in which we can expect the forecasted values to fall. It's clear from the chart that net generation is projected to rise significantly in the coming years, reflecting a notable increase in future energy production.

Table 11 (forecasted net generation value)

Forecasted Year	Forecasted Net Generation
2024	98811.084905
2025	100884.379584
2026	107011.453590
2027	115766.210144
2028	116798.274025

Here table 11 shows forecasted net electricity generation for 5 year.

4.3 Discussion

This study takes three models to predict electricity generation/consumption in Bangladesh; ARIMA for generation, VAR/VECM for consumption, and finally LSTM as a new advance technique. Assuming your model is in the top percentile or two, the numbers break down into the best that there are and as accurate as one can be analysis.Model RMSE (electricity generation), ARIMA — 912.26/ MAE-596.19 Note how the model was able to emulate generation quickly, demonstrating a fairly linear growth from 98,811.08 GWh in 2024 to 116,798.27 GWh in 2028- as shown below:- An increase of 0.5% recorded was attributed to a rise in demand for energy, mainly due to population growth and economic development, implementing electricity access. Due to the extra accuracy required, as well as the trend in generation forecasting data making ARIMA a good selection due to the right mix of complexity and simplicity.In terms of electricity consumption, the VAR / VECM model also showed the best results in RMSE (450.08) and MAE(263.88). This model proved useful to assess cross-country interactions between a number of potential disease drivers (urbanization, economic growth, population dynamics e seasonal effects). However, on similar module-markets-profile which has already been described, rise of demographical trends and urbanization as well are the major reasons for demand to grow in range from 32,832.85 GWh in 2024 up to an amount of 43,312.87 GWh in 2028 with consumption-based forecasted yields: In fact VAR/VECM is a great model for forecasting consumption precisely because of the multivariate nature of it than any other cases.Although LSTM is able to model complex temporal patterns, it underperformed with larger RMSE and MAE values compared to the ARIMA and VAR/VECM methods in this study. There could be several reasons, maybe the model is too complex or possibly it's from lack of data/data lable or training a not well trained model. Although the LSTM is promising, it needs more fine tuning and richer datasets for an accurate estimation of electricity generation and consumption in this application. Results also underscore the need for suitable model selection and forecasting. Bibliography Although ARIMA and VAR/VECM performed well given the strong theoretical backgrounds that underlie them and their strengths when it comes to relatively stable trend time series data as well as multivariate settings, deep learning techniques such as LSTM may offer some degree of improvement with bigger, more detailed datasets (although there certainly are some price to pay in terms model complexity). Further research in the area could consider hybrid approaches that combine traditional statistical models as well as deep learning architectures to achieve even more accurate forecasts. In addition, other external impacts such as policies related to energy sector modification, maturation of renewable energy technologies (RETs) and unforeseen changes in socio-economic context could be taken into account that lead towards a more accurate predictive model that can help the authorities for planning decisions. In the changing energy environment of Bangladesh, it is essential to have flexible and precise prediction models for optimal generation capacity and cost minimization which also improves grid stability based on forecasts allowing for a You tube comply with demand. Therefore, the results of this study offer not only a systematic comparison for identifying better models in terms of the current data situation but also pave some directions to revise methodology. For full generation prediction, exciting techniques with machine learning and deep learning algorithms will become more accessible and useful as databases and computing resources enhance. At current juncture, the ARIMA and VAR/VECM models are adequate to consider for short to medium-term strategic policy making implementation as they require simplicity and interpretability.

Chapter Five

Conclusion

5.1 Conclusion

From the results obtained, it can be concluded that ARIMA provides the highest performance and accurate results for predicting electricity generation in Bangladesh because of its simplicity and efficiency. I use VAR/VECM method here because it can capture the correspondence of all those influencing factors in a more complex electricity consumption. These estimates suggest that electricity generation and usage are expected to rise progressively by the year correspondingly. Being increasingly developed Bangladesh will require even further energy infrastructure investment as it attracts new generation capacity to meet its growing electricity demand, which in turn spurs additional gas demand. This understanding can provide valuable assistance to policymakers and the stakeholders in producing an energy supply that supports the needs of future Australia. Other possible directions for future studies include increasing the quality of LSTM by improving data or model finetuning. Also, incorporating renewable energy sources and the associated environmental impacts in future predictions should give a more holistic outlook of Bangladesh's energy future.

5.2 Significance of the Study

This research has both practical and academic relevance. It will:

1. Help government agencies and electricity authorities better plan for future demand and supply.
2. Support investment and infrastructure planning in the energy sector.
3. Contribute to the academic literature by comparing forecasting techniques in a developing country context.

5.3 Limitations of the Study

Despite its comprehensive approach, this research has several limitations:

1. Annual Data Only: Using yearly data (1971–2023) masks seasonal, monthly, daily demand fluctuations critical for operational planning.
2. Small Sample for Deep Learning: With only 53 observations, LSTM models risk overfitting and may not capture genuine patterns.

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