AN ALTERNATIVE TO PAKISTAN'S ELECTRICITY DEMAND FORECASTING MODEL

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CERTIFICATE

This is to certify that this thesis entitled: **"An Alternative to Pakistan's Electricity Demand Forecasting Model"**, submitted by **Mr. Shafqat Abbas** is accepted in its present form by the School of Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in Master of Philosophy in Econometrics.

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Author's Declaration

I **Mr. Shafqat Abbas** hereby state that my MPhil thesis titled "**An Alternative to Pakistan's Electricity Demand Forecasting Model**" is my own work and has not been submitted previously by me for taking any degree from Pakistan Institute of Development Economics or anywhere else in the country/world. At any time if my statement is found to be incorrect even after my Graduation the university has the right to withdraw my MPhil degree.

Date: 23-05-24

Signature of the Student

Shafqat Abbas

Dedication

This Effort is Dedicated to My Father, My Mother, and My Sister.

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I want to thank Allah Almighty for giving me the strength to complete this challenging task. Without His blessings, achieving this wouldn't have been possible. I would like to extend a special acknowledgment to my thesis supervisors, Dr. Amena Urooj from PIDE and Ms. Afia Malik from PIDE, for their constant companionship, guidance, and encouragement throughout this research expedition. They have played a pivotal role in my success with their unwavering support and insightful feedback. I am genuinely appreciative of their patience and expertise. I would also like to express my sincere gratitude to Dr. Saud Ahmad from PIDE for his invaluable discussion and encouragement that significantly contributed to this study.

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ABSTRACT

Due to the dynamic climatic conditions of Pakistan, the planning and management of electricity have become challenging tasks. All planning foundations build on accurate electricity demand forecasts, and demand overestimation may result in non-use payments for generation capacity. This study provides a detailed examination of the Indicative Generation Capacity Expansion Plan (IGCEP) demand forecast model. The GCEP is a pivotal snapshot of power planning developed by the National Transmission and Dispatch Company (NTDC) and approved by the National Electric Power Regulatory Authority (NEPRA). The IGCEP, integral to future electricity generation planning, relies on the accuracy of electricity demand projections. However, since 2018, the IGCEP forecasting model has exhibited overfitting issues, employing an annual data approach that overlooks seasonal variations. To address the challenge of overfitting, this study examines the factors that contribute to overfitting in aggregated data forecasts and finds that data aggregation influences forecast accuracy. A key aspect of this study is the exploration of electricity sales and demand as distinct entities. While the NTDC and other stakeholders in the Ministry of Energy assume that electricity sales are equivalent to demand. This research establishes that electricity planning on demand and sales are significantly different phenomena.

The findings not only rectify the overfitting issues in the IGCEP energy demand forecasting model but also offer a deep understanding of the factors influencing electricity demand in Pakistan. The study suggested a paradigm shift by moving the electricity demand forecast model from a purely economic perspective to a meteorological one. Ultimately, this shift towards a meteorological perspective provides a more accurate foundation for planning future electricity demand in Pakistan, ensuring the sustainability and reliability of power planning.

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1 Introduction

1.1 Background

Electricity demand forecasting is a critical aspect of power planning, serving as the foundation for generation, transmission, and distribution plans. It plays a crucial role in investment planning for the power sector and associated industries such as manufacturing, fuel, and resource exploration PMS [2019].The profitability and sustainability of the power system rely on accurate energy demand forecasts and the least-cost energy mix. Electricity demand forecasts can affect power generation costs and power sector revenue through demand-side management, fuel mix, optimal supply, and renewable energy share. The accurate energy demand forecasts also provide deep insights for policymakers in infrastructure development and energy security Azzuni and Breyer [2018]. In Pakistan, for the medium-term electricity demand forecast, known as the Power Management System (PMS), each distribution company (DISCO) predicts load demand separately. The National Transmission and Dispatch Company (NTDC) then combines these individual forecasts at the national level PMS [2019]. The PMS aids in generating and transmitting electricity effectively, considering three scenarios using electricity sale and generation data:

1. Base demand (factoring in load-shedding effects)
2. Low demand (excluding load-shedding effects)
3. High demand (incorporating strategies to manage demand)

To make predictions of electricity consumption, PMS has not adopted any statistical or other model; it uses the following calculation factors: (i) The growth rates in consumption per consumer for each category; (ii) Transmission and Distribution Loss Rates; (iii) Load factors for each consumer category; (iv) Coincidence or diversity factors; (v) Load Shedding or Unserved Energy.

For electricity planning, a demand forecast model with more accurate projections was required. Considering this point, NTDC has established an electricity planning model called the indicative generation capacity expansion plan (IGCEP), which covers electricity demand forecasting and generation capacity planning.

1.2 Indicative Generation Capacity Expansion Plan

After 1998, NTDC became an independent entity. It focuses only on managing electricity transmission and dispatch services. Every year since 2018, NTDC has developed an indicative generation capacity expansion plan (IGCEP). NTDC projected separate demand for each sector (domestic commercial, industrial, and agriculture) in IGCEP using the econometrics technique of non-linear multiple regression. NTDC uses annual sectoral electricity sales data as a dependent variable, economic growth, and tariffs as independent variables of respective sectors. NTDC assumes electricity sales equate to demand. However, both are distinct concepts. Electricity sales generate revenue from the total electricity generated, while factors like losses and load shedding are also part of electricity demand. In its earlier models, IGCEP-2018 projected electricity demand from 2014 to 2037, but critics questioned the reliability of these projections due to the lengthy projection period Perwez and Sohail [2014].

The National Electric Power Regulatory Authority (NEPRA) approved the last two IGCEPs, which have projected ten years of electricity demand. IGCEP is a snapshot of Pakistan's power sector that plans based on the least-cost electricity generation and incorporates existing, committed energy generation capacity and proposed candidate energy projects to meet future energy demand. Electricity demand forecasts play a crucial role in IGCEP, which has low, medium, and high demand projection scenarios for long periods. Despite the overfitted demand forecast model, NTDC adopted the same methodology for projecting electricity demand as in its first study, IGCEP-2018. Figure 1 shows actual demand and IGCEP projected demand. This study's primary focus is on the demand side of the IGCEP to evaluate and reconstruct the electricity demand forecasting model because all policy targets of the IGCEP are formulated based on electricity demand projection.

The initial three bars for each year in Figure 1 depict the NTDC peak demand projection scenarios,

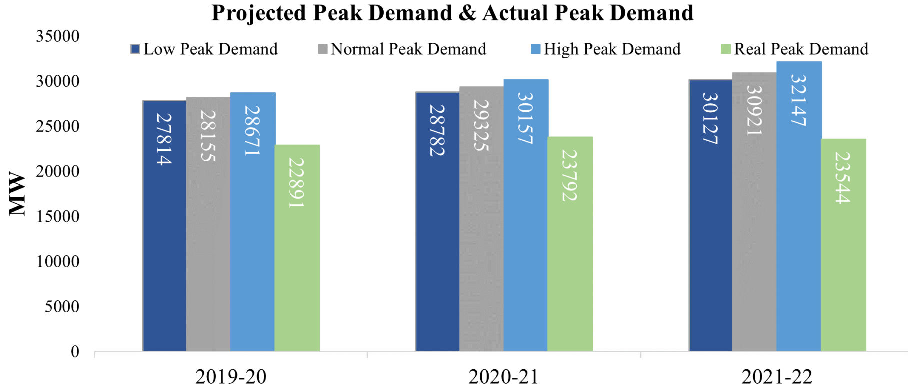

Figure 1: IGCEP-18 Projected Peak Demand and Actual Peak Demand

encompassing low, normal, and high projections. The fourth bar for each year illustrates the actual peak demand. It is evident from the comparison that the actual peak demand consistently deviates from all three scenarios put forth by NTDC. The significant difference between the actual and predicted peak demand levels highlights the challenges in accurately predicting electricity demand.

1.2.1 IGCEP Planning Framework

The planning process of the IGCEP builds its foundation on electricity demand projection. The second crucial step involves assessing the current generation capacity and comprehensively comparing it with committed energy projects. The committed energy projects are those in the installation and construction stages. To consider the least cost of electricity generation, the NTDC proposed candidate projects to fulfill the anticipated future energy demand. Notably, in IGCEP 2022, net metering is integral to the planning strategy.

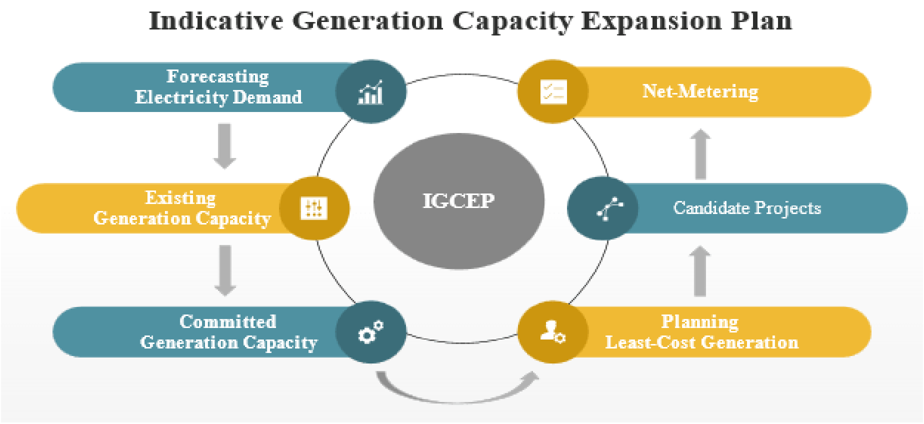

Figure 2: IGCEP 2022 Framework

1.2.2 What's Wrong with IGCEP Electricity Demand Forecast Model

Pakistan's energy sector is transitioning to renewable energy sources, based on IGCEP planning. However, accurately predicting future electricity needs remains a hurdle. This uncertainty poses a significant challenge for future energy planning. The current planning model, called the IGCEP forecast methodology, needs improvement. It forecasts electricity demand annually, resulting in overestimation and neglecting seasonal variations that are crucial for effective energy planning. To ensure the optimization of infrastructure to meet consumer demand, an alternative approach is required for accurate projections of electricity sales as well as demand and peak demand.

Before forecasting the energy demand, it is mandatory to decide on the forecasted variable scope.

Energy demand relies significantly on meteorological conditions (temperature, humidity, and rainfall); additionally, geological conditions should be considered when forecasting electricity demand Islam et al. [2020]. The IGCEP aggregates demand forecast model data from hourly electricity sales to annually. There is a need to explore data aggregation techniques for the IGCEP demand forecast model to prevent overfitting of the model. The goal of this study is to rebuild the IGCEP demand forecast model using appropriate electricity demand drivers and to find the best level of data aggregation or rule of thumb to aggregate data.

1.3 Temporal Data Aggregation

Temporal Aggregation is another name for time series data transformation from high (e.g., daily) to low frequencies (e.g., annually). Essentially, two dissimilar types of temporal aggregation existed first, non-overlapping. Where time series data is aggregated simply according to the desired time granularity. Another option is to use overlapping temporal aggregation, where time series data values are replaced by moving sums or rolling sums according to the required time buckets. (further see Table 1) Therefore, when practitioners are interested in forecasting these data series, they have three options:

1. Use the original data series to forecast and aggregate it at the desired time horizon, also known as the aggregated forecast (AD) or bottom-up approach (BU).

2. Use non-overlapping aggregated (NOA) data series that are aggregated at the desired level of time horizon forecasts one step ahead.

3. Use overlapping aggregated (OA) data series that are aggregated with overlapping at the desired level of time horizon to forecast one step ahead.

Table 1: Temporal Data Aggregation Conceptual Framework

Original Dat	**Non-overlapping Aggregation**	**Original Data**	**Overlapping aggregation**
34		34	-
39	118	39	-
45		45	118
54		54	138
66	193	66	165
73		73	193
79		79	218
36	163	36	188
48		48	163
Compare	Forecast NOA =?	Forecast BU =?	Forecat OA = ?

Recent research by]Boylan and Babai [2016] and Rostami-Tabar and Mircetic [2023] looked at the three methods discussed above: non-overlapping, overlapping, and original data series. Each has its own pros and cons, which depend on autocorrelation, the forecast horizon, and the level of data aggregation. These studies also showed that combining forecasts (BU or AD approch) makes forecasts more accurate as compared to overlapping and non-overlapping data aggregated series . The IGCEP case aggregates the data used for the demand forecast from hourly to annually using the non-overlapping data aggregation technique. Rostami-Tabar et al. [2023] have highlighted that aggregated data with overlapping techniques is more accurate in forecasting. We need to examine the different data aggregation techniques to explore the best data aggregation level for the IGCEP electricity demand forecast.

1.4 Statement of the Problem

Despite over projections, IGCEP has continued to adopt the same demand forecast model since 2018. The NTDC electricity demand forecasting model has several areas for improvement. First, the model aggregates electricity sales data from hourly to yearly using a non-overlapping data aggregation technique. Aggregation in the forecast does not exploit the substantial seasonality that is important for power planning. There is a prerequisite to appraising the accuracy of aggregated data and aggregated forecasts (forecasted data points aggregate on the desired level of time horizon). Second, NTDC and other stakeholders in the Ministry of Energy assumed electricity sales as an electricity demand. The sale of electricity is a revenue-generating part of total generation. However, by definition, power sector losses and load shedding are also part of the electricity demand. We need to forecast actual demand, including losses and load-shedding factors. Third, the IGCEP demand forecast model heavily relies on the GDP growth rate and electricity prices. However, several studies Ishaque [2018] and Hina et al. [2022] show that electricity demand is price-inelastic and Nasir et al. [2008] find out that price and income are inelastic for both the short and long terms. The IGCEP electricity demand forecast methodology needs to incorporate several other factors (temperature, humidity) that influence electricity demand in Pakistan. Fourth, Raza et al. [2022] highlights the need for modern forecasting tools to forecast electricity demand in Pakistan. Appropriate modeling and evaluation techniques are required to optimally determine supply-side scenarios Abrar and Farzaneh [2021]. I am narrowing my research problem to "An Alternative to Pakistan's Electricity Demand Forecasting Model."

1.5 Research Gap

Throughout the development of the indicative generation capacity expansion plan (IGCEP), the electricity demand forecasting methodology has remained unchanged and consistently overestimated. There is no significant research on IGCEP except for one knowledge brief that highlights numerous loopholes in IGCEP-2021; it needed to represent meeting the least cost of power generation Malik and Ahmad [2022]. Another report by the Lahore University of Management Sciences (LUMS) addressed the electricity crisis and proposed a strategic approach to power sector expansion; the LUMS Power Dispatch Model (LPDM) simulates the NTDC system to evaluate IGCEP-21. The LUMS report further suggests that developing indigenous energy sources can reduce the share of debt and energy imports. However, neither of these studies discussed demand forecast methodology or its feasibility in detail.

In the case of IGCEP, there is a need to explore the reason(s) for the overestimation of electricity demand, whether it is a problem of misappropriation of demand drivers, data aggregation, or others. So, I operationalized my topic into the following research questions and objectives.

1.6 Questions of the Research

(a) Which has higher forecast accuracy, aggregated data, or aggregated forecasts?

(b) Is there any relationship between temporal aggregation and time series features that affect forecasting accuracy?

(c) What are the appropriate drivers of electricity demand in Pakistan that help develop a more accurate model?

(d) Which IGCEP demand projection scenario is practicable, and which is not?

1.7 Objectives of the Research

(a) To examine the accuracy of forecasting with aggregated data and aggregated forecasts.

(b) To explore the relationship between temporal aggregation and time-series data features.

(c) To evaluate the IGCEP demand forecast model, investigate the demand drivers of electricity in Pakistan, and solve the overfitting problem of the model.

(d) To compare the IGCEP proposed electricity generation capacity with the proposed study electricity demand projections.

1.8 Significance of the Study

This study's methodological and analytical framework will help improve the IGCEP electricity demand forecast methodology. It also explores the optimal approach to aggregate data, which could be helpful in any forecast. The proposed study will compare the IGCEP-22 demand projection scenarios with this study's electricity demand projection. The proposed study will also address the issues of electricity demand management, how it could be better and smoother, and how it could reduce the gap between summer and winter. The direct beneficiaries are as follows:

(a) National Transmission Dispatch Company (NTDC)

(b) National Electric Power Regulatory Authority (NEPRA)

(c) Planning Commission (Energy Wing)

(d) Ministry of Energy

Chapter

2 Literature Review

Each objective in the study contributes to the overall understanding of the subject. It begins by systematically reviewing relevant literature to address the research questions. The subsequent stages involve a step-by-step exploration of the advantages and disadvantages of data aggregation for forecast accuracy. Following this, the study investigates the initial electricity demand drivers employed by NTDC for their model. The final phase of the literature focuses on the examination of meteorological factors to provide a comprehensive perspective on the subject matter.

2.1 Energy Forecast and Data Aggregation

The data transformation converted high-frequency data to low-frequency data, which has two types of data aggregation: overlapping and non-overlapping aggregation. The non-overlapping aggregation (NOA) aggregates data in simple ways at the desired level of time horizon (monthly, quarterly, or annually). However, overlapping aggregation (OA) aggregates data at the desired level of time horizon with the moving sum or rolling sum technique.

Temporal aggregation is not new; it has been studied since the seminal work of Amemiya and Wu [1972]; Tiao [1972]; and Brewer [1973]. Non-overlapping temporal aggregation can convert high-frequency data into low-frequency data; it dominates trends or cycles. While disaggregated, data has the potential to make visible the presence of seasonality. Hotta and Neto [1993] provided two reasons for temporal aggregation becoming a good idea. First, aggregated series may perform better in linear than non-linear modeling. Second, aggregated rather than disaggregated series may mitigate the outlier effect. Additionally, the additive outlier has a significant impact on both the aggregated series and the disaggregated series.

The effect of temporal aggregation on forecast performance examined by Rossana and Seater [1995], to forecasting numerous vital macroeconomic variables. The results of each variable validated temporal aggregation and simplified the complexities of low-frequency series. It may be a quarterly aggregation-level perfume better for achieving forecast accuracy. The effect of multiple temporal aggregations (MTA) on forecast performance using univariate and multivariate models investigated by Silvestrini and Veredas [2008]. The study's results provided evidence of enhanced forecasting performance with aggregation; however, deciding the optimal level of aggregation is challenging.

Deciding optimal level of data aggregation considering forecast accuracy becomes itself challenged. **?** focus on the forecasting performance of non-overlapping temporal aggregation. A single exponential smoothing is employed for estimation and the mean square error for comparing the forecast performance. An increase in aggregation level may enhance the forecast accuracy, and the smoothing constant valve decreases with the aggregation. Furthermore, highly positive autocorrelation in the original time series hinders achieving high forecast accuracy. Forecasting time series with temporal hierarchies (non-overlapping aggregation) have the advantage of decreasing forecast error and reducing uncertainty regarding the model specification. Another merit of temporal aggregation is the supported signal-to-noise ratio, which mitigates the impact of outliers on the lower-frequency aggregated time series Athanasopoulos et al. [2017].

To achieve a higher energy consumption performance forecast Spiliotis et al. [2020] examines multiple temporal aggregations (MTA). The hierarchies of energy consumption of different MTAs are considered together, which increases the complexity and uncertainty regarding the appropriate model. Employing bottom-up, top-down, and optimal reconciliation approaches are used to address aggregation consistency. They proposed a modification to the multiple aggregation prediction algorithm (MAPA) that demonstrated the optimal reconciliation approach is superior to others for achieving a high energy consumption forecast.

For electricity demand forecasts Nystrup et al. [2020] introduces four estimators for reconciling forecasts with temporal hierarchy autocorrelation. First is the autocovariance matrix with each aggregation level and second is the autocorrelation coefficient for each aggregation level. The third and fourth estimators are based on the cross-correlation matrix and its inverse. The auto and cross-covariances significantly enhance the forecast performance across all aggregation levels. Further, Nystrup et al. [2021] created eigen decomposition to get more information about the data that is available from the error structure of the forecasts for reconciling them. That was done to reduce the number of dimensions in the data. They imply the eigen decomposition techniques for dimensionality reduction simultaneously on electricity load and financial data to forecast volatility. The finding demonstrates the usefulness of the established estimator; accuracy could be improved identically for all data aggregation levels. That indicates it could be valid for all sizes of hierarchies. When the temporal hierarchy of the reconciliation forecast depends on the data-generating process (DGP), higher forecast accuracy can be achieved through auto- and cross-correlation. In the case of a strong correlation among all approaches to forecast errors, the probability of a higher forecast through reconciling would decrease. On the contrary, a low correlation between forecast errors would lead to higher accuracy gains. The structure of error correlation and level of incoherence have more significant potential to strengthen the accuracy of the forecasts.

To improve the load forecast accuracy Bergsteinsson et al. [2021] employed temporal hierarchies considering auto- and cross-covariance of forecast errors at multiple aggregation levels. They proposed three estimators, considering covariance. These estimators are expanding window (same weight), rolling window (fixed number of past errors), and exponential smoothing (put weights on past errors), respectively. These are based on forecast errors at multiple aggregation levels. The estimator of exponential smoothing attains higher accuracy in the reconciliation process. Furthermore, it highlighted the gaps for future studies to explore with extensive information on how to improve covariance estimators and the optimal level of aggregation.

Reducing the data frequencies may influence the forecast accuracy. Rostami-Tabar and Mircetic [2023] examine forecasting accuracy under both data aggregation and original data techniques. The aim was to explore whether data aggregation influences forecast accuracy or not, and whether to combine data and how. They use the M4 competition dataset forecasted with three approaches: non-overlapping, overlapping, and bottom-up to aggregate forecast (the original data series forecast is then summed up as the desired level of time horizon). Data aggregation was completed with different time horizons: daily, monthly, bimonthly, quarterly, and annually. The exponential smoothing and autoregressive moving average were applied to forecast all date series of different time horizons. The finding suggested that both aggregation techniques (overlapping and non-overlapping) may only sometimes be fruitful in achieving higher forecast accuracy. All these techniques have their own merits and demerits. However, the bottom-up technique (forecast disaggregated then aggregate) is to be more consistent about whether any trends or seasonality existed in the data series.

The time granularity in the time series forecast is necessary to decide; it may differ in itself. A time series has a higher frequency (daily or monthly), and forecasts are needed at lower frequencies (quarterly or annually). That situation leads to two options. Before forecasting, data should be aggregated (with a non-overlapping approach called aggregated data AD) at the desired level of lower frequencies than forecast. Another is after forecasting higher frequency data than aggregate forecasted (AF) values (adding up forecasted values to the required level of time granularity) of lower frequencies. Rostami-Tabar and Mircetic [2023] imply both approaches: aggregate data (AD) and aggregate forecast (AF). They use monthly data from the M4 competition dataset to examine the performance of these approaches and investigate relationships between time series features and the forecast accuracy of AD and AF. The stdudy's findings suggest that both approaches may give different results. However, AF performs significantly better than AD, particularly for long-term graduality.

Furthermore, trend, auto-correlation, seasonality, pacf, hurst, and ARCH˙LM might support the AF approach. On the other hand, entropy, nonlinearity, curvature, and lumpiness can increase the probability of better results in AD. That is no permanent choice; AF and AD approaches outpace each other in varying conditions.

2.2 Energy-Growth Nexus

The causality between energy consumption and the gross domestic product is predominantly subject to numerous studies in the energy economics literature. The curiosity to investigate the causal relationship between energy consumption and economic growth was established five decades ago. It was stirred in some way; economies slowed down all over the globe due to the innumerable oil crises in the 1970s. The raised oil prices affected energy-dependent economies and pushed them toward recession after such events in the Persian Gulf. The literature has shown interest in revitalization to explore the relationship between energy consumption and economic growth with advancing econometrics techniques.

Still, economists need help deciding the type of prevailing causality between energy consumption and economic growth. Several statistical methods were applied to explore the direction of causality among energy consumption and different economic variables. But the result persisted contentiously. For instance, consider the causal relationships among energy consumption and economic variables Kraft and Kraft [1978] examined in the case of the USA. They found that the causality direction is from GNP to energy consumption. While Akarca and Long II [1979] found granger causality runs from energy consumption to employment. An insignificant causal relationship between energy consumption and income founded by Eden and Hwang [1984] and Soytas and Sari [2003]. Through the multivariate framework, a bidirectional relationship between energy consumption and GDP was found by Gross [2012] and Lee [2006].

In the case of Canada, energy consumption and GDP were found to be independent by Soytas and Sari [2003]. However, Lee [2006] found a unidirectional causal relationship between energy

consumption and income. Omri et al. [2015] examined the causal relationship between energy consumption (nuclear and renewable) and economic growth, employed a dynamic simultaneous equation panel data model for 17 countries and data from 1990 to 2011. The study's results were fascinating, directing unidirectional causality from nuclear electricity consumption to economic growth in Spain and Belgium. In Bulgaria, Sweden, Canada, and the Netherlands, unidirectional causality led from economic development to nuclear electricity consumption.
Consider the dynamic and grave role of energy in the economic development of D8 countries Razzaqi et al. [2011] aimed to investigate the relationship between energy consumption and economic output. They used the Johnsen cointegration test, the vector error correction model (VECM) for the long run, and the Granger causality test for the short-run determination of causal linkages. The short-run analysis of Granger causality validated 'the growth hypothesis in the cases of Nigeria and Iran. "The conservation hypothesis" in the case of Pakistan, Bangladesh, Egypt, Malaysia, and Turkey. "The neutrality hypothesis" in the case of Indonesia. No single case validated the "feedback effect," covering the time horizon of 1980–2007. The cointegration test validates long-run causality between GDP and energy consumption for all members of the D8 countries. However, the results of the VECM analysis confirmed the true "growth hypothesis" in the case of Nigeria, the "conservation hypothesis" in the case of Egypt, and the "feedback hypothesis" in the cases of Pakistan, Bangladesh, Malaysia, Iran, and Turkey. The overall outcomes of the study suggest that most economies are energy-dependent in D8 countries. Interruptions in energy consumption may have diverse effects on economic growth. While few countries have bidirectional causality in the case of these economies, fluctuations in economic growth also influence energy consumption.
The relationship between energy disaggregated by its type and economic growth in the United States examined by Ewing et al. [2007], employed the generalized variance decomposition econometrics technique. The results showed that fossil fuels explain the maximum variation in economic growth. However, more is needed regarding renewable energy sources. Sari et al. [2008] investigated causality among different types of energy consumption and economic growth in the United States. Using monthly data from the ARDL bounds test, cointegration was examined in the long run. They find that natural gas and wood energy consumption have no significant relationship with economic growth.
Through a panel cointegration test, Sadorsky [2009] examined the relationship between renewable energy consumption and income in 18 developing countries. The findings highlight that emerging economies' real income per capita has a significantly positive relationship with

per capita renewable energy consumption. A bidirectional causality exists in Brazil, Pakistan, Argentina, the United States, and France. In India, Finland, Japan, the United Kingdom, Switzerland, and Hungary, no causality exists between nuclear energy and economic growth. The second nexus is renewable energy consumption and economic growth. A unidirectional causal relationship runs from renewable energy consumption to economic growth in India, Sweden, Japan, Hungary, and the Netherlands. However, a unidirectional causal relationship runs from economic growth to renewable energy consumption in Argentina, Switzerland, and Spain. A bidirectional causality exists between economic growth and renewable energy consumption in Pakistan, the United States, Canada, Belgium, Bulgaria, and France. In contrast, no causal relationship exists in Finland, Brazil, or Switzerland. Unidirectional causality is directed from economic growth to renewable energy consumption for the global panel. However, bidirectional causality exists between economic growth and nuclear energy consumption.

The causal relationship between economic growth and electricity consumption Ouédraogo [2010] empirically explored in Burkina Faso, Brazil. Employing multivariate bound tests for electricity consumption, investment, and GDP. The results of study's provide significant evidence of the cointegration between electricity consumption and real GDP and investment. However, the bidirectional causal relationship between electricity consumption and real GDP failed to detect any causality between electricity consumption and investment. Burkina Faso is included in the list of energy-dependent nations where electricity demand grows with income levels. That indicates socio-economic development in Burkina Faso is linked with electricity consumption. Using the Toda-Yamamoto causality approach, Bowden and Payne [2010] examined the long-run causality between renewable and nonrenewable energy consumption and economic growth. The study's findings were fascinating, no causality was found between industrial and commercial renewable energy consumption and economic growth. In contrast, bidirectional causality existed between residential and commercial nonrenewable energy and economic growth. Furthermore, Granger causality was found between industrial and residential renewable energy consumption.

The causality between renewable energy and economic growth through Granger causality and Johansen cointegration investigated Bobinaite et al. [2011]. The results show insignificant cointegration between renewable energy consumption and economic growth. However, univariate causality from renewable energy consumption to economic growth was reported. Satti et al. [2014] used the VECM Granger causality approach to expose the bidirectional causal relationship between coal consumption and economic growth in Pakistan. This study covers the 1994–2010 horizon, and the cumulative sum and cumulative sum of squares do not indicate any structural instability.

The causality between coal consumption and economic growth Kumar and Shahbaz [2012] re-investigates in the case of Pakistan. For this purpose, they used data from the 1971–2009 horizon, the ARDL bounds test, dynamic and fully modified OLS to compare robustness, and VECM Granger causality. The empirical results reveal a long-run causal relationship between coal consumption and economic growth. Further, this study suggests that capital, labor, and coal consumption are determinants of economic growth. Wolde-Rufael [2010] found unidirectional causality between coal consumption and economic growth in the cases of Japan, China, India, and South Korea. Using capital and labor as additional drivers of economic growth. However, bidirectional causality was found between coal consumption and economic growth in the United States and South Africa.

To considering the diverse methodologies provided different results, avoid the problem of divergent methodologies for different countries Marques et al. [2017] investigated the energy-growth nexus of various world regions using an identical method. They divided the world into four regions: North and South America, Central Asia and Europe, Asia Pacific, and the Middle East and Africa. Through the ARDL bound test and annually aggregated data covering the time horizon of 1968–2013, In the long run, the study's outcomes validated the "feedback hypothesis" in the Asia Pacific and North and South America cases and the "conservation hypothesis" in Europe, Central Asia, and the Middle East and Africa. Furthermore, across the world, heterogeneous outcomes were found during the historical economic events of the oil embargo of 1970 and the economic crises of 1980 and 2008.

According to the International Energy Agency IEA [2006], increased energy consumption in emerging economies coincides with increased real GDP. Several studies have been conducted in Pakistan on energy demand drivers by applying different econometric techniques. Several studies have investigated the causality between energy consumption and economic growth; however, their empirical results are ambiguous.

Using Hsiao's Granger causality and cointegration, Aqeel and Butt [2001] examined the independent relationship between aggregated and disaggregated energy consumption (by types) and economic growth and employment. The study infers a unidirectional causal relationship between economic growth, aggregated energy consumption, and economic growth, leading to increased petroleum consumption. However, in disaggregated energy consumption scenarios, only electricity consumption causes economic growth, and neither petroleum, gas, nor economic growth alter each other. Gas and electricity policies in Pakistan have been adopted so that the increase in gas and electricity consumption accelerates economic growth.

In the case of Pakistan, Shahbaz et al. [2012] investigated the causal relationship between renewable and non-renewable energy and economic growth. Using two econometric techniques: structural break cointegration and ARDL bound tests. The empirical results explore the cointegration among renewable and non-renewable energy consumption, economic growth, labor, and capital. Further causality analysis finds the presence of a univariate causal relationship between renewable energy consumption and economic growth, between non-renewable energy consumption and economic growth, and between economic growth and capital. By applying the cointegration technique Khan and Ahmad [2008] investigated the long-term association between energy consumption and economic growth. At the disaggregated level, their empirical results show a positive relationship between economic growth and gas consumption. However, no significant relationship is found between electricity use and economic growth.

The causal links among electricity consumption, prices, and real economic growth investigated Jamil and Ahmad [2010], using multivariate cointegration and the vector error correction model (VECM), The analysis was conducted on aggregated and disaggregated (sector-wise) levels, domestic commercial, agriculture, and industrial, for the 1960–2008 time horizon. The results infer the presence of the unidirectional causality of real GDP to electricity consumption.

The causality among energy consumption, GDP, and pollution Hussain et al. [2012] examined the case of Pakistan. Using per capita GDP, per capita CO2 emissions as pollution, and per capita industrial energy consumption as energy indicators. The analysis was based on the Kuznets curve, and the time horizon for sample data was 1971–2006. They employ co-integration, Granger causality tests, and the vector error correction model (VECM). A long-term causal relationship was found among these three variables. In contrast, a bidirectional causal relationship between per capita industrial energy consumption and CO2 emissions was validated. They compare industrial energy consumption with per capita GDP and develop causal relationships between variables, one on the aggregated (GDP per capita) level and others on the disaggregated (industrial energy consumption) level. It turns into an erroneous result. While another study Jamil and Ahmad [2010] reveals the presence of causality running from electricity consumption to economic growth and prices.

The causation between the consumption of different types of energy and economic growth Qazi et al. [2012] find a combination between electricity, oil, and gas consumption and industrial growth. Furthermore, their study probes the evidence that electricity generators cause industrial growth. However, industrial growth granger causes coal consumption and exposes no causal effect between gas consumption and industrial growth. Shahbaz and Lean [2012] probed interdependent electricity consumption and economic output. They employed a vector error correction model (VECM) and the ARDL bounds test. Zaman et al. [2012] found a positive effect on electricity demand of economic growth, population, and foreign direct investment demand drivers for electricity are considered.

The causal relationships between disaggregated energy consumption (by energy type) and Pakistan's agricultural growth and economic growth examined by Faridi and Murtaza [2013]. They applied two econometric techniques: ARDL bound to the test and an error correction model. The study outcomes validated the relationships among the variables for both the long and short runs. A unidirectional causality directed from electricity consumption to economic growth as well as agricultural sector growth was also validated in the study. That suggested a policy point of view of economic growth and agricultural output in Pakistan could be harmed due to the usual interruptions in electricity supply.

The literature on the energy-economic growth nexus has emphasized the potential trade-off between bivariate and multivariate models. The bivariate models suffer from omitted variable bias; however, multivariate models' over-parametrization is a danger for individual countries Narayan and Smyth [2014]. To address this limitation, Ahmed et al. [2015] re-investigated the nature of causality between energy consumption and economic growth in Pakistan. The maximum entropy bootstrap approach leads to robustness even in small samples and does not depend on asymptotic methods. Additionally, it could apply to non-stationary data and structural breaks and is not sensitive to lag length selection. The findings of both bivariate and multivariate analyses validated the 'conservation hypothesis', inferring unidirectional causality between economic growth and energy consumption.

Energy supply and availability are crucial factors in energy security when considering energy as an essential input for sustainable economic growth. Mahmood and Ayaz [2018] explored the causal linkages between energy security (sustainable and cheap supply and energy availability) and economic growth. They considered the energy demand and supply gap as an energy security variable for the time horizon covering 1980–2012. Using an error correction model (ECM), the study infers the unidirectional causality of the energy demand and supply gap toward economic growth in Pakistan for both long and short runs. They failed to explore any causal link between economic growth and energy demand and the supply gap, which is considered energy security.

The causal linkages between the disaggregated energy consumption of the industrial sector (by energy type) and economic growth Chandio et al. [2019] examined in case of Pakistan. Using a cointegration test and a vector error correction model. That finding infers a long-term relationship between energy consumption and economic growth. The electricity and gas consumption of the industrial sector stimulates economic growth in both the long and short runs. In contrast, oil consumption in the industrial sector has adversely impacted economic growth in the long run but is optimistic in the short run. The VECM validated the bidirectional causality between oil consumption in the industrial sector and economic growth. However, unidirectional causality was established between economic growth and electricity consumption in the industrial sector.

The causality among economic growth, energy consumption, urbanization, industrial growth, and carbon emissions Abbasi et al. [2021] investigated in case of Pakistan. The primary objective of this study is to explore the determinants of economic growth in Pakistan. For this purpose, they used data from 1972–2018 and employed two econometric techniques: ARDL and frequency domain causality (FDC) tests for short-, medium-, and long-run relationships. The empirical results reveal that industrial value-added and electricity consumption impact economic growth in the short and long run. Furthermore, they suggest a prerequisite for economic policies and planning to integrate efficient electricity management and generation.

Energy plays a vital role in economic development. Numerous studies have explored the univariate and bivariate directional causal relationships between energy consumption, economic growth, and economic growth and energy consumption. Several studies in different countries failed to probe any causal relationship between energy consumption and economic growth. From an economist perspective, Kraft and Kraft [1978] examined the relationship between energy consumption as an input and economic growth as an output, using different econometric tools over a time horizon. However, the empirical results revealed that it is difficult to reach an actual census. Electricity also plays a vital role in boosting economic development. Over the last two decades, several empirical and theoretical studies have been conducted on the causal relationship between energy consumption and economic growth. These study results have varied across regions and time horizons, suggesting that efficient energy use can enhance the economy. However, economists still cannot grasp factual censuses Salahuddin et al. [2018].

Modeling the causal relationship between energy consumption and income in emerging economies has been a dynamic part of research. However, most existing literature (Lee [2005]; Yoo [2006]; Chien and Hu [2007]; Mahadevan and Asafu-Adjaye [2007]; Squalli [2007];Chontanawat et al.

[2008]; Akinlo [2008]; Wolde-Rufael [2010] Narayan and Smyth [2014];) focuses on the relationship between the consumption of different types of energy and economic growth or real income. No study has examined the relationship between sectoral electricity consumption and sectoral growth in Pakistan.

2.3 Energy-Price Nexus

Since the oil embargo of the 1970s, numerous studies have estimated the short- and long-run price elasticities of the energy demand for different countries. The literature provides a wide range of studies on the price elasticity of energy demand at aggregated and disaggregated energy levels. Labandeira et al. [2017] quantitatively summarized all the recent and relevant studies through meta-analysis. They analyzed the price elasticities of the electricity demand at aggregated and disaggregated levels (by type of energy). They investigated the factors that influence electricity demand. The study's outcomes suggested that electricity is price-elastic for both the short and long run. The magnitude of the price elasticity of electricity demand was -0.21 for the short run and -0.35 for the long run.

Electricity is becoming increasingly important in the modern era. All energy services are derived from electricity; by default, they do not have any proper substitution for other fuels. The relationship between electricity and its price varies from country to country. In a broad-range analysis, Liddle and Hasanov [2022] investigated long-run price and output elasticities. The study aims to analyze industrial electricity demand at aggregated levels for high-income and middle-income countries, which contain high-income countries (mostly OECD countries) and middle-income countries (non-OEDC countries). The dynamic Pannal model was used to estimate long-run output and price elasticities. The reveals that output and price elasticity are significant in high-income countries. However, a different situation is noted in middle-income countries. The output elasticity is substantial and more effective than that of high-income countries. In contrast, price elasticity has a low magnitude and is inelastic in middle-income countries.

Forecasting energy demand or investigating the causal relationship between energy and its determinate functional form plays a crucial role. The role of the applicable state is often debated in literature. Hina et al. [2022] develop a non-nested test to compare the two demand systems, double log, and LA-AIDS (the almost ideal demand system), to explore the appropriate and helpful form of energy determinants. The outcome infers that all compensated and uncompensated own price elasticities show that all types of energy have a negative sign except electricity. Which has a positive sign that reflects the theoretical insignificance of electricity prices concerning electricity demand. Barrientos et al. [2018] employed a structural vector autoregressive (SVAR) model to determine the effect of price changes on electricity consumption. They used the industrial sector data from Colombia. The findings of this study suggest that electricity consumption did not respond significantly to changes in electricity prices.

In case of nonlinear tariffs or marginal incentives are substantial Lanot and Vesterberg [2021] calculate the price elasticity of electricity demand. Using bunching and the 2SLS method on data from the Swedish domestic sector. The study's outcomes suggest that price elasticity becomes small in the case of nonlinear tariffs or when marginal incentives are high. In such cases, the total price change effect does not shift equally among all consumers. Furthermore, electricity prices based on maximum consumption led to ineffective incentives.

Numerous studies have been conducted on the price elasticities of electricity demand in Pakistan. These studies are based on electricity consumption data that does not represent the total or actual electricity demand owing to the demand-supply gap. Considering this gap, Ishaque (2018) conducted a study incorporating the load-shedding factor into the electricity consumption of Pakistan Electric Power Company (PEPCO) and K-Electric. Employing the ARDL model results of the study explored for the long run, electricity demand is income elasticity at an aggregated level. The disaggregated level of the agriculture sector is income-elastic.

Furthermore, the electricity demand was found to be inelastic at all levels. Previous studies have highlighted that, assuming electricity consumption is a demand, price is an insignificant driver of electricity demand. Ishaque [2018] also provides evidence of price-inelastic electricity demand, including the supply gap (load shedding) associated with electricity consumption. Nasir et al. [2008] evaluated both income and price elasticities of electricity demand and drew some fascinating conclusions. In the short and long run, the electricity price is inelastic. Which opposes the electricity conservation policy; increasing only prices could be ineffective. The income elasticity of electricity demand is elastic for short and long runs, which refers to electricity behaving like a normal good in Pakistan. It also indicates that, over time, people depend more on electricity.

Electricity demand drivers investigated Khan and Ahmad [2008] in the case of Pakistan. Employed co-integration and the ARDL technique. The results suggest that real income, actual electricity prices, and average temperature are significant determinants of electricity demand in the long run. Furthermore, income elasticity has substantial and positive signs, which implies that electricity behaves like normal goods. While the price elasticity of demand has significant negative signs, indicating that electricity is not a necessity, it is a luxury in Pakistan. It could also be justified by the fact that more than 70 percent of the population resides in urban areas, yet several rural areas still need to be electrified. Therefore, electricity is necessary for metropolitan regions and a luxury for rural regions.

The price elasticities of electricity at the firm level Chaudhry [2010] analyzed the World Bank Enterprise Survey data for Pakistan. The study outcomes across all firms indicate that the price elasticity of electricity demand is -.057. The textile sector (-0.81) has the highest elasticity across all firms, and the electronics sector (-0.31) is the lowest. To explore the answer, 'Does a change in electricity price influence electricity demand in Pakistan?'. Sarwar and Hanif [2018] used aggregated electricity demand data. The primary aim of the study was to explore appropriate electricity demand drivers. The ARDL and Johansen cointegration techniques have been used to estimate and analyze the outcomes. It shows that the number of consumers, the square of real GDP per capita, and the stock of appliances are appropriate electricity demand drivers in Pakistan. However, the price of electricity was found to be irrelevant in forecasting the electricity demand. It reveals that electricity behaves like a necessary good in Pakistan. Moreover, the climatic variable temperature was found to have a positive and insignificant relationship in the short run, while a significant positive relationship was found in the long run.

Underlying the energy demand trend (UEDT) aggregated and disaggregated (by sector) level, Javid and Qayyum [2014] explored the electricity demand drivers for Pakistan. They used the annual structural time-series technique for the 1972–2012 time horizon. To identify the significance and magnitude of the income and price elasticities. The result also reveals the UEDT for the entire economy and sector. The outcomes infer that the nature of the trend is nonlinear stochastic in form. The UEDT shows an upward slope for sectoral electricity consumption, indicating that exogenous factors rebound from technological advancements in energy efficiency.

Furthermore, the price may only manage electricity demand for some parts of the economy. The domestic sector, which has more than a 45 percent share of electricity consumption, did not respond to changes in electricity prices. That is because consumers cannot shift from electricity to other sources.

Electricity prices are used as a transition parameter to forecast the electricity demand in Pakistan. Nawaz et al. [2014] employ a smooth transition autoregressive (STAR) model on time series data covering from 1971 to 2012 forecasted electricity demand. They highlighted that electricity demand in Pakistan follows a nonlinear trend, and average actual prices lie below optimal levels. However, the demand for electricity is mainly determined by the level of development. Owing to the weak relationship between prices and electricity demand, the policy of price appreciation to limit or smooth electricity demand may not work. Hung and Huang [2015] analyzed the dynamic electricity demand for the domestic sector in Taiwan through a partial adjustment model. The data, composed of 19 countries covering 2007–2013, addresses electricity price endogeneity by increasing block pricing. The estimates validated electricity demand seasonality differences in the summer and non-summer seasons. Consumers can adjust their electricity consumption concerning price changes in the non-summer season, but this is not valid in the summer season. Own-price elasticities were also found to differ due to seasonality. The summer periods have low price elasticities compared to the non-summer seasons. Moreover, income elasticities for both the short- and long-run were inelastic. It indicates that electricity behaves as a necessity for consumers.

Numerous studies cover the price elasticities of grid-connected populations of electricity demand. In contrast, few studies have been conducted on off-grid communities or a portion of the population that still needs access to electricity. Müller et al. [2018] used 2SLS to estimate the price elasticity of off-grid electricity demand. They tackle many econometric complications to develop models, such as the absence of electricity consumption data and its prices. The instrumental approaches addressed were determined by electricity demand and cost considerations. The study's findings suggest that off-grid electricity demand is more price-inelastic than that of grid-connected consumers. At the national and sub-national levels, Akhtar et al. [2020] investigated electricity demand drivers for the domestic sector using the two-stage least squares (2SLS) method on monthly data. They find five significant electricity demand drivers in Pakistan: income, dwelling size, household size, appliances, and luxury appliances. Another study by Zaman et al. [2015] to examine electricity demand determinants implies Johansen cointegration and multivariate Granger causality. Using Pakistani data from 1972 to 2012. The outcomes reveal that electricity demand determinants—economic growth, the number of electricity consumers, and electricity prices—are cointegrated. Moreover, bidirectional causality exists between electricity consumption and economic growth, but not with electricity prices. Furthermore, they suggest revising electricity pricing policies based on their study findings.

To design policies for Pakistan, how can energy be secured sustainably? Khalid et al. [2021] investigating the potential of inter-fuel and inter-factor substitution between energy and non-energy factors like labor and capital. They estimated the substitution elasticities of the labor and capital non-energy factors in pairs with energy types (coal, gas, hydropower, and petroleum). Employing ridge regression on time series data from 1980 to 2017. The outcomes indicate that labor and capital energy are substitutes that validate that the government should focus more on technological advancement. Furthermore, the gradual elimination of energy subsidies is proposed to tackle energy inefficiencies and encourage capital incentive production.

Since 2013, the National Electric Power Regulatory Authority (NEPRA) has implemented an increasing block electricity pricing policy to control circular debt and electricity demand. The basic implication of the policy was to manage electricity demand by increasing tariffs on electricity consumption. However, a lower consumption block was exempt. The core objective of the policy was to cross-subsidies the domestic sector with two other commercial and industrial sectors. To examine the efficiencies and implications of increasing the block electricity pricing policy. Malik [2021] analyzed primary data from the rural and urban regions of the Sargodha district. The results highlight the heterogeneous elasticities of all five electricity consumption blocks (slabs). The first block, which is exempt from increasing tariffs, is -0.391. The second to fourth block electricity price elasticities were -988, -1.229, and -0.955, respectively. The fifth block, the high-income group, shows a low electricity price elasticity of -0.489, indicating that this group is more concerned about the standard of living.

Extensive price elasticity of demand has been used to assess consumer behavior regarding electricity prices. Price elasticity concerning electricity demand is used primarily to design plans for demand management and predict future demand. Electricity demand and prices are inevitably related to each other. It is challenging to develop a model for balancing peak demand effectively on the generation side and optimizing electricity bills on the consumer side Lin et al. [2023]. Currently, Pakistan is facing an exponential increase in energy demand; however, the government plummeted subsidies on electricity to mitigate the effect of the fiscal burden. Ilyas et al. [2022] analyzed the impact of subsidy elimination in the residential sector on households. The results suggest that an increase in electricity prices negatively influences household expenditure. Moreover, the impact is more significant in wealthy and poor households. Furthermore, the indirect effect of subsidy elimination was more effective than the direct effect. The elimination of subsidies for electricity raises prices, which causes an increase in prices.

Several countries have reported that consumers react to electricity pricing mechanisms by switching the peak and off-peak hours of electricity consumption. It could be a better tool for electricity demand management than linear or fixed tariffs. Based on such evidence, Ciarreta et al. [2023] investigated the theoretical framework of the time-of-use (ToU) pricing mechanism. This model implies Spanish data. The objective of this study was to explore whether time-of-use (peak and off-peak hour consumption) pricing or a linear tariff has greater efficiency in managing the electricity demand side. The results indicate that the modified consumption pattern ToU pricing mechanism has greater efficacy and welfare gains than fixed tariffs. Price elasticities are win-win under the ToU pricing mechanism for retailers and consumers.

2.4 Energy-Temperature Nexus

In the literature, electricity demand forecasting has been done with different demand drivers and forecast horizons for various countries. Climate change makes it challenging to manage increasing electricity demand and its predictability. To manage power systems efficiently, system needs to incorporate the climate change impact on electricity demand and explore some measures to address the climate change impact on increasing peak electricity demand. Climate change has significantly influenced electricity consumption. The fluctuating amplitude of electricity demand depends on the interaction of several ambiguous mechanisms. Climate change itself is anticipated to surge in future electricity demand for households.

Electricity demand-temperature nexus is almost binding globally; varying electricity demand patterns are due to moderately temperate climates. Hekkenberg et al. [2009] hypothesized that upward electricity demand trends are expected to increase cooling appliance usage, which shifted towards temperature dependence demand. They investigated the electricity demand trends in the Netherlands. The findings are consistent with the proposed hypothesis. The electricity demand for May, June, July, September, and October, and holidays during the summer season, are temperature dependent. Furthermore, the peak values of the winter season are generally around the minimum summer season demand, under the expectation of a temperate climate. This significant difference owing to temperature creates challenges on the generation side, which may have severe consequences for electricity generation capacity planning.

To combine the fuzzy model (Takagi-Sugeno-Kang) with fuzzy regression, Nadimi et al. [2009] examined the impact of weather on electricity demand. They developed a type III fuzzy inference machine that merges linear and nonlinear fuzzy regressors. Daily electricity consumption data with the average daily air temperature in Tehran. The temperature volatility reduced by fuzzy data compared with hybrid fuzzy regression estimates the relationship between average electricity consumption and air temperature variations.

Although electricity demand is a crucial indicator due to its direct link with all economic activities, it also significantly depends on non-economic activities, particularly temperature. Moral-Carcedo and Pérez-García [2015] investigated the best techniques to analyze the impact of temperature on the daily electricity demand in Spain. Smooth transition, threshold regression, and switching regression were used for this determination. The linear transition technique is appropriate for two reasons. First, it can capture the smooth repose of electricity demand concerning temperature changes, and second, it can capture seasonality in the form of hot and cool days.

The literature widely avails of temperature-sensitive electricity demand on an aggregated level. Fewer studies have investigated temperature-sensitive electricity demand at disaggregated Moral-Carcedo and Pérez-García [2015] also assessed temperature-sensitive electricity demand for firms in Spain to cover this gap. The temperature-driven variation in sectoral electricity demand (domestic, commercial, and service) was analyzed in depth. The finding indicated that aggregated electricity demand is insensitive to temperature. However, sector-wise electricity demand bases highly become temperature-sensitive. The composition effect may lead to insensitive aggregate firms' electricity demands. Furthermore, the service sector has a more temperature-sensitive electricity trend. In contrast, no significant decline was found in the industrial sector.

To assess the impact of temperature on electricity demand, Yi-Ling et al. [2014] analyzed the correlation between residential electricity consumption and temperature. They estimated hot-degree days (HDD) and cool-degree days (CDD), using Shanghai's daily residential electricity data. The findings show two peaks based on seasonality, which depend entirely on the base temperature in the 10∘C winter and 22∘C summer seasons. These base temperatures are estimated through HDD and CCD; the apparent temperature is below 10 °C in winter and above 22 °C in summer. Furthermore, the spatial distribution of degree days validated the urbanization effect. So, the middle of the city encounters more extraordinary cool-degree days and hot-degree days. The future temperature projection also implies significant increases in hot and cool-degree days. It may be an appropriate way to forecast future electricity demand if the base electricity consumption trend does not change.

To assess the temperature impact on the building sector's peak and total electricity demand. Santamouris et al. [2015] analyzed the effect of an increase in ambient temperature on the electricity consumption of building sectors in urban regions. For this purpose, they critically reviewed eleven past studies for peak electricity demand and fifteen studies for total electricity demand, which deal with electricity demand and ambient temperature. Similarly, fifteen studies analyzed the total electricity demand and ambient temperature. The threshold for ambient temperature was estimated over which start to increase electricity demand by almost 18 and lowest around 12 C, and higher than 23 C. The results show a rise in one-degree temperature causes an increase in total electricity demand of 0.5 percent to 8.5 percent and triggers peak electricity demand of 0.45 percent to 4.6 percent. Furthermore, such an increase in electricity demand triggers stress on consumers and the power system.

The cooling and heating degree days methodology has been widely used as a parameter of climate change to predict total and peak electricity demand. These degree days are primarily based on the outdoor temperature. Shin and Do [2016] additionally incorporated the impact of latent heat to calculate the degree days. For this purpose, two buildings were selected for the experiment to analyze the accuracy and applicability of the enthalpy-based cooling degree days (CDD). The cooling degree days were separately calculated for base-temperature CCD and enthalpy-based CDD. Employing linear regression to predict the cooling energy consumption. The infer based on the percentage error enthalpy-based method is 2 percent less than the base-temperature CDD method. However, the study's findings could be more general for two reasons. First, it is on a small scale, just covering buildings, and second, it was just conducted to predict cooling energy consumption, while heating energy consumption needs to be included here.

A novel technique proposed Chang et al. [2016] to examine the air temperature impact on monthly electricity demand. In contrast to the standard method, a cross-temperature response (CTR) function was introduced. Which also allowed the estimation of non-climatic variables through temperature densities. The proposed methodology uses domestic and commercial sector electricity consumption data for Korea. For the household sector, there is no evidence that non-climate indicators influence electricity demand in response to air temperature. However, due to commercial consumers' low responsiveness to cold temperatures, followed by price response, irrefutable evidence is found for the commercial sector. Retail consumers respond more to electricity prices, regardless of temperature, in the winter season.

In another study, Binita and Ruth [2017] analyzed the impact of outdoor temperatures on buildings in an urban region. Deriving the heating and cooling degree days identified through systematic base temperature. Employed two models' multiple linear and dynamic regression, electricity demand was predicted by 2030. The outcomes of both models reveal that the outdoor temperature has primarily influenced the building's electricity consumption on weekdays. Moreover, building sector electricity consumption in the summer has more responded to outdoor temperature, followed by the transition and winter. Newer and older buildings' electricity consumption responsiveness differs to summer outdoor temperature, and overall, brick buildings primarily respond to summer outdoor temperature.

Urbanization and climate change are two leading indicators that will address future electricity peak demand. The world is exponentially shifting towards urbanization, and climate change is occurring due to several factors, including urbanization. To understand the importance of these two indicators, Burillo et al. [2019] predicted peak electricity demand for Log Angeles, considering future urbanization and climate change. Using hourly data, the long-run peak electricity demand is forecast for the domestic and commercial sectors. Due to higher growth in building infrastructure, which can lead to an additional load of air conditioners, peak electricity demand was expected to rise in the summer seasons. An hourly electricity peak demand increase was estimated for two scenarios: 9.5–12.8 GW to 13.0–17.3 GW and 14.7–19.2 GW by 2060. The marginal change in air temperature was reported to increase by 4–8 percent in electricity peak demand. The technological advancement in energy appliances and building infrastructure significantly increases productivity to prevent peak electricity demand. The air conditioner efficiency enhancement was not beneficial to smoothing or shifting peak electricity demand. In contrast, total annual energy consumption can be reduced by improving the SEER ratings of air conditioners. Due to the future increase in air conditioner penetration, the intensity of temperature-sensitive peak electricity demand will also increase.

Temperature-sensitive electricity demand analyzed Alberini et al. [2019] through a regression using Italian household electricity consumption data. The time-fixed effect separates the impact of air temperature from other seasonal and non-seasonal conditions. Significant evidence has been established regarding the correlation between seasonal residential electricity demand and temperature. Unchanged (relatively narrow range) electricity demand for residences was found around 24.4 °C; after that, it sharply rose with temperature. The total share of the temperature-sensitive hourly electricity demand was estimated to be only 12 percent.

Model the electricity demand forecast with appropriate electricity demand drives. Chabouni et al. [2020] examine the air temperature information in the form of cooling and heating degree days and consider electricity demand drivers in the case of Algeria. Using workdays, weekends, and holidays as dummy variables. They employed a simple linear regression on the daily electricity consumption data. The results reveals cooling and heating days had a significantly greater impact on the daily electricity demand. On the contrary, all holidays decreased electricity consumption in all seasons. Moreover, the holy month of Ramadan during the summer increases electricity consumption.

To analyze the impact of climate change on electricity demand, Zhang et al. [2020b] used the temperature response function on residential electricity consumption data from Jiangsu, China. Using panel data at the city and assessing the climate change impact, cooling and heating degree days are incorporated in the model. To estimate the relative sensitivity of residential electricity demand, precipitation, population, urbanization, and disposable income were included in the model. The findings suggest that higher heating and cooling demands cause an increase in residential electricity demand in the winter and summer seasons, respectively. Rural disposable income leads to a rise in electricity demand, whereas marginal urban disposable income has a negative impact. The urbanization rate in Jiangsu also positively influenced residential electricity demand. Energy policies that mitigate temperature-sensitive electricity demand would be beneficial in reducing the cost of climate change.

Using a semi-parametric approach, Harish et al. [2020] examined the residential electricity demand response concerning temperature shocks in Delhi and the aggregate level in India. On average, 11 percent of electricity demand increased for India, while for Delhi, it increased by 30 percent at temperatures above 30 °C from electricity demand at 21–24 °C. A continuous increase in temperature may lead to more diverse situations. Using micro-level data for Delhi. Findings highlighted the lower response temperature-sensitivity electricity demand of low-income households due to the absence of heating and cooling appliances.

The effect of weather on electricity consumption examined Silva et al. [2020] in Portugal, incorporating electricity price and economic activity as control variables. The U-shaped relationship between temperature and electricity consumption was determined. However, a change in the average temperature did not significantly impact electricity demand due to the mild weather in Portugal. Extreme temperatures have a more substantial impact on electricity consumption, and frequent extreme weather events increase electricity demand.

Under the socioeconomic pathways (SSPs), Zhang et al. [2020a] projected the electricity demand of Jiangsu province's domestic and commercial sectors. Using linear and policy models, the linear model forecasted electricity demand considering socioeconomic and climate factors; on the other hand, the policy model considers policy factors. The climate factor covered hot-degree days (HDD) and cool-degree days. The finding shows that CDD has a three-fold greater impact on electricity demand than HDD. The policy model results were lower than the linear model, which indicated policy factors have a softer impact on electricity demand than climate factors.

The appropriate electricity demand drivers are fundamental to balancing electricity demand and production. Residual electricity consumption is a major component of the power system. It has a significant share in electric power consumption and significantly influences demand variation. Do et al. [2021] explored the drivers of the residual electricity demand. Employing two regression models, linear and quantile. The finding infers that days of the week, holidays, and temperature significantly impact total and residual electricity demand. Air temperature is appropriate for modelling both residual and total electricity demand. Furthermore, hot-degree days and cool-degree days have a more significant impact on residual electricity demand than total electricity demand, and residual electricity demand is more difficult to predict than total electricity demand.

Exploring the electricity demand response to daily temperature is critical due to different demographic and climate situations. Phu [2021] examines the non-linear temperature impact on electricity demand in the case of Vietnam. A cubic function of the temperature sensor to electricity demand is derived for Vietnam's north and south regions, which validates that the variations in electricity demand are weather induced.

Three data-driven models were used by Wang et al. [2021] to forecast the daily electricity consumption of cities in the USA. These are linear regression models, machine learning models for time series, and tabular data. The light-GBM model is the best forecast based on the minimum loss function. The outcomes indicated that the temperature-sensitive share of electricity demand is 30–50 percent. In the summer, one incremental degree Celsius temperature may cause an overall increase in electricity demand of 5 percent, in Los Angeles at 4.7 percent, in Sacramento at 6.2 percent, and in New York at 5.1 percent.

The varying temperature associated with climate change is reflected as an electricity demand driver. To better understand the influence of air temperature on electricity demand. Zhang et al. [2021] analyzed the impact of moderating income growth and varying temperatures on electricity consumption in the urban domestic sector. They constructed a domestic electricity response model using unbalanced data from 23 cities in China. Income growth, cool and hot days, and their interactions are used as electricity demand drivers. A hypothesis proposed the adverse impact of moderating income growth on temperature changes. Outcomes reveal these are all significant electricity demand drivers. However, disposable income growth weakens the positive effect of cooling and heating demand on domestic electricity consumption. The moderating income indicates a crowding-out result. That is due to the evident demand of urban regions to adjust their cooling and heating comfort. Furthermore, structural change suggested that energy consumption shifts from electricity to natural gas and technological advancements for home appliances.

How residential electricity demand responds to income, prices, and air temperature. Liddle and Huntington [2021] critically analyzed 26 high-income and 29 middle-income countries. The dynamic Pannal model was employed. The income elasticities of high-income countries were calculated the least, followed by middle-income countries. Lower-price elasticities are intended, followed by high-income countries. Positive and significant elasticities of HDD in both high- and middle-income countries, while CDD elasticities have a similar impact only in middle-income countries. Moreover, higher levels of elasticity in middle-income countries validate the lower ownership of luxury appliances, such as air conditioners, washing machines, and refrigerators. Lower price elasticities in middle-income countries validate the more significant subsidization of power sectors in these countries.

The precise electricity demand forecast may provide support for improving the capability of the electric power supply. To meet the future electricity needs of Beijing, Zhang et al. [2022] forecasted electric power demand under socioeconomic pathways (SSPs). Employing a linear model with the temperature-electricity consumption response function. The finding infers that different model estimated Beijing's electric power demand, which develops the relationship between electricity consumption and temperature like a U-shaped curve. Under the linear model, cool-degree days considerably impact electrical power demand more than hot-degree days. Incremental one-degree days cause an increase of 5.3 million KWh of electricity consumption, and a rise of one hot-degree day causes an increase of 0.9 KWh. Furthermore, they suggest a linear model is appropriate to develop the correlation between air temperature and electricity consumption.

Assessing the climate change effect on future electricity demand Hiruta et al. [2022] employed multivariate adaptive regression with meteorological and human behavior indicators. For this purpose, they selected numerous climate zones in Japan for the time horizon of 2020–2080. All regions' total electricity demand growth was like in hot seasons. Nationwide electricity demand was projected to be just 1.8 percent from 2020 to 2080. However, the national growth in electricity demand in the summer season was 14.2 percent. The net change in electricity demand was balanced with an increase in summer and a decrease in winter electricity demand. High-intensive but low-frequent electricity demand spikes were projected for 2020–2080 in the summer seasons.

How the heat consumption evolution of a building stock will influence future climate change examined Nishimwe and Reiter [2022] in Belgium until 2050. The UK Met Office equation was employed to calculate hot-degree days and cool-degree days, adjusting the 15∘C base temperature. Using Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. They predicted future temperatures from historical data. Through the degree days method, heat consumption was projected until 2050.

The variability can be tackled with centralized storage, but it is not feasible with high costs. The remaining solution is to shift demand in a smooth pattern or to lower the span of its variability. Through shifting demand, electricity consumption patterns might be reshaped. Roberts et al. [2022] analyzed the shape of temperature-sensitive electricity demand in the 31 continental regions of the USA. They find that shifting temperature-sensitive electricity demand can reduce the variability span. The benefits of reducing the span of variability can mitigate the difficulty of peaks and critical demand hours. A significant fraction of the temperature-sensitive demand is only shiftable within a day, not seasons. Uncertainty existed regarding temperature-sensitive electricity demand. Temperature-sensitive electricity demand has great potential to become price-elastic electricity consumption. It may be reshaped concerning demand timing through proper planning.

Chapter

3 Data and Methodology

This study's foundation is built on two data series: electricity sales and electricity demand from 2013 to 2022. Meanwhile, the NTDC and other stakeholders in the Ministry of Energy assume that electricity sale is equivalent to demand. Figure 3. shows that electricity demand and sales are significantly different. Electricity sale is computed as the difference between total energy generation and losses. However, electricity demand is the unification of total electricity generation and demand management measures (load shedding, etc.). We utilized both electricity sale[1] and demand data in this study.

(a) Electricity Sale = Total Electricity Generation – Technical and Nontechnical losses

(b) NTDC Demand = Total Electricity Generation + Demand Management

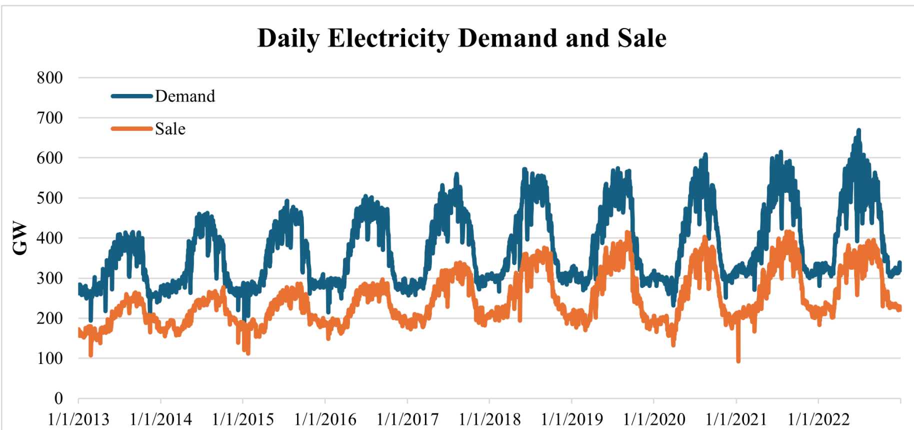

Figure 3: Electricity Demand and Sale

3.1 Methodology for First and Second Objectives

The first objective is to examine whether data aggregation influences forecasting accuracy or not. The second objective is to explore relationships between data aggregation and time series data features (described in Table. 3), which influence forecast accuracy. For this purpose, we used the traditional forecast technique, seasonal autoregressive integrating moving average (SARIMA), machine learning technique, Extreme Gradient Boost (XGBoost), and the deep

[1] Electricity sale data is not available at a daily frequency. It originated from daily electricity generation data. Considering the monthly loss factor for daily.

learning technique, Recurrent Neural Network (RNN-LSTM). The objective is to apply diverse forecast techniques to explore the rationality among results of all forecast techniques results

3.1.1 Seasonal Autoregressive Integrated Moving Average

SARIMA models stand as a cornerstone, offering a robust framework for predicting time series data. SARIMA models, an extension of the Autoregressive Integrated Moving Average (ARIMA) method, are particularly adept at capturing the seasonal variations of the datasets. The SARIMA models provide a comprehensive approach to modeling time-dependent structures. Their ability to account for seasonality makes them invaluable in the forecasting field.

$$\text{SARIMA} = [p, d, q][P, D, Q]_m$$
$$\text{Non seasonal Part of the Model} = \text{[p,d,q]}$$
$$\text{Seasonal Part of the Model} = [P, D, Q]_m$$

Where 'm' represents the number of seasons in one year and uppercase and lowercase notations represent the seasonal and non-seasonal parts of the model respectively.

$$(1 - \o_1\beta)(1 - \o_1\beta^m)(1 - \beta)(1 - \beta^m) = (1 - \theta\beta)(1 - \vartheta\beta^m)\varepsilon_t \tag{1}$$

'm' for monthly, bimonthly, and quarterly terms is 12, 6, and 4 respectively.

3.1.2 Extreme Gradient Boost

Extreme Gradient Boosting (XGB) is an advanced machine learning technique to forecast time series data. One of the critical strengths of XGB lies in its ability to capture complicated patterns in datasets. XGB operates by building a multitude of decision trees sequentially, with each tree refining the predictions of the previous ones. The XGB algorithm optimizes its predictions through this iterative process, continuously improving its accuracy. Additionally, XGB incorporates techniques such as regularized learning and parallel processing, enabling it to handle large datasets with numerous variables effectively.

The score is measured individually for each tree.

$$\widehat{y}_t = \sum_{k=1}^{K} f_k(x_i), f_k \varepsilon F \tag{2}$$

In equation 1. 'K' is the total number of trees. 'F' is set of Classification and Regression Trees (CARTs) and 'f' is functional space of F. The objective function of equation 1 is given:

$$obj(\theta) = \sum_{i}^{n} l(y_i, \widehat{y_i}) + \sum_{k=1}^{K} \mho(f_k) \tag{3}$$

The above objective function is a set of loss functions and regularization parameters. The first term represents the loss function, and the second one represents the regularization parameter. To minimize the loss function. Here we add a new tree.

$$\widehat{y_t}^{(0)} = 0$$
$$\widehat{y_t}^{(1)} = f_1(x_i) = \widehat{y_t}^{(0)} = f_1(x_i)$$
$$\widehat{y_t}^{(2)} = f_1(x_i) + f_2(x_i) = \widehat{y_t}^{(1)} = f_2(x_i)$$
$$....................$$

$$\widehat{y_t}^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \widehat{y_i}^{(t-1)} = f_t(x_i) \tag{4}$$

The above function can be defined further:

$$obj^{(t)} = \sum_{i=1}^{n} l(y_i, \widehat{y_i}^{(t)}) + \sum_{i=1}^{t} \mho(f_k) = \sum_{i=1}^{n} l(y_i, \widehat{y_i}^{(t-1)} + f_t(x_i)) + \mho(f_t) + constant \tag{5}$$

$$obj^{(t)} = \sum_{i=1}^{n}(y_i - (\widehat{y_i}^{(t-1)} + f_t(x_i)))^2 + \sum_{i=1}^{t} \mho(f_i) = \sum_{i=1}^{n}[2(\widehat{y_i}^{(t-1)} - y_i) f_t(x_i) + f_t(x_i)^2] + \mho(f_t) + constant \tag{6}$$

Apply Taylor expansion:

$$obj^{(t)} = \sum_{i=1}^{n}[l(y_i, \widehat{y_i}^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \mho(f_t) + constant \tag{7}$$

where

$$g_i = \partial_{\widehat{y_i}^{(t-1)}} l(y_i, \widehat{y_i}^{(t-1)})$$
$$f_t = w_{q(x)},\ \mathrm{w}\epsilon R^T, q : R^d \to [1, 2, 3, ..., T]$$

Removing constant to simplifying the equation:

$$\sum_{i=1}^{n}[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \mho(f_t) \tag{8}$$

Before regularization define model:

$$f_t x = w_q(x), w \epsilon R^T, q : R^d \to [1, 2, 3, ..., T] \tag{9}$$

'w' is a vector score of a tree, and 'q' is the function corresponding leaf. 'T' represents leaves. The regularization term:

$$\mho(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{10}$$

updated objective function:

$$obj^{(t)} \approx \sum_{i=1}^{n}[g_i w_{q(x_i)} + \frac{1}{2}h_i w_{q(x_i)}^2(x_i)] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 = \sum_{j=1}^{T}[(\sum_{i \epsilon I_j} g_i)w_j + \frac{1}{2}(\sum_{i \epsilon I_j} g_i)w_j + \frac{1}{2}(\sum_{i \epsilon I_j} h_i + \lambda)w_j^2] + \gamma T \tag{11}$$

Simplifying the objective function:

$$obj^t = \sum_{j=1}^{T}[G_i w_j + \frac{1}{2}(H_i + \lambda)w_j^2] + \gamma T \tag{12}$$

where

$$G_i = \textstyle\sum_{i \epsilon I_j} g_i$$

$$H_i = \textstyle\sum_{i \epsilon I_j} h_i$$

The above equation w˙j are independent of the given structure and the best objective reduction. We get.

$$w_j^* = -\frac{G_i}{H_i + \lambda} ojb^* = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_i}{H_i + \lambda} + \gamma T \tag{13}$$

Optimization of a tree not possible directly. Optimization of one level of tree at a time. We spilt a leaf into two leaves and then get score.

$$Gain = \frac{1}{2}[\frac{G_L^2}{H_L + \lambda} + \frac{G_L^2}{H_{L+\lambda}} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}] - \gamma \tag{14}$$

3.1.3 Long Short-Term Memory

LSTM networks capture long-term dependencies and patterns in sequential data, unlike traditional neural networks. Specialized memory cells equip LSTMs to store and retrieve information over extended periods, making them highly effective for time-series forecasting tasks. The critical innovation in LSTM architecture lies in its three interacting gates: the input gate, the forget gate, and the output gate. These gates regulate the flow of information within the network, allowing LSTMs to selectively remember or forget specific information.

The input gate stores the relevant information from the current input in the memory cell. The forget gate discards information from the previous cell state. The output gate determines the information to be output from the current cell state. This gating mechanism enables LSTMs to capture and learn complex sequential patterns.

$$\text{previous cell}=\Delta = t$$
$$X_t^{'} = \text{h}\dot{}\Delta X_t$$
$$X_t = \text{input data}$$

1. Forget Gate:

LSTM acquires to filter the data in forget gate. X_t' is processed by sigmoid function to get f_{t1}.

$$f_{t1} = \sigma(w_f.X_t^{'}) + b_f \tag{15}$$

LSTM remembers large observations of historical data. f̌t1 represent useful data.

2. Input (update) Gate:

In the input gate LSTM acquires new data and $X_t^{'}$ processed by sigmoid function to get i_t.

$$i_t = \sigma(w_i.X_t^{'} + b_i) \tag{16}$$

3. Candidate Cell State:

i_t filter useful data in $X't$ and additionally $X't$ processed by LeakyReLu function to calculate c't.

$$c_t^{'} = leakyReLu(w_c.X_t^{'} + b_c) \tag{17}$$

$$f_{t2} = i_t * c_t^{'} \tag{18}$$

4. Cell State:

c_t updated in update gate.

$$c_t = f_{t1} * c_\Delta + f_{t2} \tag{19}$$

5. Output Gate:

Output gate gives the LSTM outputs. $X't$ processed by sigmoid function to get Ot.

$$O_t = \sigma(w_o.X_t^{'} + b_o) \tag{20}$$

6. Hidden State:

O_t which c_t to retained for results and ct processed by LeakyReLu function to get ht

$$h_t = O_t * LeakyReLu(c_t) \tag{21}$$

3.2 Methodology for Third and fourth Objectives

The third objective focuses on exploring appropriate electricity demand drivers in Pakistan and developing a model that will provide more accurate electricity demand projection. Initially, examine the electricity demand drivers (sectoral growth rates and electricity tariffs) that NTDCs use in their model. For this purpose, we employed the Granger causality test and calculated electricity's price elasticity, then examined daily temperature data (at a 2-meter height from earth) that was extracted from a NASA satellite.

In the literature, researchers and practitioners (Yi-Ling et al. [2014] Shin and Do [2016] and Zhang et al. [2020b]) preferred the use of temperature data in the form of cooling degree days (CDD) and heating degree days (HDD), which originate from temperature and effectively capture seasonality. Therefore, this study adopted a degree-day approach. HDD signifies the electricity consumption for heating, whereas CDD indicates the electricity usage for cooling.

$$\text{HDD} = \text{Consumption of electricity for heating purposes}$$
$$\text{CDD} = \text{Consumption of electricity for cooling Purposes}$$

The calculation of these degree days involves establishing a reference point or inflection point. Electricity data standardizing based on the number of total electricity connections and daily temperature data weighted average out concerning electricity consumption. Using a polynomial equation[2], a reference temperature (point of inflection) is determined. HDD and CDD are estimated using the following mathematical equation with the help of a reference temperature:

[2]The order of the polynomial equation used was 3 according to the best-fitting data points.

$$HDD_t = max(T_{ref} - T_t, 0) \tag{22}$$

$$CDD_t = max(T_t - T_{ref}, 0) \tag{23}$$

T_{ref} = point where electricity consumption inelastic with temperature[3]

T_t = weighted average temperature of the current day [4]

3.2.1 Assumptions and Limitations of the Proposed Techniques

In the daily electricity demand forecasting model for Pakistan, some limitations and assumptions are held, which are as follows:

(a) HDD and CDD calculated independently for electricity sale and demand. The calculation of degree days relies on NASA satellite daily temperature data, which might impact the accuracy and continuity of the results.

(b) Normalization of the electricity data is based on the number of electricity connections rather than the population. This approach is taken because Pakistan has not yet achieved 100 percent electrification.

(c) All three data series represented the entire NTDC system, except K-Electric and Captive Power Plant Generation.

(d) The electricity sale projection assumes that distribution companies' (DISCOs) efficiency will not significantly change in the next three years.

[3] We calculated reference temperatures twice to estimate heating and cooling degree days: once for an overall ten years covering the study data frame (reference temperature for electricity demand 15.5°C and for sales 14.5 °C) and once for each year (ten reference temperatures respective to each year). This means we calculate HDD and CDD twice, using them for model training, testing, and forecast validation. We discovered that using individual reference temperatures for each year resulted in a lower forecast error compared to the overall reference temperature approach. Therefore, we chose to use individual reference temperatures for each year to improve forecast accuracy in our model development. What causes the forecast error to decrease when using individual reference temperatures to estimate degree days? This variation is attributed to the differences in electricity generation and consumption patterns that vary annually. On the other hand, the overall reference temperature case reference temperature is aggregated, and this aggregated pattern of temperature does not exactly follow the electricity generation and consumption. Reference temperature for electricity demand from 2013 to 2022 are 15.5°C, 15°C, 16°C, 16°C, 14.5°C, 16°C, 15.5°C, 15°C, 17°C, and 15°C respectively. Similarly for electricity sales reference temperatures from 2013 to 2022 are 14°C, 15°C, 15°C, 17.5°C, 13.5°C, 16°C, 15°C, 15°C, 16°C, and 14.5°C respectively.

[4] To calculate the weighted average temperature, we obtained data from the NASA satellite. We extracted two types of temperature above two meters on earth, the maximum temperature of the day and the minimum temperature of the day, for 66 districts covering all ten distribution companies (DISCOs). Calculating the weighted average temperature involves two steps: first, collecting the data, and then creating clusters for each DISCO with their respective districts. Next, we select a single maximum and minimum temperature from each DISCO and calculate the average for each DISCO. Subsequently, we calculate the weighted average temperature considering the electricity consumption share of each DISCO for every year.

3.3 Forecasting Techniques

We repeat the same methodology as the first objective. However, we omitted the seasonal SARIMA model because it cannot effectively capture daily seasonality across a full year (365 days) and add a third data series peak demand for the third objective. Peak demand refers to the highest demand within a day. Peak demand is more important for electricity generation capacity planning than sales and total demand because it provides insight into the required electricity generation capacity.

By utilizing the XGB and LSTM algorithms without and with HDD and CDD, we used daily electricity sales, demand, and peak demand data from 2013 to 2022. We use the first six years of data from all three daily data series for training, the following seventh year for testing, and the last three years for forecast validation.

After conducting an electricity demand projection with appropriate demand drivers (HDD and CDD), we compare this projection with the IGCEP-22 electricity demand projection. The objective is to investigate which IGCEP electricity demand projections scenario (low, medium or high) is practicable and which is not. To achieve this fourth objective of the study, the assessment compares the existing generation capacity and proposed energy projects in IGCEP-22 with the energy demand projection of this study.

Chapter

4 Results Discussion

4.1 Exploration of Data Aggregation Association with Forecast Accuracy

We employed three distinct forecasting techniques, SRIMA, XGB, and LSTM, to explore the association between forecast accuracy and time series data aggregation. The objective behind applying traditional and machine learning techniques is to validate whether results are rational across different forecasting techniques. For this purpose, both datasets are aggregated at different levels. The initial base of data aggregation was monthly. All other aggregated data series originated from monthly to bimonthly and quarterly with non-overlapping and overlapping techniques. For all data series and forecasting techniques, we split data for training and testing and then forecasted (within sample data) the next three years. We evaluate all data series results based on the mean absolute percentage error. Below, we describe the detailed results.

4.1.1 SARIMA Model Results

For SARIMA, lags are selected based on a low AIC value, and all seasonal and non-seasonal differences are automatically taken using the Python package and libraries "statsmodels.tsa" and "seasonal˙decompose." Table No. 2 provide the details of all lags in the data series.

Table 2: SARIMA Specified Lags

Sale Data Series	SARIMA	AIC
Monthly	(1, 0, 0) x (0, 1, 1, 12)	-368.572
Bimonthly NOA	(1, 1, 1) x (0, 1, 0, 6)	-182.261
Bimonthly OA	(1, 0, 1) x (0, 1, 1, 12)	-504.744
Quarterly NOA	(1, 0, 0) x (1, 0, 0, 4)	-112.044
Quarterly OA	(1, 0, 1) x (0, 1, 1, 12)	-560.276
Demand Data Series	**SARIMA**	**AIC**
Monthly	(1, 1, 1) x (1, 1, 0, 12)	-359.748
Bimonthly NOA	(1, 1, 1) x (1, 1, 0, 6)	-176.877
Bimonthly OA	(1, 0, 1) x (0, 1, 1, 12)	-490.625
Quarterly NOA	(1, 0, 0) x (0, 1, 0, 4)	-116.577
Quarterly OA	(1, 0, 1) x (1, 1, 0, 12)	-545.077

We evaluated the results of all forecasted series based on the mean absolute percentage error.

The BU monthly series (which predicts monthly series and then adds them up at the desired time frame every two months or every three months) and the aggregated data series with overlapping data have better forecast accuracy than the non-overlapping aggregated data series of electricity demand and sale. Table No. 3 shows the results.

Table 3: SARIMA Forecast Performance

Sale	**MAPA**	**Demand**	**MAPA**
BU Monthly	7.6272	BU Monthly	**5.8824**
Bimonthly NOA	11.7064	Bimonthly NOA	5.942
Bimonthly OA	**7.6183**	Bimonthly OA	7.2743
BU Quarterly	7.233	BU Quarterly	**5.6905**
Quarterly NOA	7.6053	Quarterly NOA	6.0882
Quarterly OA	**6.7286**	Quarterly OA	5.7004

4.1.2 Long Short-Term Memory Model Results

For the LSTM model, we split all electricity demand and sales aggregated series into training and testing sets and forecasted next three years. The results showed that the BU approach (monthly and quarterly series) had low forecast errors compared to both overlapping and non-overlapping datasets of total electricity sales and demand. This was similar to the SARIMA results. However, after the BU approach, overlapping (OA) outperforms the non-overlapping (NOA) techniques in forecast performances. Table No. 4 presents the results.

Table 4: LSTM Forecast Performance

Sale	**MAPA**	**Demand**	**MAPA**
BU Monthly	**26.271**	BU Monthly	**23.9308**
Bimonthly NOA	41.4411	Bimonthly NOA	49.4804
Bimonthly OA	31.7617	Bimonthly OA	24.0068
BU Quarterly	**27.8695**	BU Quarterly	**22.5243**
Quarterly NOA	53.0942	Quarterly NOA	48.7292
Quarterly OA	28.9545	Quarterly OA	23.7045

4.1.3 Extreme Gradient Boost Model Results

Employing the Extreme Gradient Boost (XGB) as the third model achieved the diverse analysis and deep insights needed to find rational results. Like other models (SARIMA and LSTM), the BU approach and overlapping aggregated (OA) series had better forecast performance than non-overlapping aggregated datasets for electricity demand and sale. The BU monthly and overlapping (OA) approach for bimonthly and quarterly series has a minor difference in forecast performance.

Table 5: XGB Forecast Performance

Sale	**MAPA**	**Demand**	**MAPA**
BU Monthly	**26.271**	BU Monthly	**23.9308**
Bimonthly NOA	41.4411	Bimonthly NOA	49.4804
Bimonthly OA	31.7617	Bimonthly OA	24.0068
BU Quarterly	**27.8695**	BU Quarterly	**22.5243**
Quarterly NOA	53.0942	Quarterly NOA	48.7292
Quarterly OA	28.9545	Quarterly OA	23.7045

4.1.4 Result Summary of the First Objective

Under the first objective, this study investigated different electricity datasets using different data aggregation levels and forecasting methods. We forecasted electricity demand and sale aggregated data series from monthly to bimonthly using non-overlapping aggregation, bimonthly with overlapping periods, and similarly aggregated quarterly data. By comparing forecast performance across different techniques, the study explored how the choice of aggregation method, especially non-overlapping and overlapping periods, influenced the forecast accuracy. This analysis provided valuable insights into the impact of data aggregation methods on forecasting electricity.

The study discovered that the BU approach provided better forecast performance. While the forecast performance of bimonthly and quarterly series aggregated with overlapping techniques ranks second, the series aggregated with non-overlapping techniques ranks with the worst forecast performance. The results infer an association between data aggregation and forecast performance. These results suggest that we should avoid forecasting electricity demand with aggregated data, especially with non-overlapping techniques. It should forecast with a higher frequency (daily or monthly) to incorporate seasonal factors for better forecast performance.

Why are higher-frequency (BU monthly or aggregated with OA) data series forecasts more accurate as compared to others, and how can we decide the optimal level of data aggregation considering forecast performance? Exploring this point, we compared the forecast error of all data series across three diverse forecasting techniques with the time series data features of each data series in the next section.

4.2 Exploration Data Features Association with Data Aggregation

Each time series of data possesses unique characteristics that differentiate it from others. The other name for these characteristics is time series data features. These data features are described in Appendix Table B1. We analyzed these varying data features across different data aggregation levels with a forecast error at each data aggregation level. Seven data features out of thirteen became significant in our case, varying with forecast accuracy. These seven features of each electricity sale and demand series are plotted with the forecast error of the respective data series in Figures 4 and 5.

The preceding Figures depict forecast errors associated with data features, revealing a sub-

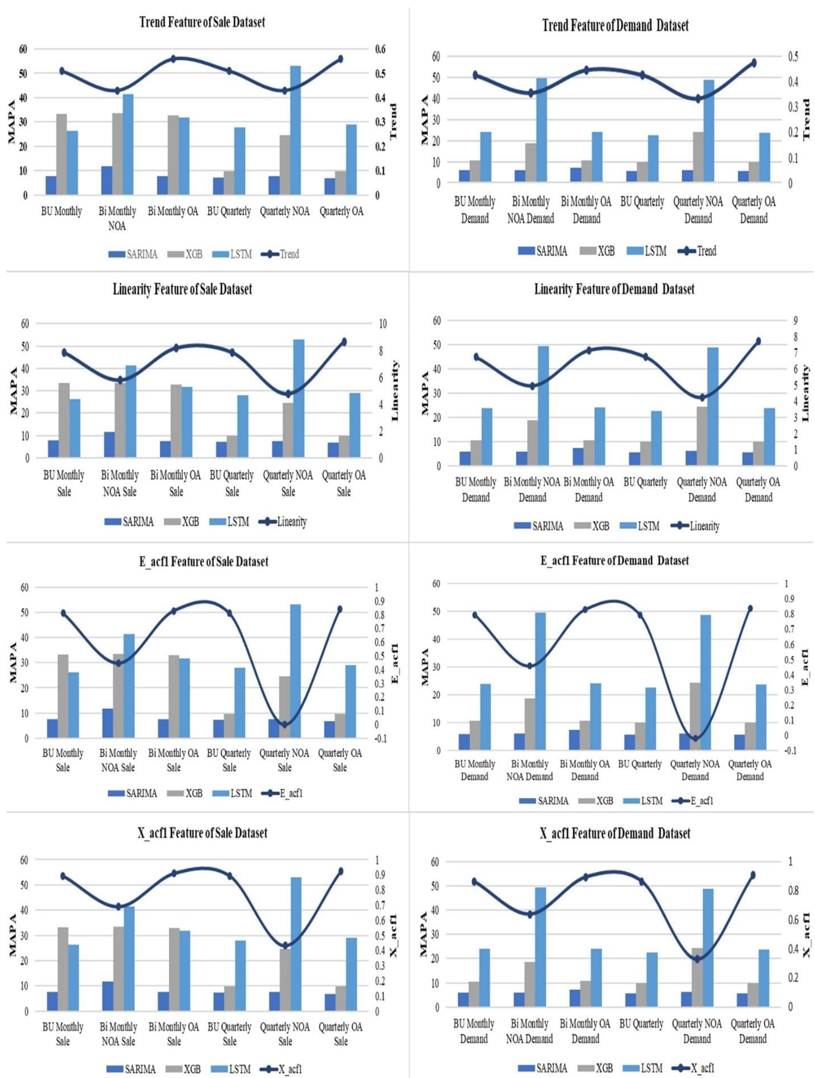

Figure 4: Time series data feature with Forecast Error

stantial reduction in forecast accuracy due to data aggregation. These data features, such as

$trend$, $linearity$, $e - acf1$, $x - acf1$, and $diff1 - acf$, exhibit a decrease that is associated with a reduction in forecast accuracy. When these values go up, forecast errors go down. Conversely, diminishing the magnitude of data feature $spikes$ and $diff2-acf10$ results in decreased forecast errors and improved forecast accuracy, and vice versa. We found that the best point to aggregate data based on forecast accuracy is to get the most out of $trend$, $linearity$, $e - acf1$, $x - acf1$, and $diff1 - acf$ while keeping $spikes$ and $diff2 - acf10$ to a minimum at all levels of data aggregation.

Remarkably, when comparing model comparisons, SARIMA outperforms XGB and LSTM across all levels of data aggregations. However, all data series compromise the performance of XGB and LSTM, despite their ability to capture complex data patterns. However, the results associated with time series data features and forecast accuracy are found to be almost rational across SARIMA, XGB, and LSTM.

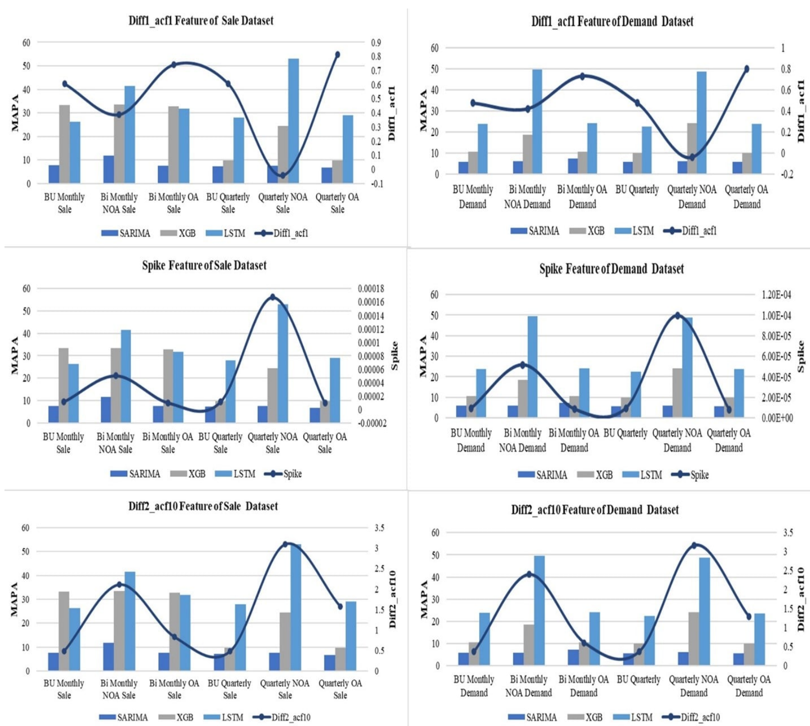

Figure 5: Time series data feature with Forecast Error

4.2.1 Result Summary of the Second Objectivee

The study's second objective is to investigate if a relationship exists between data aggregation and time series features that influence forecast accuracy. Furthermore, the study aims to determine the optimal level of data aggregation that enhances forecast accuracy or establish a rule of thumb for data aggregation that provides more forecast accuracy. The results reveal that seven time series data features significantly influenced forecast accuracy in our study. The study found that the best level of data aggregation is the one where *trend*, *linearity*, $e - acf1$, $x - acf1$, and $\mathrm{di}ff1 - acf$, magnitude are at their highest and data feature *spikes* and $diff2 - acf10$ are at their lowest.

4.3 Daily Electricity Demand Forecasting Model

The third objective of this study is to explore appropriate electricity demand drivers and develop a more accurate electricity demand forecasting model for Pakistan. The results of the first two objectives suggest we forecast high-frequency data as much as possible, then aggregate forecasted values (bottom-up approach) as the desired level of time horizon because forecasts are based on low-frequency aggregated series, reducing forecast accuracy. Considering the results of the first two objectives, we had the option to forecast all three data series (sale, demand, and peak demand) with either hourly or daily frequency. However, we ultimately decided to use daily frequency. At the hourly level, all three data series may give more accurate predictions because hourly series have stronger data features associated with forecast accuracy compared to daily and monthly aggregated series. These features include *trend*, *linearity*, $e - acf1$, $x - acf1$, and $\mathrm{di}ff1 - acf$, which have the highest magnitudes. On the other hand, *spikes* and $diff2 - acf10$ have the lowest magnitudes. However, an hourly forecast reduces the projection time horizon (a few months), but we want to project all three series for at least two to three years. So, we decided on the optimal level of data aggregation daily. For the daily electricity demand forecast model, we split the daily weighted average temperature data into HDD and CDD as electricity demand drivers, which are discussed in methodology chapter No.3.

4.3.1 Discussion on Electricity Demand Drivers of IGCEP Model

For the daily electricity demand forecast, we need electricity demand drivers at daily frequency. So, we cannot utilize electricity demand drivers (sectoral tariffs and GDP growth rates), which adopted IGCEP for their demand forecast model, for two reasons. First, several studies Nasir et al. [2008] and Hina et al. [2022] have examined the price- and income-inelastic nature of electricity consumption for both the short and long run. Furthermore, these variables are not available at a daily frequency. However, we also examine the GDP growth and tariffs of each sector, employing the Granger causality test and calculating price elasticity based on yearly frequency. We found that the GDP growth rate and tariff of each sector do not Granger cause electricity sales except in the industrial sector (see Appendix Table B2 and B3). Furthermore, outcomes reveal that more than half of the last two decades have demonstrated price inelasticity in the electricity demand for all sectors (See Appendix Figure A3). The electricity price is inelastic due to the tariff differential subsidies Awan et al. [2019] and Malik [2021]. Insignificant demand drivers are the second reason for overfitting the IGCEP demand forecast model after data aggregation.

4.3.2 Model Training and Testing

We achieved the third objective by employing the LSTM and XGB algorithms without and with degree days (DD). We used data from 2013 to 2022 for training, testing, and forecast validation. The first six-year data of all three series on daily frequency is used for training, the following seventh year for testing, and the last three for validation. The hyperparameters for both LSTM and XGB are selected through the hyperparameter tuning process. To reach optimal hyperparameters, we use the Grid Search Cross-Validation (GridsearchCV) method, which selects required parameters based on the lowest mean absolute percentage errors. The hyperparameters and all three data series training and testing details are given in Appendix Tables B4, B5, and B6.

4.3.3 LSTM and XGB Model without DD Performance Comparison

After training and testing all three data series (sales, demand, and peak demand) with optimal hyperparameters, we forecasted the next three years (1095 days) of each data series using in-sample data and calculated the MAPA. Remarkably, XGB consistently outperformed LSTM. Table 6 outlines the mean absolute percentage error (MAPA) for both LSTM and XGB. Notable is XGB's consistently superior performance over LSTM across all electricity data series. These comprehensive analyses have led to the selection of XGB as the finalized model for forecasting all three electricity data series: sales, demand, and peak demand.

Table 6: Forecast Performance Comparision of LSTM and XGB

Data Series	Satages	LSTM	XGB	LSTM with DD	XGB with DD
Energy Sale	Test	12.03	7.13	4.25	5.11
	One Year	9.23	10.19	11.48	**6.42**
	Two Year	7.67	8.59	11.85	**6.21**
	Three Year	7.70	9.06	11.96	**6.48**
Energy Demand	Test	5.55	5.26	4.18	3.68
	One Year	8.61	7.63	12.84	**4.72**
	Two Year	10.0	7.29	15.67	**6.70**
	Three Year	9.07	8.33	16.63	**7.65**
Peak Demand	Test	4.68	4.62	3.45	3.27
	One Year	8.63	6.12	6.14	**5.39**
	Two Year	12.0	6.51	6.36	**5.64**
	Three Year	14.63	7.70	7.62	**6.96**

4.3.4 Electricity Sales Demand and Peak Demand Projection

Before the projection (post-sample data) of all three data series, this study validated forecasts (within sample data) of the final model XGB with DD in two ways. One has original independent variables (HDD and CDD), and the second has repeated last-year (365 observations) independent variables for the desired forecast horizon (three years). The first approach provides the model with actual HDD and CDD data to forecast the next three years. The second method repeated (keeping constant last-year values) the HDD and CDD data from the previous year for the subsequent forecast validation horizon (three years). The forecast performance of both methods is given in Table No. 7.

Figure 6 shows that the comparison of results indicates a 1 percent accuracy sacrifice when

Table 7: : XGB with Actual DD and Constant DD Forecast Error

Data Series	Satages	Actual DD	Constant DD
Energy Sale	One Year	9.23	10.19
	Two Year	7.67	8.59
	Three Year	7.70	9.06
Energy Demand	One Year	9.23	10.19
	Two Year	7.67	8.59
	Three Year	7.70	9.06
Peak Demand	One Year	9.23	10.19
	Two Year	7.67	8.59
	Three Year	7.70	9.06

using repeated (constant) independent variables. So, instead of forecasting HDD and CDD separately, we repeated last year's (2022) HDD and CDD values for the next three years of projection. Because the traditional way of projecting independent variables, adding them to a multivariate model, and then forecasting dependent variables makes the forecasts less accurate.

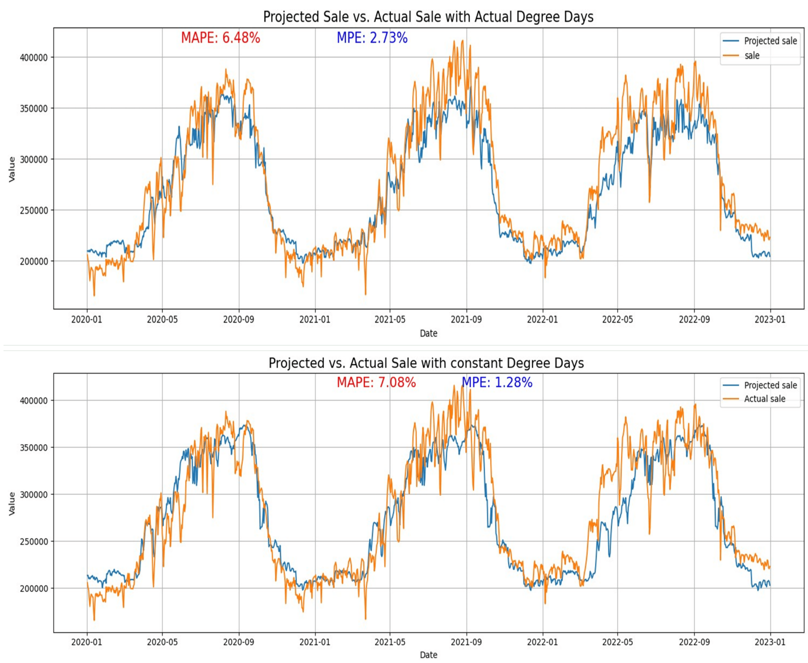

Figure 6: Energy Sale Forecast with Actual and Constant Degree Days

Using XGB with degree days, we project the daily energy sales demand as well as peak demand for the next three years. These projections are the first scenario in each series, and the second scenario has 6 percent of the error of the first scenario up to three years.

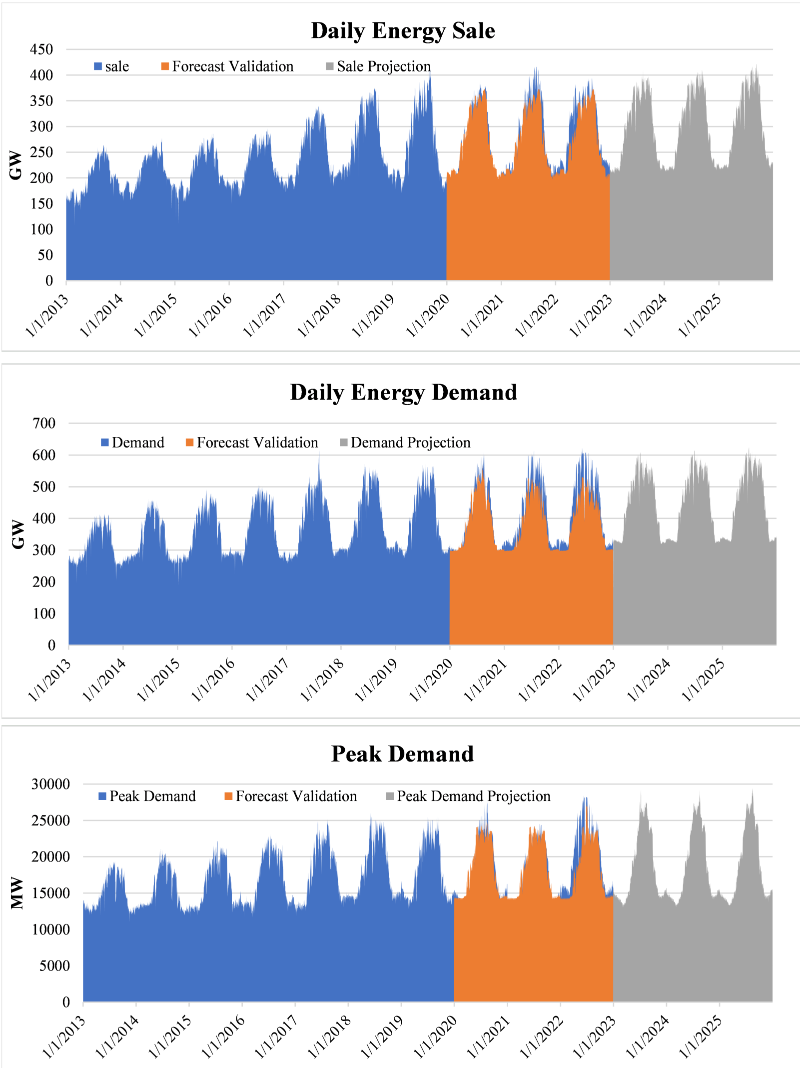

Figure 7: Energy Sale Forecast with Actual and Constant Degree Days

4.3.5 Energy Sale Projection Comparison

To compare this study's energy sales projection with IGCEP projections, we aggregated this study's daily energy sales projection up to annual (with the BU approach that suggested this study's first and second objective results) and compared them with IGCEP projections. Figure 8 demonstrates that NTDC significantly overestimates the energy sales in different IGCEPs. However, in the forecast validation portion, the energy sales projection of this study is based on metrological factors (HDD and CCD) that closely follow the patterns of actual energy sales in the forecast validation portion.

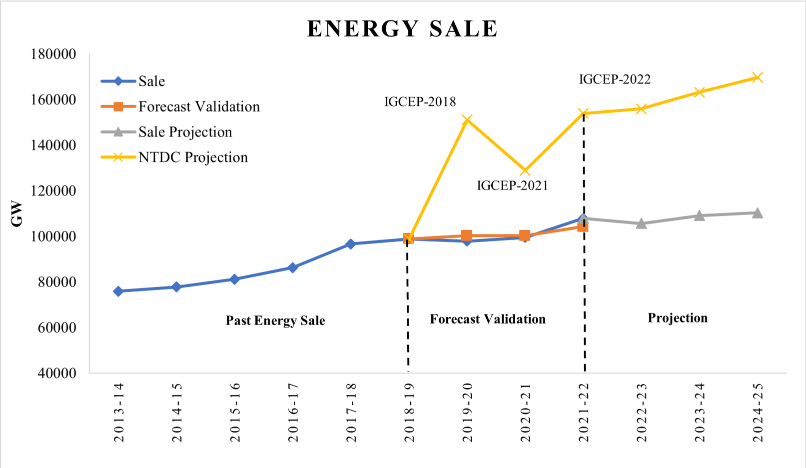

Figure 8: Energy Sale Projection Comparison

4.3.6 Energy Demand and Sale Gap

This study projected both energy sales and energy demand separately. That explored a different policy approach for electricity planning. Figure 9 illustrates the gap between energy demand and energy sales; the center line represents total energy generation. The gap between total generation and energy sales represents the non- revenue part of generation, indicating losses as well as free electricity for recommended government employees. The gap between energy demand and total generation represented an unexplored part of demand (load shedding). The projected energy demand and sales showed that if DISCO's performance does not improve, this gap will grow over the year. This point is more important for energy planning and policy prospects than without improving DISCO's performance by installing more generation capacity, which leads to extra capacity payments. The gap between energy demand and sales indicates that inefficiencies within the energy sector pose a greater challenge than generation capacity.

4.3.7 Peak Demand Projection Comparison

NTDC and other stakeholders mistakenly assumed energy sales as demand and, similarly, falsely assumed that the highest generation hours in a day represented peak demand. However, that is not the true definition of peak demand. Before comparing them, it is essential to establish a clear definition of peak demand. The actual peak demand is the highest demand hour in each day, including demand management (losses and load shedding). Figure 10 shows that the IGCEP peak demand projection, which is based on the highest generation, exceeds

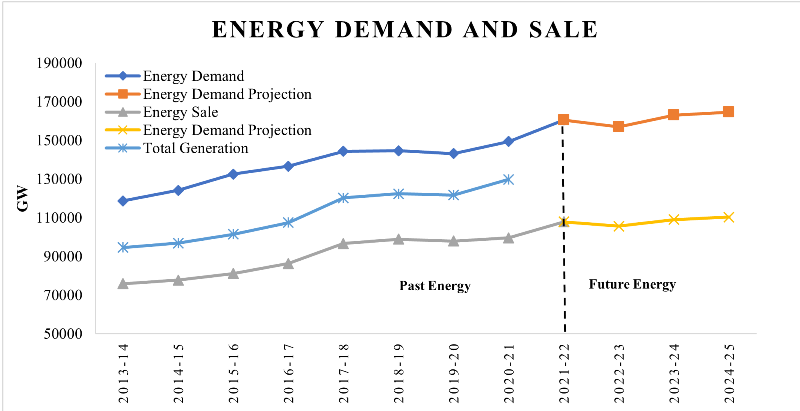

Figure 9: Energy Demand Projection Comparison

the actual peak demand due to IGCEP's inappropriate forecasting methodology. Furthermore, peak demand projections significantly vary from one IGCEP to another, with a bust after the first boom indicating the next version projection of the IGCEP. Let's imagine that IGCEP projected actual peak demand data (including load shedding factor) using the same methodology. How much would those projections overestimate the actual peak demand? Figure No.

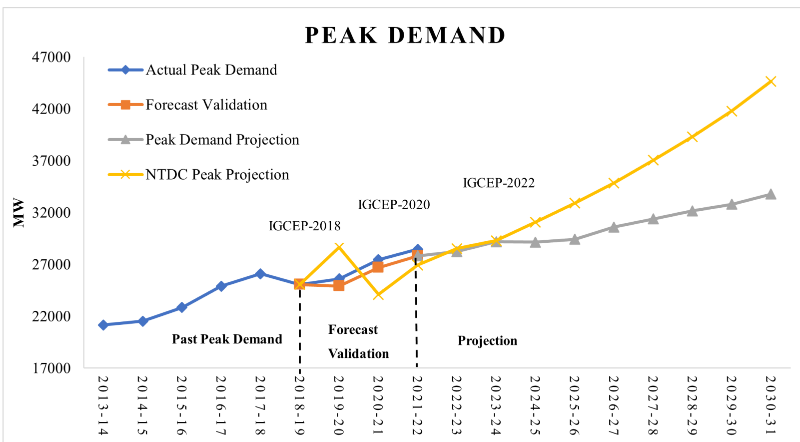

Figure 10: Peak Demand Projection Comparison

9 shows projected peak demand, followed by metrological factors that mimic the patterns of actual peak demand patterns in the forecast validation portion. However, the IGCEP peak demand projection is not based on actual peak demand and is also overestimated.

4.3.8 Results Summary of Third Objective

By utilizing LSTM and XGB algorithms without and with degree days (DD), we validate forecasting models comprehensively. We used daily data from 2013 to 2022 for testing, training, and validation. For training, we use the first six years of data from all three series, followed by the next year for testing, and the last three years for validation. The results of forecast validation recommend that XGBs with DD have better forecast performance. We finalized XGB techniques for energy projections.

For energy projection, we compare two distinct techniques: actual DD and constant DD (repeated last year) using XGB with DD. The results revealed that 1 percent accuracy scarifies with constant DD. So, we preferred the inclusion of constant DD (as independent variables) to model for projections rather than separately projecting DD. After confirming the accuracy through validation, the model successfully projected the next three years, comprising 1095 data points. The anticipated error for these projections is less than 7 MAPA ensuring reliable and precise forecasting for this extended period. These results highlight the model's proficiency in energy predictions, vital for effective medium-term planning in electricity demand forecasting. Furthermore, these projections are compared with the IGCEP projection after being aggregated at the annual level.

4.4 Energy Projection Comparison with Proposed Energy Generation Capacity

The fourth objective of this study is to compare projections with proposed IGCEP electricity generation capacity scenarios up to 2030–31. We compared the peak demand projection of this study with the IGCEP-22 proposed energy generation capacity of both scenarios: low demand and high demand. We evaluated the electricity generation capacity; how much is the proposed capacity in IGCEP-22, and how much will be required until 2030-31?

4.4.1 IGCEP-22 Proposed Electricity Generation Capacity

IGCEP-22 plans to boost renewable energy shares for future energy generation. For this purpose, from 2023 to 20231, hydropower generation capacity will increase from 10798 MW to 22560 MW, wind from 1840 to 6868, and solar from 1230 to 13670. The generation capacity net addition of renewables is 29230, including hydropower, wind, and solar, will be 11762, 5028, and 12440, respectively.

On the non-renewable side, only local coal will contribute 1290 MW and cross-border 1000 MW. However, the RLNG share will reduce to 2342 MW, the RFO share will reduce to 2286 MW, and the gas share will reduce to 811 MW. Imported coal will remain unchanged. In this way, the non-renewable capacity increases by 2390 and decreases to 5439 MW, and the net decrease will be 3049 MW. Overall, 26181 MW of additional generation capacity is proposed by IGCEP-22 for 2023–20231. Figure 11 shows the entire IGCEP generation Capacity planning.

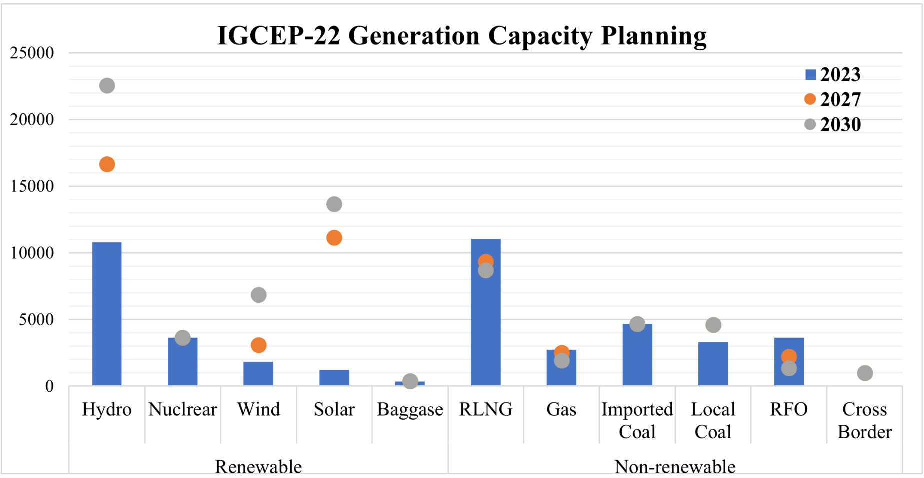

Figure 11: Proposed Generation Capacity of IGCEP-22

4.4.2 Electricity Generation Capacity Planning Comparison

In this study, the projected peak demand is compared with the proposed electricity generation capacity scenarios of IGCEP-22. Tables 8 and 9 represent low and high electricity demand scenarios, respectively.

In the low-demand scenario, IGCEP-22 proposed to extend energy generation capacity up to 65262 MW until 2030-31, which will extend total generation capability up to 46988 MW. Our study projected peak demand comparison with generation capacity shows 16890 MW and 13196 MW surplus generation capacity and capability respectively. The generation capability estimates are obtained by applying a 0.72 factor to the total installed capacity. This 0.72 factor takes into account the installed generation capacity and dependable capacity of the existing scenario and assumes the same ratio will exist in the future.

[5] Similarly, peak demand projections are compared with the proposed electricity generation capacity for a high-demand scenario. Under the high-demand scenario, IGCEP-22 proposed to extend energy generation capacity up to 69372 MW until 2030-31, which will extend total generation capability up to 49947 MW. The comparison of this proposed capacity with peak demand projections shows that 20678 MW of capacity will become surplus from actual need,

[5] In Tables 8 and 9, peak demand projections are till 2026 and onward from 2027 to 2031, stimulated by growth rates of 2pc, 2.5 pc, and 3pc, respectively.

Table 8: Projected Peak Demand Comparison with Low Demand Scenario

Year	Net Addition	Capacity	Capability	Projection	Extra Capability	Extra Capacity
2023	4738	43259	31146	29186	1960	2509
2024	1224	44483	32027	29159	2868	3672
2025	8429	52912	38096	29427	8669	11097
2026	991	53903	38810	30015	8794	11257
2027	2711	56614	40762	30615	10146	12987
2028	3609	60223	43360	31381	11979	15333
2029	769	60991	43913	32165	11748	15038
2030	1648	62639	45100	32808	12291	15733
2031	2623	65262	46988	33792	13196	**16890**

and that will be approximately 16155 MW of electricity generation capability. This compari-

Table 9: Projected Peak Demand Comparison with High Demand Scenario

Year	Addition	Capacity	Capability	Projection	Extra Capability	Extra Capacity
2023	4738	43259	31146	29186	1960	2509
2024	1224	44483	32027	29159	2868	3672
2025	8429	52912	38096	29427	8669	11097
2026	2860	55772	40155	30015	10140	12979
2027	3460	59232	42647	30615	12031	15399
2028	4128	63360	45619	31381	14237	18224
2029	1504	64863	46701	32165	14536	18606
2030	1836	66749	48059	32808	15250	19521
2031	2623	69372	49947	33792	16155	**20678**

son indicates that if the proposed generation capacity under IGCEP-22 is implemented, it will lead to extra capacity payments due to the over-installation of generation capacity. Under a low-demand scenario, extra energy generation capacity and capability will reach 16890 MW and 13196 MW, respectively, by 2031. If a higher demand scenario is implemented, surplus energy generation capacity and capability will reach 2068 MW and 16155 MW, respectively, until 2031.

4.4.3 Proposed Energy Capacity and Non-Operative Energy Capacity

In Figure 12, Part A represents energy projects that will be retired during the planning time frame (2022–31). The Cabinet Committee on Energy (CCoE) has decided to stop the generation of energy from the 2020 MW Guddu-II, Jamshoro U1, U4, and Muzaffargarh-I U1 to U4 units. KAPCO 3 has a 300 MW capacity, which will retire in 2023; KAPCO 1 and 2 have a 1300 MW generation capacity, which will retire in 2026; and Liberty's 225 MW generation capacity will retire in 2027. Other energy projects will be retired 3 to 5 years before their retirement date (* represents the year of stop production and # represents the year of retirement of energy projects); basically, these projects will be replaced with hydro or solar projects that will be proposed under the IGCEP-22. Furthermore, IGCEP-22 proposed to partially or fully (* represents partially) stop generation from some energy projects. Part B of Figure 12, represents those energy projects that will not operate within the planning time frame without the provision of any justification by IGCEP. We calculated how much IGCEP-22 was going to replace and how much it would enhance the actual energy capacity. In Figure 13, Part A

Figure 12: IGCEP Proposed and Non-operative Energy Generation Capacity

represents a comparison of how much IGCEP proposed new energy capacity, how much would retire and become non-operational. Part B of Figure 13, summarizes the entire scenario, which shows that under the low-demand scenario, IGCEP proposed 32181 MW of energy generation capacity, and the total retired and non-operational capacity is 14513 MW. In this way, the net addition of energy generation capacity is 17668. our study peak demand projections also estimated that surplus energy generation capacity will reach 16890 by 2031 (See Table 8). Similarly, under the high-demand scenario, IGCEP proposed 40542 MW of new energy generation capacity until 2031. However, 14513 MW has a share of retired and non-operational energy generation capacity. The remaining 26029 has a net addition of energy generation capacity. This comparison highlighted that 35 percent to 45 percent of the total proposed energy generation capacity will be retired and remain non-operational. So, it looks like an energy generation capacity replacement plan rather than a capacity expansion plan. Furthermore, IGCEP has not considered the fixed cost of the non-operational generation capacity before installing the least-cost energy generation capacity. There is a need for a separate study of the cost-benefit analysis of capacity replacement.

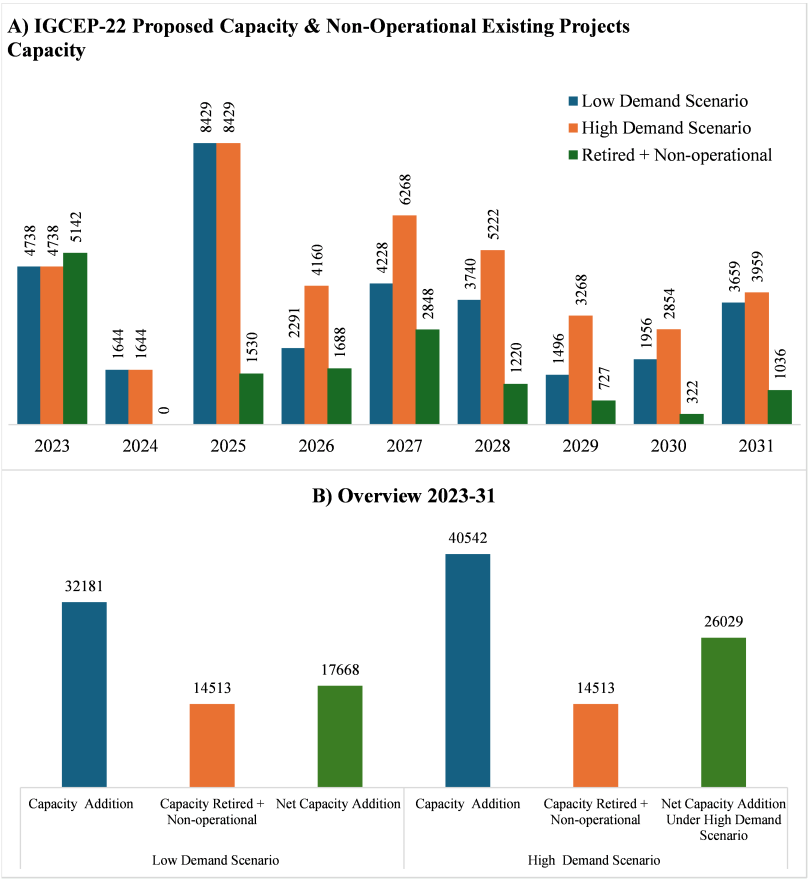

Figure 13: IGCEP Proposed and Non-operative Energy Generation Capacity

4.4.4 Unlocking the Efficient Utilization of Net-Metering Energy Resources

For the first time in IGCEP-22, net metering has become part of the planning process. The net metering goal is to add 480 MW of generation capacity per year. The net addition is 4800 MW of generation capacity through net metering. This net-metering will contribute to the energy mix being higher during daylight hours because solar has the major share in net-metering.To fully utilize net-metering resources, it should be a priority to ensure that peak demand occurs during the day. However, in the current scenario, more than half-year peak demand occurs late in the evening (6 pm to 11 pm), when net metering has zero share. If peak demand within a day occurs early in the evening, net metering can make a maximum contribution to peak demand. This peak demand shift will not only reduce reliance on non-renewable sources, but it will also ensure a more economical and stable consumption pattern for consumers. Shifting peak demand hours from evening to daytime enables the efficient utilization of net-metering resources.

We only suggest net-metering, Chashma Nuclear, and Diamer Bhasha hydro projects share energy generation for the future because actual peak demand is growing slowly over the year. However, IGCEP-22 proposes significant surplus capacity that will lead to capacity payment accumulation. If net-metering resources are utilized efficiently, that is enough for the future need for energy generation capacity. Furthermore, in 2029, Chashma Nuclear and Diamer Bhasha hydro projects will enhance energy generation capacity by 1200 MW and 4525 MW respectively. It is necessary to ensure peak demand will occur during the afternoon when net metering has the maximum contribution to the energy mix.

To shift peak demand, it is necessary to implement a variable pricing mechanism, considering peak, off-peak, and normal hours within a day. Daily demand hours should be categorized into three distinct periods: peak demand hours, off-peak demand, and normal demand hours. The implementation of variable pricing, with higher energy prices during peak hours and lower prices during off-peak hours. Normal energy prices would apply during the remaining hours. Offering low prices during off-peak hours serves as an incentive for consumers to manage their consumption effectively during these times. Conversely, higher energy prices during peak hours discourage consumers from excessive consumption. This pricing strategy would encourage a more balanced and efficient use of energy resources while optimizing cost efficiency and promoting smoother energy consumption. The load shifting time horizon contributes to peak, off-peak, and normal hours, which can be adjusted as per requirement since these are not fixed.

4.4.5 Results Summary of Objective Four

As part of the fourth objective of the study, we compared the IGCEP-22 generation capacity planning with actual peak demand projections conducted under this study and by IGCEP. The proposed IGCEP-22 generation capacity mainly contributes to renewable, mainly hydro power and solar. Which proposes to meet future energy demand.

This comparison showed that the overestimation of peak demand by IGCEP will lead to the installation of surplus energy generation capacity. Which may later turn to capacity payment without utilizing generation capacity. Our study explored that the extra generation capability will reach almost 16890 MW in the low-demand scenario and 20678 MW in the high-demand scenario by 2031. The study warns against increasing the energy generation capacity and only suggests that net metering with a shift in peak demand from late evening to early evening will be sufficient to cover future energy demand.

4.5 Policy Discussion

The government formulates, various policies to address the issues of the power sector. The National Electric Policy 2013 provided policy targets with complete guidance for three subsectors: generation, transmission, and distribution. Several reasons have led to a primary focus on the generation sector for the implementation of policy initiatives, resulting in the incomplete achievement of the set goal of the policy. For an integrated and competitive power market, the NEPRA Amendment Act (Section 14A) provided a foundation. Under this amendment, the government established the National Electric Power Policy (NEPP-2021) for the development and sustainability of the competitive power market. The NEPP-2021 focused on the optimal utilization of indigenous resources with an environmentally friendly approach and establishing competitive market designs for the power sector. For the utilization of renewable resources, NEPP-2021 follows the Alternative Renewable Energy Policy (AREP-2019). One of the biggest problems in the power sector is tackling the gap between summer and winter energy. Policies and generation capacity expansion plans prioritize meeting peak demand rather than mitigating impact of the winter-summer energy demand gap.. Figure No. 14 represents the peak demand winter-summer gaps

We examine peak demand days during 2022. Interestingly, just 29 days in 2022, demand

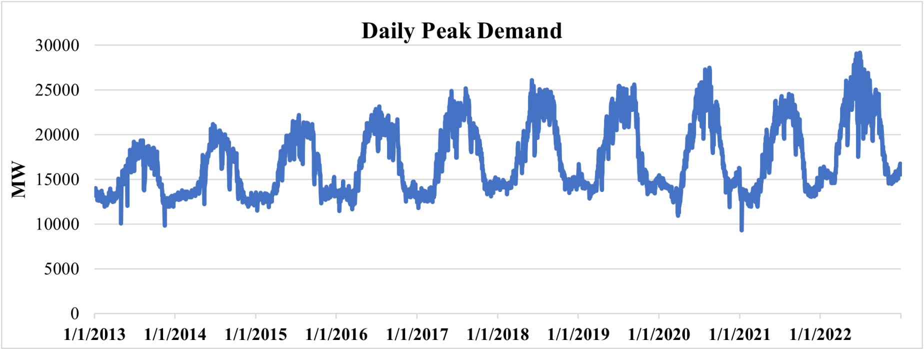

Figure 14: Peak Demand Seasonal Gap

exceeded 26,000 MW. Further, in these 29 days, demand exceeds this threshold on average by 9 to 10 hours per day. It is not a policy-oriented point to enhance generation capacity for 268 hours and rest-of-year bear capacity payments. The varying temperature is the main reason creating winter summer electricity demand We examined the temperature sensitivity electricity sales demand and peak demand in the next section.

4.5.1 Temperature Sensitive Peak Demand

A daily temperature-weighted average, considering electricity consumption across all ten DISCOs regions with 66 districts, was used to create a third-order polynomial equation. This equation sketches a temperature-sensitive electricity peak demand, which has a point of inflection at 16 degrees that distinguishes the electricity peak demand for the summer and winter seasons. Figure 15 shows that the summer season experiences an average peak demand rise of 638 MW with a one-degree temperature increase. In contrast, during the winter season, a one-degree temperature decreases results in a comparatively lower average peak demand increase of 362 MW. Two key factors contribute to this reduced peak demand in winter. Firstly, the winter season is shorter compared to the summer. Secondly, during the winter, domestic consumers have a perfect substitute for electricity in the form of cheap gas. Consequently, consumers may shift their home appliances from electricity to gas during the winter, influencing energy demand dynamics.

4.5.2 Temperature Sensitive Energy Demand and System Capability

The process was replicated for energy demand, energy generation, and energy sale, employing polynomial equations to draw temperature-sensitive curves for each. Points of inflection were

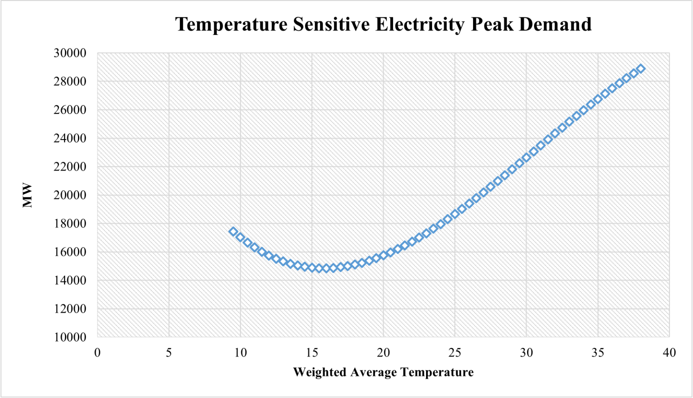

Figure 15: Temperature Sensitive Electricity Peak Demand

identified at 15.5, 15.5, and 14.5 for energy demand, energy generation, and energy sale, respectively. These variations stem from the distinct patterns inherent in each series. Figure 16 shows an increase of one degree in temperature during the summer, associated with an increase in energy demand of an average 15 GW, system generation of 10.55 GW, and energy sales of 5.74 GW. In contrast, winter conditions result in a respective increase of 8.9 GW, 8.32 GW, and 4.4 GW. This illustrates the seasonal sensitivity of the energy system, showing responses to temperature changes in summer and winter. The disparity between energy generation and

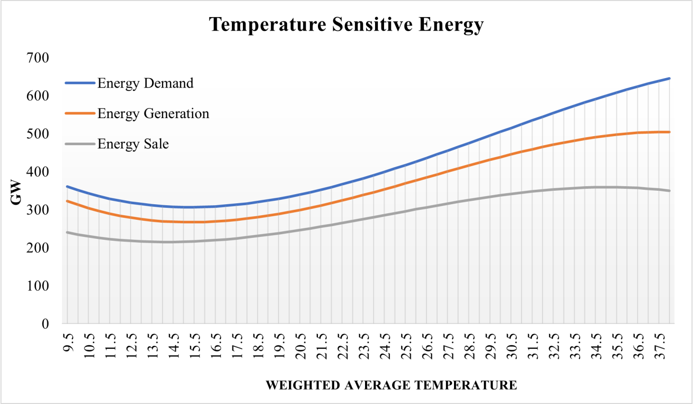

Figure 16: Temperature Sensitive Energy Demand and Generation

energy sales reflects technical and distribution losses, which escalate with rising temperatures in summer and falling temperatures in winter. The gap between energy demand and generation signifies system incapability or inefficiencies, including high losses and inadequate demand management.

4.5.3 Valley Filling Through Strategic Load Growth

In Pakistan's power sector, the persistent issue is the demand gap between the winter and summer seasons. The winter-summer demand gap causes generation capacity payments without utility due to a lack of demand during the winter season. To tackle this issue, this study suggests Valley filling and strategic load growth. These are approaches used for energy demand management. We proposed both in combination, especially to reduce the demand gap during the winter-summer season. In other words, plans to fill the gap between one summer and the next with strategic load growth (storage technologies, price mechanisms, etc.). In Pakistan, the domestic sector has two sources of energy in the form of electricity and natural gas, and both have significantly different prices from each other. During the summer, the domestic sector commonly uses home appliances that run on electricity, while in the winter, gas-related home appliances are used because gas is a cheaper energy source in Pakistan compared to electricity. Figure 17 shows the complete scenario. Adjusting the price mechanism to make domestic consumers prefer electricity to gas during the winter will significantly increase electricity demand during the winter season.

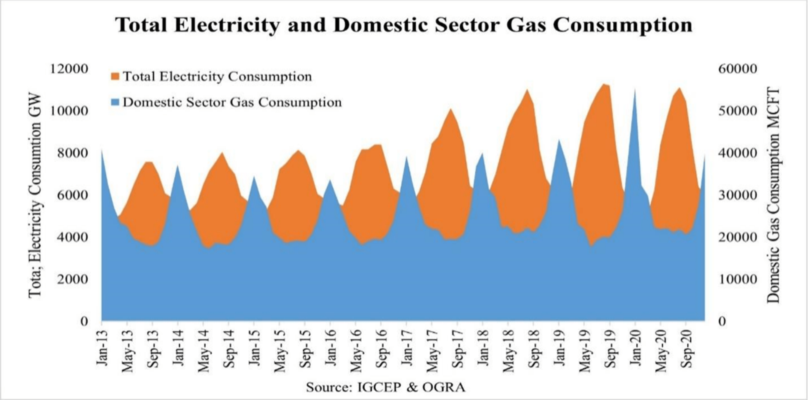

Figure 17: Total Electricity and Domestic Sector Gas Consumption

Chapter 5

5 Conclusion and Policy Recommendation

5.1 Conclusion

The data aggregation significantly influences forecast accuracy. The results infer that data at higher frequencies exhibits greater accuracy in predictions, attributed to the time series features of the data. Key time series features, including trend, linearity, x˙acf1, e˙acf1, diff1˙acf1 (with higher values), and spike, diff2˙acf10 (with lower values), are used to identify the optimal level of data aggregation for superior forecasting precision. In the electricity demand forecasting model for Pakistan, metrological variables are more appropriate than economic variables. The study also estimated temperature-sensitive electricity peak demand, energy demand, and energy sales, providing insights that align more closely with real-world scenarios.

This study adopts a pioneering approach to projecting actual demand, a practice commonly observed in NTDC and among other stakeholders. In the past, there has been a mistaken assumption that energy sales equate to energy demand, resulting in misinterpretations and inaccuracies. Similarly, NTDC often uses maximum generation as a proxy for peak demand, despite notable disparities between the two.

Our study explored that the extra generation capability will reach almost 16890 MW in the low-demand scenario and 20678 MW in the high-demand scenario by 2031. The study warns against increasing the energy generation capacity and only suggests that net metering with a shift in peak demand from late evening to early evening will be sufficient to cover future energy demand. Because installed capacity is sufficient to meet energy sales (NTDC assumes energy demand), DISCOs have issues meeting actual demand due to inefficiencies. DISCOs are creating hurdles to meeting the actual energy demand of the NTDC system. Without improving DISCO's efficiency, installing more energy generation capacity may lead to a higher energy price or accumulate more circular debt due to the extra capacity payments.

Further IGCEP-22 planning is completely missing how to reduce the summer-winter energy demand gap. IGCEP-22 plans to pursue peak demand (which is also overestimated) and proposes installing more generation capacity. This study also suggested variable price mechanisms within a day and over the seasons. This would reduce the summer-winter gap and create a smooth consumption pattern throughout the day and season.

5.2 Way Farword

(a) Based on an in-depth analysis, this study proposes that NTDC should implement an electricity demand forecasting model that prioritizes meteorological factors over economic considerations. Implementing the suggested methodology with actual demand data, which incorporates meteorological factors, at the DISCO level would achieve greater precision in forecasts instead of applying it to the entire NTDC system. The study suggested repeating forecasting exercises annually. This iterative approach will ensure planning and resource allocation aligns with the most current and relevant information, enhancing the overall effectiveness of forecasting efforts.

(b) Before installing additional power generation capacity, it is imperative to prioritize significant reforms aimed at improving the performance of DISCOs. The inefficiencies within DISCOs currently pose a major obstacle to meeting the actual electricity demand. Installation of more energy generation capacity without improving DISCO's efficiency will lead to extra capacity payments without utilization.

(c) Shifting peak demand hours to daytime makes for more cost-effective energy generation and efficient utilization of net metering resources. Aligning peak demand with peak sunlight hours enables more effective and sustainable management of electricity demand.

5.3 Recommendations

(a) The planning process for IGCEP should include measures to address and mitigate energy demand seasonal gaps. To establish more balanced energy consumption patterns, it is essential to transition from a uniform tariff system to a variable pricing mechanism. This study recommends the implementation of the variable price mechanism, distinguishing between peak, off-peak, and normal hours within a day.

(b) Adjusting the pricing mechanism for electricity and gas can play a crucial role in incentivizing desired consumption patterns to reduce the winter-summer demand gap. For instance, during the winter, domestic consumers tend to prefer electricity over gas. Therefore, aligning the pricing in a way that consumers prefer electricity during the winter season can help stimulate electricity demand during this period. This adjustment not only supports a more efficient energy consumption pattern but will also contribute to a more resilient and responsive energy infrastructure.

References

K. R. Abbasi, M. Shahbaz, Z. Jiao, and M. Tufail. How energy consumption, industrial growth, urbanization, and co2 emissions affect economic growth in pakistan? a novel dynamic ardl simulations approach. *Energy*, 221:119793, 2021.

S. Abrar and H. Farzaneh. Scenario analysis of the low emission energy system in pakistan using integrated energy demand-supply modeling approach. *Energies*, 14(11):3303, 2021.

M. Ahmed, K. Riaz, A. M. Khan, and S. Bibi. Energy consumption–economic growth nexus for pakistan: Taming the untamed. *Renewable and Sustainable Energy Reviews*, 52:890–896, 2015.

A. T. Akarca and T. V. Long II. Energy and employment: a time-series analysis of the causal relationship. *Resources and Energy*, 2(2-3):151–162, 1979.

M. H. Akhtar, N. Iqbal, B. Tariq, and R. Ab-Rahim. Determinants of residential electricity demand: Empirical evidence from pakistan. 2020.

A. E. Akinlo. Energy consumption and economic growth: Evidence from 11 sub-sahara african countries. *Energy economics*, 30(5):2391–2400, 2008.

A. Alberini, G. Prettico, C. Shen, and J. Torriti. Hot weather and residential hourly electricity demand in italy. *Energy*, 177:44–56, 2019.

T. Amemiya and R. Y. Wu. The effect of aggregation on prediction in the autoregressive model. *Journal of the American Statistical Association*, 67(339):628–632, 1972.

A. Aqeel and M. S. Butt. The relationship between energy consumption and economic growth in pakistan. *Asia-Pacific Development Journal*, 8(2):101–110, 2001.

G. Athanasopoulos, R. J. Hyndman, N. Kourentzes, and F. Petropoulos. Forecasting with temporal hierarchies. *European Journal of Operational Research*, 262(1):60–74, 2017.

Awan, H. S., G. Samad, and N. Faraz. *Electricity Subsidies And Welfare Analysis In Pakistan.* PIDE, 2019.

A. Azzuni and C. Breyer. Definitions and dimensions of energy security: a literature review. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(1):e268, 2018.

J. Barrientos, E. Velilla, D. T. Orozco, F. Villada, and J. M. López-Lezama. On the estimation of the price elasticity of electricity demand in the manufacturing industry of colombia. *Lecturas de Economía*, (88):155–182, 2018.

H. G. Bergsteinsson, J. K. Møller, P. Nystrup, Ó. P. Pálsson, D. Guericke, and H. Madsen. Heat load forecasting using adaptive temporal hierarchies. *Applied Energy*, 292:116872, 2021.

K. Binita and M. Ruth. Estimation and projection of institutional building electricity consumption. *Energy and Buildings*, 143:43–52, 2017.

V. Bobinaite, A. Juozapaviciene, and I. Konstantinaviciute. Assessment of causality relationship between renewable energy consumption and economic growth in lithuania. *Engineering Economics*, 22(5):510–518, 2011.

N. Bowden and J. E. Payne. Sectoral analysis of the causal relationship between renewable and non-renewable energy consumption and real output in the us. *Energy Sources, Part B: Economics, Planning, and Policy*, 5(4):400–408, 2010.

J. E. Boylan and M. Z. Babai. On the performance of overlapping and non-overlapping temporal demand aggregation approaches. *International Journal of Production Economics*, 181: 136–144, 2016.

K. R. Brewer. Some consequences of temporal aggregation and systematic sampling for arma and armax models. *Journal of Econometrics*, 1(2):133–154, 1973.

D. Burillo, M. V. Chester, S. Pincetl, E. D. Fournier, and J. Reyna. Forecasting peak electricity demand for los angeles considering higher air temperatures due to climate change. *Applied Energy*, 236:1–9, 2019.

N. Chabouni, Y. Belarbi, and W. Benhassine. Electricity load dynamics, temperature and seasonality nexus in algeria. *Energy*, 200:117513, 2020.

A. A. Chandio, A. Rauf, Y. Jiang, I. Ozturk, and F. Ahmad. Cointegration and causality analysis of dynamic linkage between industrial energy consumption and economic growth in pakistan. *Sustainability*, 11(17):4546, 2019.

Y. Chang, C. S. Kim, J. I. Miller, J. Y. Park, and S. Park. A new approach to modeling the effects of temperature fluctuations on monthly electricity demand. *Energy Economics*, 60: 206–216, 2016.

A. A. Chaudhry. A panel data analysis of electricity demand in pakistan. *Lahore Journal of Economics*, 15, 2010.

T. Chien and J.-L. Hu. Renewable energy and macroeconomic efficiency of oecd and non-oecd economies. *Energy Policy*, 35(7):3606–3615, 2007.

J. Chontanawat, L. C. Hunt, and R. Pierse. Does energy consumption cause economic growth?: Evidence from a systematic study of over 100 countries. *Journal of policy modeling*, 30(2): 209–220, 2008.

A. Ciarreta, M. P. Espinosa, and C. Pizarro-Irizar. Pricing policies for efficient demand side management in liberalized electricity markets. *Economic Modelling*, 121:106215, 2023.

L. P. C. Do, Š. Lyócsa, and P. Molnár. Residual electricity demand: An empirical investigation. *Applied Energy*, 283:116298, 2021.

S. Eden and B.-K. Hwang. The relationship between energy and gnp: further results. *Energy economics*, 6(3):186–190, 1984.

B. T. Ewing, R. Sari, and U. Soytas. Disaggregate energy consumption and industrial output in the united states. *Energy policy*, 35(2):1274–1281, 2007.

M. Z. Faridi and G. Murtaza. Disaggregate energy consumption, agricultural output and economic growth in pakistan. *The Pakistan Development Review*, pages 493–514, 2013.

C. Gross. Explaining the (non-) causality between energy and economic growth in the us—a multivariate sectoral analysis. *Energy Economics*, 34(2):489–499, 2012.

S. Harish, N. Singh, and R. Tongia. Impact of temperature on electricity demand: Evidence from delhi and indian states. *Energy Policy*, 140:111445, 2020.

M. Hekkenberg, R. Benders, H. Moll, and A. S. Uiterkamp. Indications for a changing electricity demand pattern: The temperature dependence of electricity demand in the netherlands. *Energy Policy*, 37(4):1542–1551, 2009.

H. Hina, F. Abbas, and U. Qayyum. Selecting correct functional form in consumption function: Analysis of energy demand at household level. *Plos one*, 17(12):e0270222, 2022.

Y. Hiruta, N. N. Ishizaki, S. Ashina, and K. Takahashi. Regional and temporal variations in the impacts of future climate change on japanese electricity demand: Simultaneous interactions among multiple factors considered. *Energy Conversion and Management: X*, 14:100172, 2022.

L. Hotta and J. C. Neto. The effect of aggregation on prediction in autoregressive integrated moving-average models. *Journal of Time Series Analysis*, 14(3):261–269, 1993.

M.-F. Hung and T.-H. Huang. Dynamic demand for residential electricity in taiwan under seasonality and increasing-block pricing. *Energy Economics*, 48:168–177, 2015.

M. Hussain, M. Irfan Javaid, and P. R. Drake. An econometric study of carbon dioxide (co2) emissions, energy consumption, and economic growth of pakistan. *International Journal of Energy Sector Management*, 6(4):518–533, 2012.

I. E. A. IEA. World energy outlook 2006. Technical report, IEA, 2006.

R. Ilyas, K. Hussain, M. Z. Ullah, and J. Xue. Distributional impact of phasing out residential electricity subsidies on household welfare. *Energy Policy*, 163:112825, 2022.

H. Ishaque. Revisiting income and price elasticities of electricity demand in pakistan. *Economic research-Ekonomska istraživanja*, 31(1):1137–1151, 2018.

M. Islam, H. S. Che, M. Hasanuzzaman, and N. Rahim. Energy demand forecasting. In *Energy for sustainable development*, pages 105–123. Elsevier, 2020.

F. Jamil and E. Ahmad. The relationship between electricity consumption, electricity prices and gdp in pakistan. *Energy policy*, 38(10):6016–6025, 2010.

M. Javid and A. Qayyum. Electricity consumption-gdp nexus in pakistan: A structural time series analysis. *Energy*, 64:811–817, 2014.

W. Khalid, H. Özdeşer, and A. Jalil. An empirical analysis of inter-factor and inter-fuel substitution in the energy sector of pakistan. *Renewable Energy*, 177:953–966, 2021.

M. A. Khan and U. Ahmad. Energy demand in pakistan: a disaggregate analysis. *The Pakistan Development Review*, pages 437–455, 2008.

J. Kraft and A. Kraft. On the relationship between energy and gnp. *The Journal of Energy and Development*, pages 401–403, 1978.

S. Kumar and M. Shahbaz. Coal consumption and economic growth revisited: structural breaks, cointegration and causality tests for pakistan. *Energy exploration & exploitation*, 30 (3):499–521, 2012.

X. Labandeira, J. M. Labeaga, and X. López-Otero. A meta-analysis on the price elasticity of energy demand. *Energy policy*, 102:549–568, 2017.

G. Lanot and M. Vesterberg. The price elasticity of electricity demand when marginal incentives are very large. *Energy Economics*, 104:105604, 2021.

C.-C. Lee. Energy consumption and gdp in developing countries: a cointegrated panel analysis. *Energy economics*, 27(3):415–427, 2005.

C.-C. Lee. The causality relationship between energy consumption and gdp in g-11 countries revisited. *Energy policy*, 34(9):1086–1093, 2006.

B. Liddle and F. Hasanov. Industry electricity price and output elasticities for high-income and middle-income countries. *Empirical Economics*, 62(3):1293–1319, 2022.

B. Liddle and H. Huntington. How prices, income, and weather shape household electricity demand in high-income and middle-income countries. *Energy Economics*, 95:104995, 2021.

Y. Lin, Z. Xiong, and J. Zhu. Optimization of the electricity consumption behaviors of users under uncertain electricity prices and consumption patterns. *Energy Reports*, 9:646–657, 2023.

R. Mahadevan and J. Asafu-Adjaye. Energy consumption, economic growth and prices: A reassessment using panel vecm for developed and developing countries. *Energy policy*, 35 (4):2481–2490, 2007.

T. Mahmood and M. T. Ayaz. Energy security and economic growth in pakistan. *Pakistan Journal of Applied Economics*, 28(1):47–64, 2018.

A. Malik and U. Ahmad. Thoughts on integrated generation capacity expansion plan (igcep) 2021-30. *Pakistan Institute of Development Economics*, 2022(56), 2022.

S. Malik. Residential electricity consumers and increasing block pricing policy in pakistan: Evidence based on household level primary data. *Journal of Economic Impact*, 3(2):80–87, 2021.

L. M. Marques, J. A. Fuinhas, and A. C. Marques. On the dynamics of energy-growth nexus: Evidence from a world divided into four regions. *International Journal of Energy Economics and Policy*, 7(3):208–215, 2017.

J. Moral-Carcedo and J. Pérez-García. Temperature effects on firms' electricity demand: An analysis of sectorial differences in spain. *Applied energy*, 142:407–425, 2015.

M. F. Müller, S. E. Thompson, and A. J. Gadgil. Estimating the price (in) elasticity of off-grid electricity demand. *Development Engineering*, 3:12–22, 2018.

R. Nadimi, F. Ghaderi, et al. A hybrid tsk-fr model to study short-term variations of the electricity demand versus the temperature changes. *Expert Systems with Applications*, 36 (2):1765–1772, 2009.

P. K. Narayan and R. Smyth. *Applied econometrics and a decade of energy economics research.* Monash Univ., Department of Economics Clayton, 2014.

M. Nasir, M. S. Tariq, and A. Arif. Residential demand for electricity in pakistan. *The Pakistan Development Review*, pages 457–467, 2008.

S. Nawaz, N. Iqbal, and S. Anwar. Modelling electricity demand using the star (smooth transition auto-regressive) model in pakistan. *Energy*, 78:535–542, 2014.

A. M. R. Nishimwe and S. Reiter. Using artificial intelligence models and degree-days method to estimate the heat consumption evolution of a building stock until 2050: A case study in a temperate climate of the northern part of europe. *Cleaner and Responsible Consumption*, 5:100069, 2022.

P. Nystrup, E. Lindström, P. Pinson, and H. Madsen. Temporal hierarchies with autocorrelation for load forecasting. *European Journal of Operational Research*, 280(3):876–888, 2020.

P. Nystrup, E. Lindström, J. K. Møller, and H. Madsen. Dimensionality reduction in forecasting with temporal hierarchies. *International Journal of Forecasting*, 37(3):1127–1146, 2021.

A. Omri, N. B. Mabrouk, and A. Sassi-Tmar. Modeling the causal linkages between nuclear energy, renewable energy and economic growth in developed and developing countries. *Renewable and Sustainable Energy Reviews*, 42:1012–1022, 2015.

I. M. Ouédraogo. Electricity consumption and economic growth in burkina faso: A cointegration analysis. *Energy economics*, 32(3):524–531, 2010.

U. Perwez and A. Sohail. Forecasting of pakistan's net electricity energy consumption on the basis of energy pathway scenarios. *Energy Procedia*, 61:2403–2411, 2014.

L. V. Phu. Nonlinear temperature response of electricity loads and implications for power development policies in vietnam. *ENERGY AND BUILDINGS*, 251, 2021.

PMS. Power market survey pms. Technical report, National Transmission Dispatch Company, 2019.

A. Q. Qazi, K. Ahmed, and M. Mudassar. Disaggregate energy consumption and industrial output in pakistan: An empirical analysis. Technical report, Economics Discussion Papers, 2012.

M. A. Raza, K. L. Khatri, A. Israr, M. I. U. Haque, M. Ahmed, K. Rafique, and A. S. Saand. Energy demand and production forecasting in pakistan. *Energy Strategy Reviews*, 39:100788, 2022.

S. Razzaqi, F. Bilquees, and S. Sherbaz. Dynamic relationship between energy and economic growth: evidence from d8 countries. *The Pakistan Development Review*, pages 437–458, 2011.

M. J. Roberts, S. Zhang, E. Yuan, J. Jones, and M. Fripp. Using temperature sensitivity to estimate shiftable electricity demand. *Iscience*, 25(9), 2022.

R. J. Rossana and J. J. Seater. Temporal aggregation and economic time series. *Journal of Business & Economic Statistics*, 13(4):441–451, 1995.

B. Rostami-Tabar and D. Mircetic. Exploring the association between time series features and forecasting by temporal aggregation using machine learning. *Neurocomputing*, page 126376, 2023.

B. Rostami-Tabar, T. E. Goltsos, and S. Wang. Forecasting for lead-time period by temporal aggregation: Whether to combine and how. *Computers in Industry*, 145:103803, 2023.

P. Sadorsky. Renewable energy consumption and income in emerging economies. *Energy policy*, 37(10):4021–4028, 2009.

M. Salahuddin, K. Alam, I. Ozturk, and K. Sohag. The effects of electricity consumption, economic growth, financial development and foreign direct investment on co2 emissions in kuwait. *Renewable and sustainable energy reviews*, 81:2002–2010, 2018.

M. Santamouris, C. Cartalis, A. Synnefa, and D. Kolokotsa. On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—a review. *Energy and buildings*, 98:119–124, 2015.

R. Sari, B. T. Ewing, and U. Soytas. The relationship between disaggregate energy consumption and industrial production in the united states: an ardl approach. *Energy Economics*, 30(5):2302–2313, 2008.

A. Sarwar and U. Hanif. Pakistan's electricity demand analysis 1975-2016. *Empirical Economic Review*, 1(1):109–138, 2018.

S. L. Satti, M. S. Hassan, H. Mahmood, and M. Shahbaz. Coal consumption: An alternate energy resource to fuel economic growth in pakistan. *Economic Modelling*, 36:282–287, 2014.

M. Shahbaz and H. H. Lean. The dynamics of electricity consumption and economic growth: A revisit study of their causality in pakistan. *Energy*, 39(1):146–153, 2012.

M. Shahbaz, M. Zeshan, and T. Afza. Is energy consumption effective to spur economic growth in pakistan? new evidence from bounds test to level relationships and granger causality tests. *Economic Modelling*, 29(6):2310–2319, 2012.

M. Shin and S. L. Do. Prediction of cooling energy use in buildings using an enthalpy-based cooling degree days method in a hot and humid climate. *Energy and Buildings*, 110:57–70, 2016.

S. Silva, I. Soares, and C. Pinho. Climate change impacts on electricity demand: The case of a southern european country. *Utilities Policy*, 67:101115, 2020.

A. Silvestrini and D. Veredas. Temporal aggregation of univariate and multivariate time series models: a survey. *Journal of Economic Surveys*, 22(3):458–497, 2008.

U. Soytas and R. Sari. Energy consumption and gdp: causality relationship in g-7 countries and emerging markets. *Energy economics*, 25(1):33–37, 2003.

E. Spiliotis, F. Petropoulos, N. Kourentzes, and V. Assimakopoulos. Cross-temporal aggregation: Improving the forecast accuracy of hierarchical electricity consumption. *Applied Energy*, 261:114339, 2020.

J. Squalli. Electricity consumption and economic growth: Bounds and causality analyses of opec members. *Energy economics*, 29(6):1192–1205, 2007.

G. C. Tiao. Asymptotic behaviour of temporal aggregates of time series. *Biometrika*, 59(3): 525–531, 1972.

Z. Wang, T. Hong, H. Li, and M. A. Piette. Predicting city-scale daily electricity consumption using data-driven models. *Advances in Applied Energy*, 2:100025, 2021.

Y. Wolde-Rufael. Coal consumption and economic growth revisited. *Applied Energy*, 87(1): 160–167, 2010.

H. Yi-Ling, M. Hai-Zhen, D. Guang-Tao, and S. Jun. Influences of urban temperature on the electricity consumption of shanghai. *Advances in climate change research*, 5(2):74–80, 2014.

S.-H. Yoo. The causal relationship between electricity consumption and economic growth in the asean countries. *Energy policy*, 34(18):3573–3582, 2006.

K. Zaman, M. M. Khan, M. Ahmad, and R. Rustam. Determinants of electricity consumption function in pakistan: Old wine in a new bottle. *Energy policy*, 50:623–634, 2012.

M. Zaman, F. Shaheen, A. Haider, and S. Qamar. Examining relationship between electricity consumption and its major determinants in pakistan. *International Journal of Energy Economics and Policy*, 5(4):998–1009, 2015.

H. Zhang, B. Chen, Y. Li, J. Geng, C. Li, W. Zhao, and H. Yan. Research on medium-and long-term electricity demand forecasting under climate change. *Energy Reports*, 8:1585–1600, 2022.

M. Zhang, C.-H. Cheng, and H.-Y. Ma. Projection of residential and commercial electricity consumption under ssps in jiangsu province, china. *Advances in Climate Change Research*, 11(2):131–140, 2020a.

M. Zhang, K. Zhang, W. Hu, B. Zhu, P. Wang, and Y.-M. Wei. Exploring the climatic impacts on residential electricity consumption in jiangsu, china. *Energy Policy*, 140:111398, 2020b.

M. Zhang, Y. Chen, W. Hu, N. Deng, and W. He. Exploring the impact of temperature change on residential electricity consumption in china: The 'crowding-out'effect of income growth. *Energy and Buildings*, 245:111040, 2021.

6 Appendix A

6.1 Figure A1

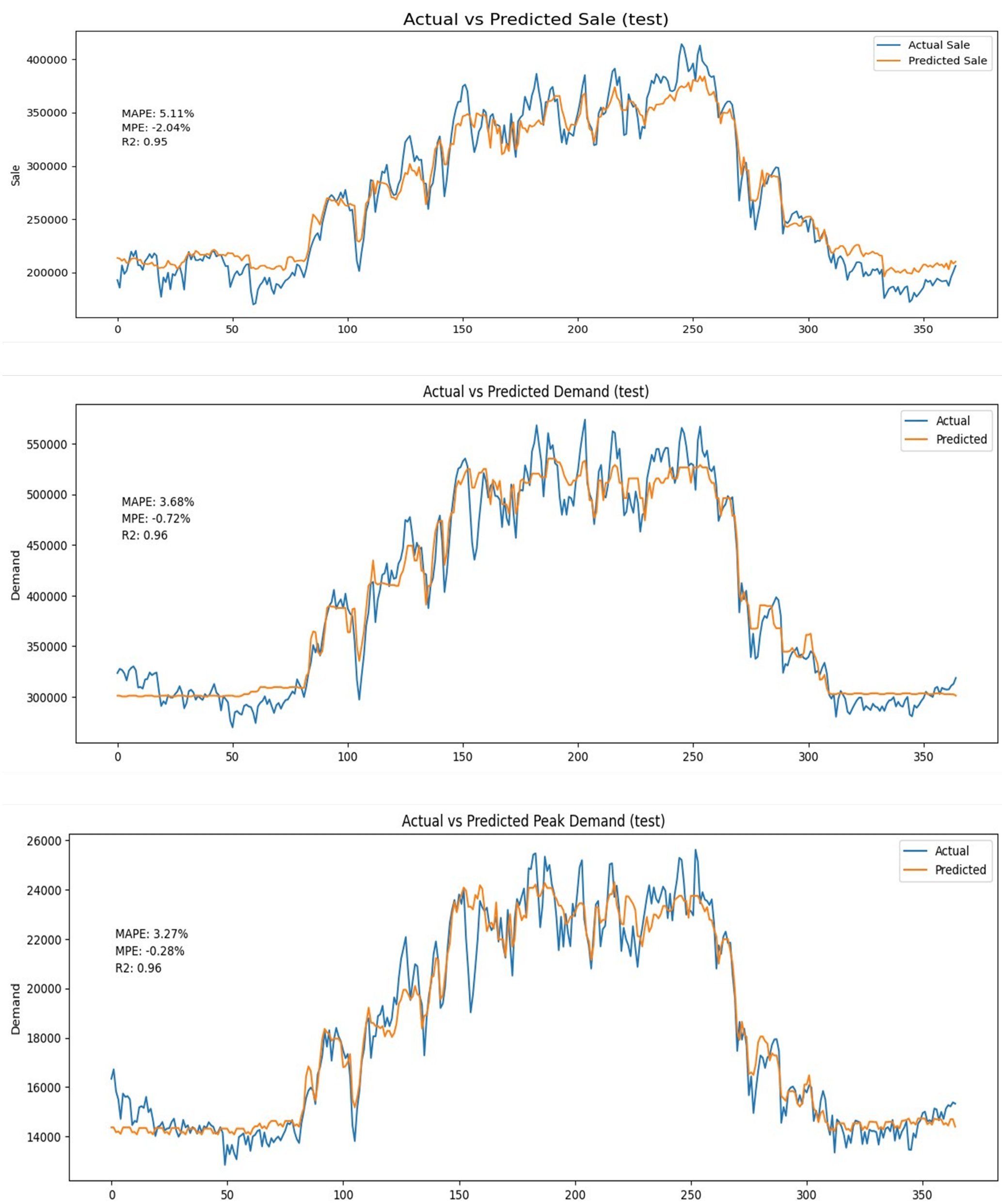

Figure 18: Model Training and Testing

6.2 Figure A2

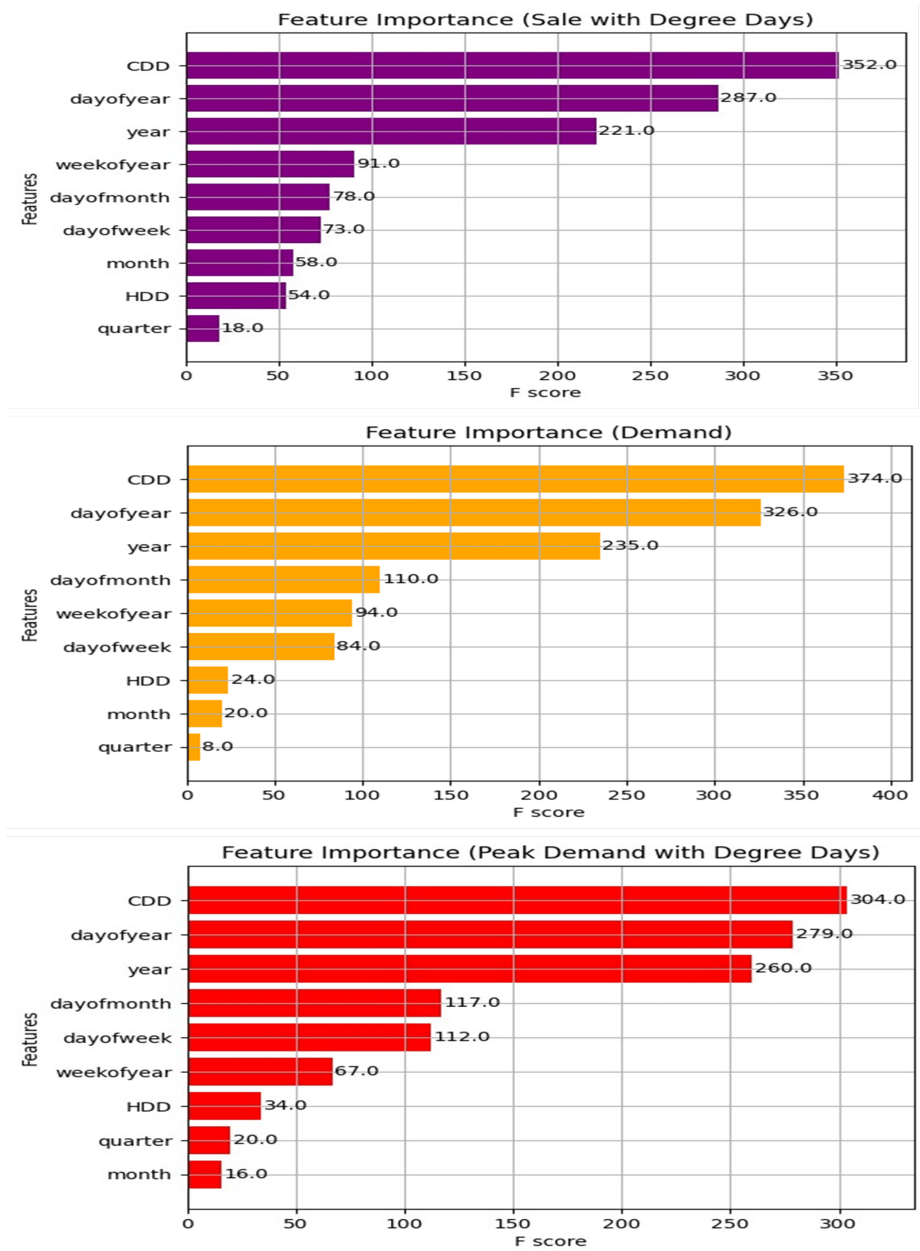

Figure 19: XGB Features Robustness

6.3 Figure A3

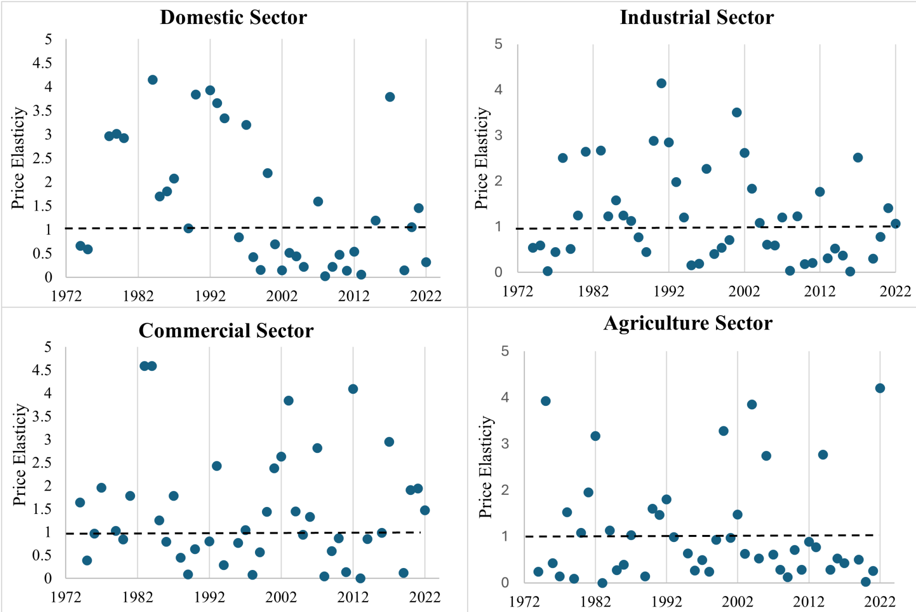

Figure 20: Price Elasticises of All Economic Sectors

7 Appendix B

7.1 Table B1

Time Series Data Features

Feature	Description
trend	Strength of trend, a value close to 1 indicates a highly trended series
spike	Prevalence of spikes in the remainder component of the STL decomposition
curvature	Curvature of the trend component of the STL decomposition
e˙acf1	First autocorrelation coefficient of the remainder series
e˙acf10	Sum of squares. first ten autocorrelation coefficients of the remainder series
entropy	Entropy measures disorder or uncertainty in the sequence of values.
x˙acf1	First autocorrelation coefficient
x˙acf10	Sum of squares of the first ten autocorrelation coefficients
diff1˙acf1	First autocorrelation coefficient from the differenced series
diff1˙acf10	Sum of squares. first ten autocorrelation coefficients from the differenced series
diff2˙acf1	First autocorrelation coefficient from the twice differenced data
diff2˙acf10	Sum of squares. first ten autocorrelation coefficients differenced 2 series

7.2 Table B2

Pairwise Granger Causality

Hypothesis	F-stat	Probability
Total DGP does not cause domestic Sale	0.8654	0.3573
Domestic Tariff does not cause domestic Sale	0.8429	0.3636
Industrial DGP does not cause industrial Sale	1.4768	0.2362
Industrial Tariff does not cause industrial Sale	**5.5055**	**0.0031**
Commercial DGP does not cause commercial Sale	0.1498	0.5674
Commercial Tariff does not cause commercial Sale	0.2525	0.4355
Agriculture DGP does not cause Agriculture Sale	2.6805	0.0601
Agriculture Tariff does not cause Agriculture Sale	0.8730	0.4633

7.3 Table B3

Granger Causality (Block Exogeneity Wald Test)

Dependent	Independent	Lags	Chi-square	Probability
Domestic Sale	Domestic Tariff and Total GDP GR	1	1.4565	0.4828
Industrial Sale	**Industrial Tariff and Industrial GDP GR**	**3**	**24.4231**	**0.0004**
Commercial Sale	Commercial Tariff and Commercial GDP GR	2	0.3631	0.8340
Agriculture Sale	Agriculture Tariff and Agriculture GDP GR	3	10.3155	0.1120

7.4 Table B4

LSTM Hyperparameters (Validation Model)

Data Series	Activation Function	CV	Optimizer	LSTM Units	Epochs	Batch Size
Sale	ReLu	2	Adam	150	14	16
Demand	ReLu	2	Adam	150	14	16
Peak Demand	ReLu	2	Adam	150	14	16

7.5 Table B5

XG Hyperparameters (Validation Model)

Data Series	Max Depth	Learning Rate	Estimators	Colsample bytree	CV
Sale	3	0.2	200	0.9	8
Demand	4	0.1	100	0.9	2
Peak Demand	4	0.1	100	0.9	2

7.6 Table B6

XG Hyperparameters (Final Model)

Data Series	Max Depth	Learning Rate	Estimators	Colsample bytree	CV
Sale	3	0.3	100	0.9	6
Demand	3	0.3	100	0.9	10
Peak Demand	7	0.1	200	0.7	7