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Abstract: With the globally increasing electricity demand, its related uncertainties are on the rise as well. Therefore, a deeper insight of load forecasting techniques for projecting future electricity demands becomes imperative for business entities and policy makers. The electricity demand is governed by a set of different variables or "electricity demand determinants". These demand determinants depend on forecasting horizons (long term, medium term, and short term), the load aggregation level, climate, and socio-economic activities. In this paper, a review of different electricity demand forecasting methodologies is provided in the context of a group of low and middle income countries. The article presents a comprehensive literature review by tabulating the different demand determinants used in different countries and forecasting the trends and techniques used in these countries. A comparative review of these forecasting methodologies over different time horizons reveals that the time series modeling approach has been extensively used while forecasting for long and medium terms. For short term forecasts, artificial intelligence-based techniques remain prevalent in the literature. Furthermore, a comparative analysis of the demand determinants in these countries indicates a frequent use of determinants like the population, GDP, weather, and load data over different time horizons. Following the analysis, potential research gaps are identified, and recommendations are provided, accordingly.

Keywords: demand determinants; forecasting horizon; load forecasting; low and middle income countries

1. Introduction

Technological advancements are changing the shape of the grid by converting a demand driven power system towards a generation power driven system. This is essentially due to a multitude of factors including increased the penetration of renewable energy resources (RES) and new technologies at consumer side (electric vehicles, energy storage). This creates uncertainties in terms of the future electricity demand. Therefore, the importance of load forecasting has increased multifold for the future

grid with limited safety margins and increasing risk levels. However, the rise in global electricity demand is consistent and still expected to grow more than twice the rate of the global energy demand [1]. Forecasting in the energy sector is a crucial input for many power system applications of both a technical and managerial nature. These applications range from energy generation (from different renewable and non-renewable resources), energy management at different nodes and sectors, energy pricing and many others. The primary purpose of having a forecasted load for these application is to ensure a safe, reliable and affordable energy supply [2]. Load forecasting has been a research topic for decades, however, due to the eminent changes in the grid, load forecasting is attracting attention of more researchers today than ever before. Considering the last twenty years, for example, as shown in Figure 1, a rising trend in the research contributions of "electricity load forecasting" highlights its significance of its application domain.
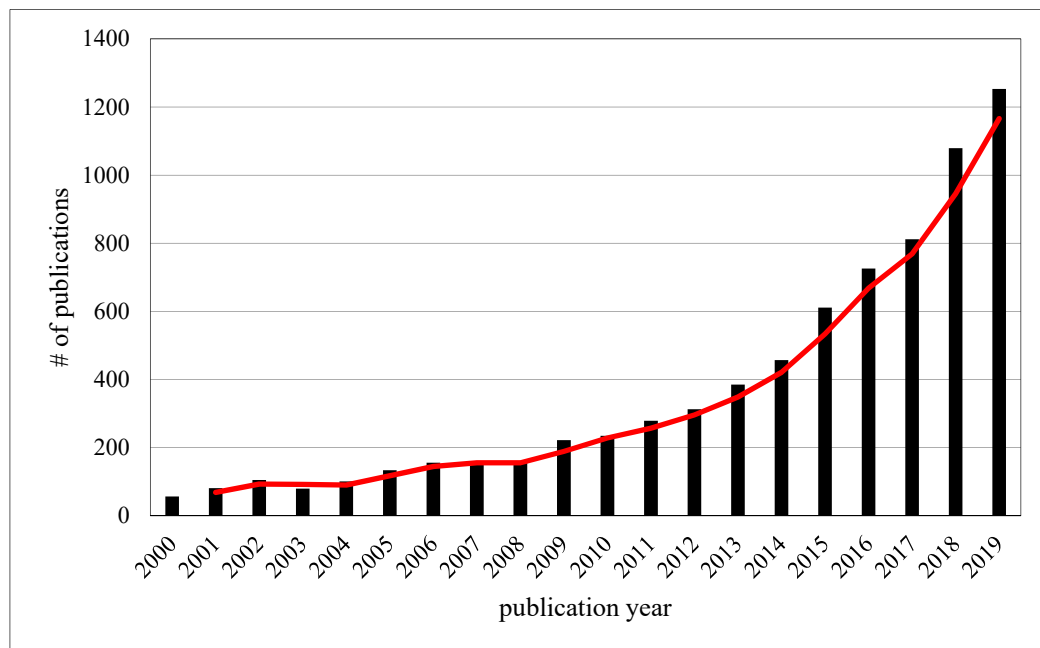

Figure 1. Global research trends in electricity load forecasting since the year 2000 [3].

Rising research trends in electricity load forecasting are primarily due to the integration of new technologies. These technologies may include intermittent renewable generation, distributed generation, smart meters, and electric vehicles, etc. The state of the art load forecasting techniques are expected to perform better in the presence of these technologies which have a higher penetration in developed countries. However, the development of new load forecasting techniques, such as multiple layer perceptron and deep neural networks, have helped in improving the load forecasts in developing countries as well.

Electric loads, on all horizons, i.e., short, medium and long terms, are highly variable in nature. Electricity demand does not only change at utility, but also at sectoral or regional levels. It also depends significantly on the economic profile of a country. For example, the electricity demand trends are different for both developed and developing economies. The demand growth rate for developed countries is 0.7% annually, whereas in developing countries it has risen to a rate of 3% a year [1]. Similarly, major demand determinants in developed and developing countries are different as well. In developed countries, for example, growth in demand is majorly driven by digitalization and electrification [1]. However, in developing countries, demand determinants which hold a comparatively larger significance in electricity consumption growth are income levels, industrial output and the services sector [1].

Besides many other factors, the economic indicators of a country largely impact its electricity demand [1]. With increasing economic activity, the electricity demand tends to rise [4]. To predict such demand trends with a higher accuracy, the inclusion of economic variables in the forecasting models becomes paramount [5]. Therefore, while comparing such forecasting practices between different countries, an understanding of their economic profiles hence becomes an important factor. To make such a comparison, authors have used the World Bank's classification of different countries based on their income levels—an important economic indicator of any country [6]. According to this classification, 138 countries are placed in the category of "Low & Middle Income Countries (LMICs)". From these 138 countries, we identified 15 LMICs suitable for a comparative analysis with a reference country i.e., Pakistan. We used the following selection criteria as shown in the Figure 2a. This process involved four different parameters: the gross domestic product (GDP (current USD)), kWh per capita, CO2 emissions (metric tons per capita), and access to electricity (percentage of the population). Countries with higher parameter values than the reference values were selected. These parameters from all 137 LMICs were compared with the reference parameters (Pakistan). After the comparison, countries with higher values of the mentioned parameters than those for Pakistan were finally selected for our comparison [6]. These countries, as per the World Bank's statistics from 2018, constitute almost 31% of the world's GDP and hence hold a significant importance in terms of a global perspective. It must also be noticed that Nigeria was not included in our final list of countries. As is shown in Figure 3, Nigeria, did not comply with our selection criteria, except for its GDP value.
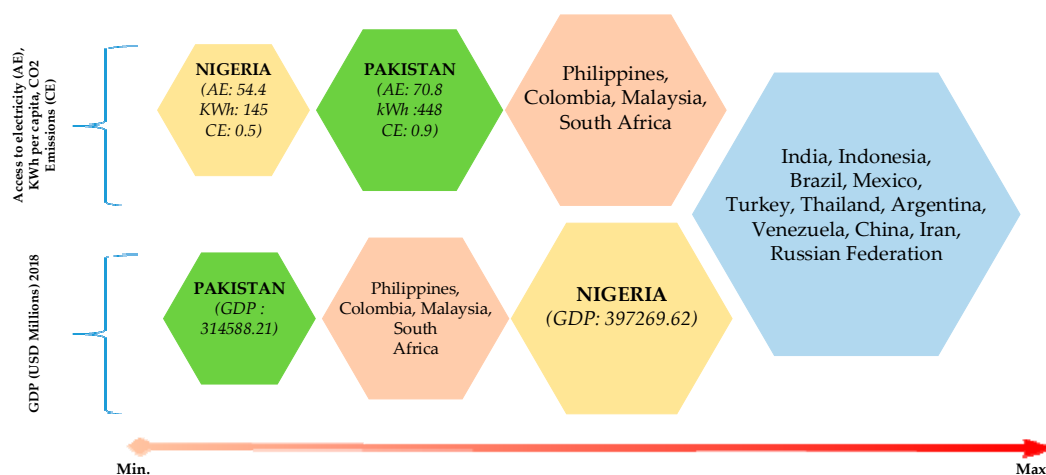

(a)

Figure 2. *Cont.*

(b)
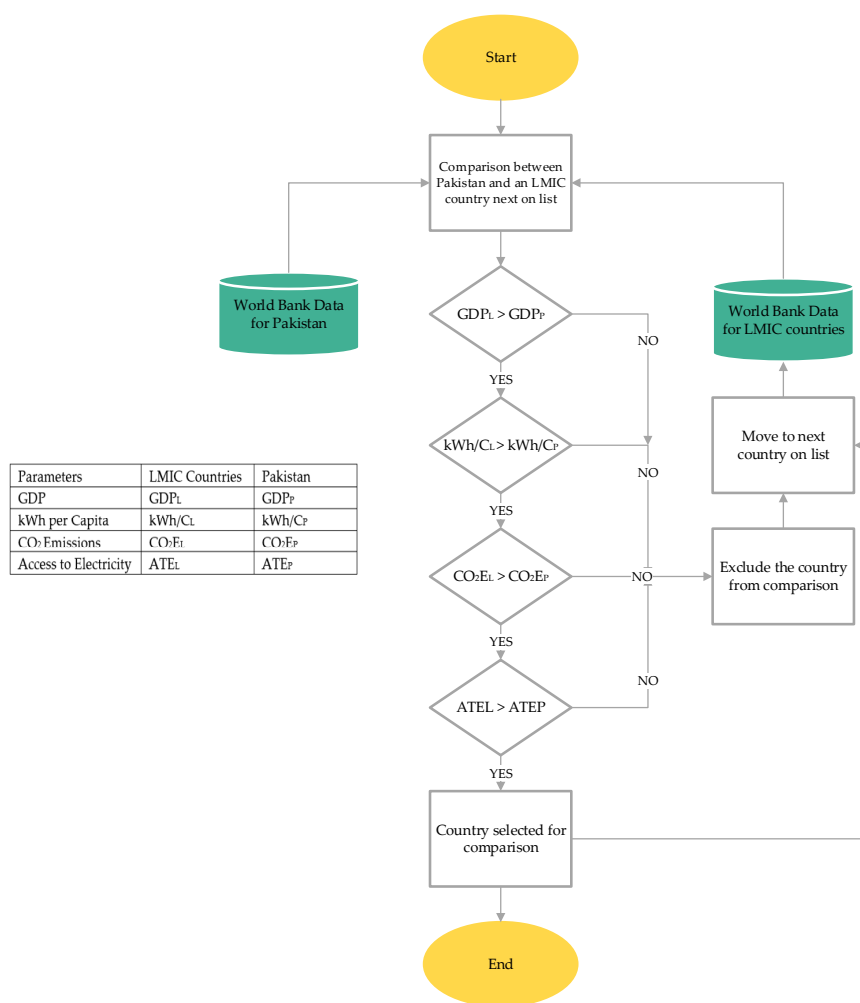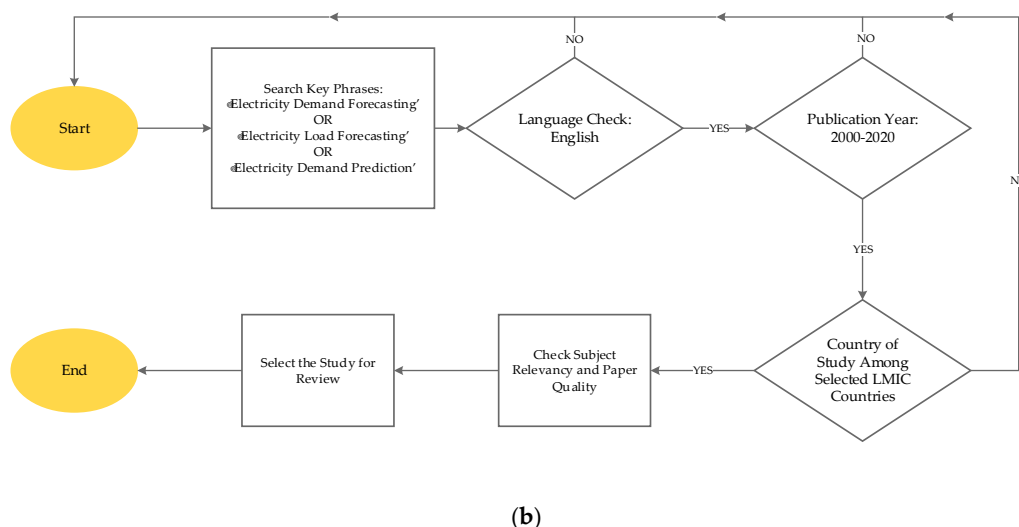
Figure 2. Methodology: (**a**) the country selection process for the comparison with Pakistan; (**b**) the article selection process.

Figure 3. Selection of countries based on their gross domestic product (GDP), access to electricity, kWh/capita, and CO_2 emissions.

In this paper, we have reviewed and analyzed a total of 69 research articles from 16 different countries (including Pakistan), published over the period of last twenty years (2000–2020). Moreover, literature available in the English language was the only literature considered for this study. As shown in Figure 2b, our major key phrases for the literature search, besides country names, included "electricity demand forecasting", "electricity load forecasting", and "electricity demand prediction". During our literature search, we came across several forecasting models and techniques. The ones frequently used by researchers are (a) bottom-up models, (b) top-down models, (c) time series techniques, (d) regression analyses (e) artificial intelligence-based techniques and (f) additive models. In Figure 3, a comparison of the selected countries based on the four filtering parameters is shown.

Prior to writing this review, the authors also identified different orientations in which other review studies on electricity load forecasting are available in the literature. For example, forecasting techniques and models are reviewed and analyzed based on their forecasting performances as presented in [7–9]. In addition to this, review studies with a specific focus on forecasting horizons and application areas are also available. For example, comprehensive reviews on load forecasting for residential consumption, smart buildings, and commercial consumption are presented in [10–12]. Similarly, some review studies have focused on application areas such as smart grids and microgrids as well [11,13,14]. Assisting their readers in selecting a forecasting model, tutorial reviews can also be found in the literature [2,15,16].

Most of these published articles focus on the forecasting for developed countries with very limited focus on the developing countries. Unlike these studies, this study not only reviews the electricity load forecasting techniques, but also its demand determinants based on different forecasting horizons. The strengths and weaknesses of the forecasting techniques and models are briefly discussed along with commentary on a variety of demand driving variables. The study lays out a methodological framework for comparing forecasting practices and demand determinants for any developing country to adopt to and make comparisons. However, this work entails such comparisons for Pakistan with other comparable LMICs. Besides the proposed comparative approach, it also draws the attention of policy and decision makers by facilitating them in adopting the right demand determinants and forecasting methods for their specific needs.

We have reviewed literature from only selected LMICs for comparison. Following the review, we drew a comparison with ongoing research trends on electricity load forecasting and its demand determinants with the reference country, i.e., Pakistan. We have also given an overview of the forecasting practices carried out over last twenty years in Pakistan and fifteen other LMICs. In a comparative analysis with Pakistan, this study shows how different demand determinants are shaping the rise of the future electricity demand in these regions.

This study also provides in depth detail for decision and policy makers on how electricity demand determinants may vary from one time horizon to another. It also unfolds that these determinants may significantly vary in their correlation to electricity demand as the demography pertaining to the forecast model changes. This information plays an essential role for policy makers to understand any forecast model at hand. Moreover, authors' analysis of forecasting methodologies for their advantages and limitations can be instrumental for decision makers while selecting a forecasting methodology for a given region and time horizon.

The rest of the paper follows this structure: Section 2 discusses the importance and dynamics of load forecasting in Pakistan. In Section 3, the literature on different forecasting methodologies and their comparison is presented. Section 4 provides a detailed comparison of demand forecasting methodologies and their determinants. The conclusion is presented in Section 5, followed by the literature references.

2. Importance of Load Forecasting for Pakistan—A Global Perspective

Electricity demand growth trends in developed economies are now flattening [1]. Meanwhile, the annual demand growth rate in developing economies is four times higher than that in developed economies. Estimated to constitute almost 90% of the global electricity demand by 2040 [1], developing economies therefore carry a significant status in the global energy perspective. Such a growth in electricity demand needs to be carefully forecasted using robust forecasting methods. Practically, forecasting a non-linear quantity like the electric load is a complicated task and barely achieves 100% accuracy [2]. Resulting inaccuracies in these forecasts can have serious technical and economic impacts. In the long term, for example, the right allocation of resources, asset management, and investments in power infrastructure can be greatly affected by inaccurate forecasts [17].

Similarly, on a very short term horizon, the unit commitment and generators' availability can have serious impacts following an under or over forecasted load [18]. A resulting inadequacy in capacity planning, loss of load, and outage costs can plunge an already developing economy further into serious economic crisis [17,18]. For example, in 2018, Pakistan paid 4.7 billion USD in terms of the idle capacity charges which partly resulted due to inaccurate demand forecasts [19]. Therefore, the right selection of demand determinants, their combinations, and selection of suitable forecasting models and techniques become important prerequisites for obtaining reliable forecasts.

In Pakistan, there exists a unidirectional causal relationship between its economic growth and electricity demand [20]. Recent economic cooperation between China and Pakistan worth 46 billion USD, i.e., the China–Pakistan Economic Corridor (CPEC), is expected to add 2.5% to Pakistan's current GDP [21]. Consequently, Pakistan's GDP is expected to increase in the future. As shown in Figure 4,

growing trends in Pakistan's GDP per capita and kWh per capita consumption are signaling towards an increasing electricity demand in the future as well. Besides factors adding positively to its GDP, load shedding and unplanned electricity outages negatively impact Pakistan's economic growth [22]. In 2013, for example, Pakistan lost 7% of its GDP due to production losses caused by excessive load shedding in the country [22]. Moreover, an economic crisis in a country also has offsetting effects on its electricity demand [23]. Therefore, while building demand forecast models for Pakistan, the past records and future possibilities of economic crises in the country must also be taken into account.
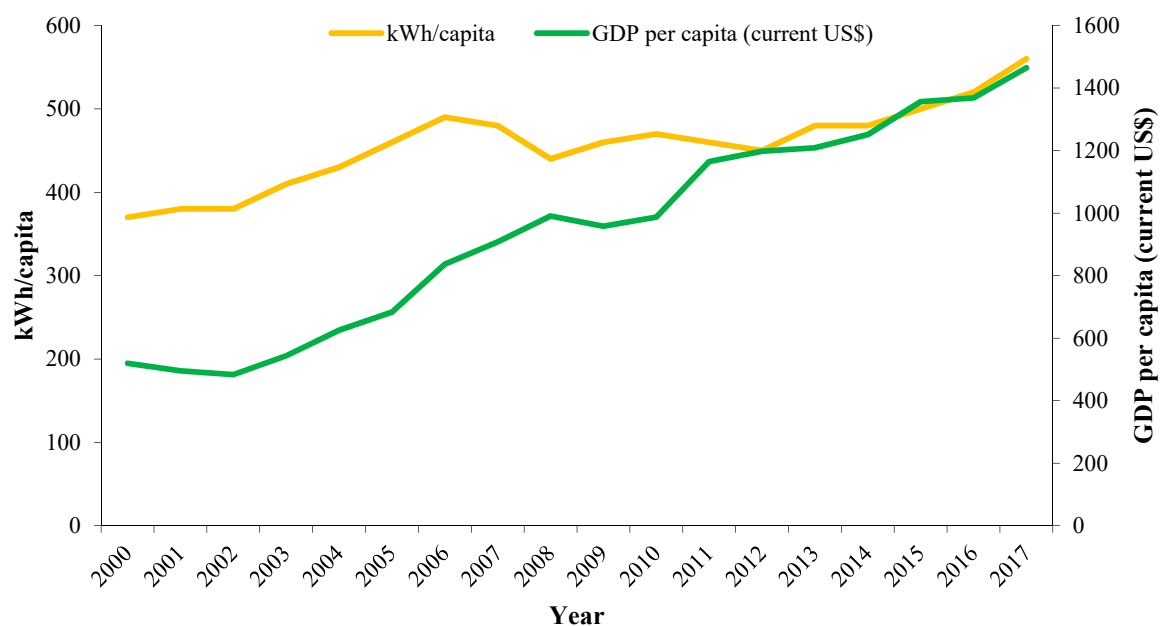
Figure 4. The growing GDP per capita and kWh per capita consumption in Pakistan [24,25].

In addition to its economic growth, the electricity demand in Pakistan is highly driven by different climatic variables as well. Due to the seasonal variability in its climate zones, the bulk power from the north flows to the country's load centers (north-east and south) in the summer, whereas, in the winter, this bulk power flows from major generation centers in the south to load centers (north-east and south) [26]. Moreover, rising temperatures in the country result in electricity demand growth due to the increasing use of air-conditioning in summer [27]. Today, Pakistan stands amongst 28 countries which are most affected due to climate change [28]. It is estimated that a rise of one degree celsius in temperature can result in an additional 109.3 GWh of electrical energy demand in Pakistan [27]. Given the situation and significance of weather variables in load forecasting, it now becomes imperative for forecasters in Pakistan to build forecast models inclusive of its changing climatic conditions.

3. Forecasting Methodologies—Models and Techniques

Based on their forecasting horizons, electricity load forecasts can be broadly categorized into three distinct categories. These categories are:

- Short term load forecasting (STLF)
- Medium term load forecasting (MTLF)
- Long term load forecasting (LTLF)

STLF is usually carried out over time periods ranging from hours to days or weeks ahead [11]. It helps in facilitating electricity markets for the day ahead planning of the electricity supply, and in demand side management (DSM) as well [29]. MTLF, on other hand, deals with the forecasting horizons of months to even years ahead [7]. Such forecasts help in revenue assessments, unit maintenance scheduling, and energy trading etc. [30]. For LTLF, the forecast horizon stretches from roughly five

years to even decades ahead [30]. These forecasts provide a deeper insight for policy makers and help with the efficient management of assets and effective power systems expansion planning. Table 1 shows a few application domains of load forecasts over these time horizons. It is important to note that this is an optimal categorization of forecasting horizons which comes with no set rules. Different researchers may use different time scales for short, medium and long term forecasts.

Table 1. Load forecasting applications over different time horizons [31].

Application	STLF	MTLF	LTLF
Energy purchasing	Yes	Yes	Yes
Transmission & distribution (T&D) planning	No	Yes	Yes
Operations	Yes	No	No
DSM	Yes	Yes	Yes
Financial planning	No	Yes	Yes

3.1. Bottom-Up Models

Bottom-up models produce forecasts at the customer/device level and then sum it up across different customers/devices to a higher aggregation level [32]. While projecting and assessing future energy demands, these models benefit from technological advances by incorporating the detailed load data. For example, in Brazil, the long term yearly electricity consumption for the paper and pulp industry was forecasted by using a bottom-up modeling approach [33]. For this purpose, the authors used the yearly electricity consumption data between 1995–2015.

Bottom-up models are known for their ability to take technological advances into account while forecasting the future electricity demand. However, they do not consider the macroeconomic impacts of long term energy policies and are often considered less suitable for long term forecasting periods [15,34]. Inclusive of its pros and cons, there are many forecasting tools which incorporate a bottom-up modeling framework such as LEAP, MARKAL, and MARKAL-EFOM (TIMES G5 Model). LEAP has been frequently used by researchers for forecasting purposes, whereas TIMES G5 showed occasional appearances in the load forecasting literature. MARKAL, however, is used for energy modeling and planning purposes only [7].

Long Range Energy Alternatives Planning (LEAP)

Since its inception at the Stockholm Environment Institute in 1980 [35], LEAP has been widely used for forecasting practices by researchers, engineers, policy makers and implementers. It is a software package with a bottom-up framework for making forecasts. With its features for including greenhouse gas emissions, LEAP has become an instrumental tool for synthesizing integrated energy policies for future [36]. It offers a decent degree of flexibility in modeling different scenarios ranging from energy demand and supply to the climate change mitigation [35]. In [37], a comparative analysis for the anticipated electricity supply and demand, Greenhouse Gas (GHG) emission reduction and the net present value (NPV) is presented for Pakistan. The authors based this analysis on three different scenarios: business as usual (BAU), new coal (NC) and green future (GF). By developing three different demand side scenarios, the most cost effective scenario, as well as the one complacent with regard to the environmental policies of Pakistan, is identified [38]. In this study, the authors incorporated a range of demand determinants such as the GDP, GDP growth rate, population, population growth rate, and energy intensity growth rate. This study took advantage of LEAP's scenario-based modeling approach and the freedom it offers in developing these scenarios based on a choice of suitable variables. In [39], the authors proposed four supply side scenarios as: the reference, renewable energy technologies, energy efficiency and conservation, and clean coal maximum. These scenarios, with the inclusion of CO_2 emissions, were compared in terms of economic and environmental aspects. Another LEAP model is applied by devising BAU, NC, and GF as three different scenarios [40]. In China, five important scenarios to predict the future electricity supply and demand have been developed [41]. Simplistic, yet

comprehensive, grounds were discovered to analyze a framework incorporating the possible future scenarios for the energy demand and CO_2 projections in Colombia [42]. Using three different scenarios, the authors drew a comparison with the government's power sector expansion plans in Pakistan [43]. By projecting the future gaseous emissions in Pakistan, recommendations to the government were made to include more renewable energy resources and lessen oil and fossil fuel imports.

In addition to scenario-based modeling, LEAP offers the flexibility in developing models based on geographical constructs and sectoral divisions. For example, a LEAP-based study was carried out to forecast the long term electricity demand for the residential sector of Pakistan [44]. In this sectoral demand forecast for the period 2005–2030, results were compared and verified with those provided by the government of Pakistan [45]. For the residential, commercial and industrial consumption sectors, the regional electricity demand for Gilgit Baltistan in Pakistan was forecasted using LEAP models for the period 2016–2040 [46]. Inclusion of variables such as the population growth rates, GDP, income growth rate and household size gives users the freedom to exercise a wide range of scenarios based on different control variables. In China, a LEAP model was developed to forecast the energy consumption in Beijing for the period 2017–2035 [41]. This model was developed under the strict constraints of CO_2 emissions, rendering the region a low carbon economy. In transportation domains as well, a LEAP model is used to monitor the growing energy demand in two cities of Pakistan [47].

3.2. Top-Down Models

Top-down forecast models produce demand projections at the consumption group level by aggregating customers into larger groups [32]. With their ability to feedback information pertaining to the economic growth, these models are helpful for understanding the impacts of energy policies on a country/region's economy. Since they do not include technological aspects, they lack in providing information on technological progress [34]. With a top-down modeling framework, econometric forecast models are one of the commonly used forecasting methods for predicting the electricity demand.

Econometric Forecast Models

To study the relationship between economic indicators and the electricity demand, econometric forecasting models are used usually over medium and long term periods. These models help researchers understand the relationships between indicators such as the GDP, population growth, income per capita, price elasticities, etc., and their impact on future electricity consumption [7].

In a comparative analysis with regression techniques, econometric modeling is preferred for long term electricity forecasting in Russia. It is established that these models take into account more factors comparatively and are hence more suitable for the purposes of strategic modeling [48]. Using both economic and demographic variables, the electricity demand for Pakistan for the year 2025 was forecasted to be 11,500 GWh by using an econometric model [49]. In [50], the authors forecasted the long term electricity demand for the Venezuelan electric power system using econometric modeling. In this model, demand determinants such as the electricity prices, GDP, population, and number of consumers, etc., were used. The econometric approach to forecast the electricity demand in Brazil specifically highlights the dependency of electricity consumption on spatial patterns [51]. In China, the electricity demand forecast for Tianjin was carried out by combining an econometric model and system dynamics model under China's new normal economy [52].

3.3. Regression Analysis

To study the relationship between a set of variables (both dependent and independent), a regression analysis makes use of the Ordinary Least Squares (OLS) estimation to produce the forecast parameters [2]. The main advantage of regression analysis is that it allows to develop a statistical relationship between the dependent and independent variables. For example, the relationship between the electricity load, as a dependent variable, and the GDP, population and weather data, etc., as independent variables can be established. While producing these statistical relationships, forecasters

are required to have knowledge of statistical modeling. This adds to the major drawbacks of a regression analysis [2].

Many variants of regression analyses can be found in the literature. These variants include a linear regression, multiple linear regression (MLR), smooth transition autoregressive models, bagged regression tree, support vector machines (SVM) and so on. A MLR, for example, uses the weighted least square estimation technique to develop a relationship between the input and output variables [13]. Its mathematical representation is given as below [53]:

$$Y_t = v_t a_t + e_t \tag{1}$$

where Y_t—measured values for load, t—sampling time, v_t—vector of demand determinants and e_t—model error.

In the EUNITEComp2001, an SVM model appeared to be the winning entry for medium term forecasts [54]. Moreover, the inclusion of a regression analysis in some of the top entries of Gefcom2012 further vouches for its significance in the forecasting world [55].

Electricity demand forecasts for both short and long term can be conveniently produced using an MLR analysis [2]. Utilizing the past hourly load data and temperature data, the short term electricity demand for Sulawesi Island in Indonesia was forecasted [56]. In the Philippines, the electric load for a grid was forecasted using a multiple linear regression analysis [57]. The model takes past load data and future development plans as input variables. For forecasting the electricity consumption of Mexican border states' maquiladora industries, a multiple linear regression model was used using Microsoft Excel's regression tools [58]. A MLR-based econometric model and univariate time series model show similar forecast results for Pakistan's future electricity consumption [49]. A multiple regression method when applied to India's electricity demand data reaps results quite comparable with a partial end-use technique [59]. For South Africa, the use of a regression-SARIMA modeling framework revealed some important demand governing variables in the country [60]. Based on past load data, the electricity demand forecasting was carried out for Malaysia using a regression-based ARIMA model [61]. When compared to other methods, a MLR sometimes may give less accurate results. For example, the electricity forecast for the agricultural and services sectors of Pakistan was carried out using a MLR in comparison to the OLS technique [62]. This comparison shows the MLR resulting in less accurate forecasts. Similarly, the Artificial Neural Network (ANN) model outperforms the MLR model while giving a long term forecast for the electric energy consumption in Thailand [63]. A demand forecast for Pakistan using the STAR (smooth transition autoregressive) model has been given based on an extensive time series data set of 41 years, i.e., between 1971 and 2012 [64].

Regression models, being non-black box in nature [2], reveal insightful information pertaining to demand driving variables such as the GDP, population, income per capita, weather, calendar days [29]. The relationships between these drivers and electricity demand can be instrumental for researchers and policy makers in devising energy policies and in demand side management. Meanwhile, concerns related to the accuracy levels of these models may counterweigh their above-mentioned merits.

3.4. Time Series Forecasting Techniques

Time series techniques refer to techniques applied on time series data. These techniques make use of a trend analysis to predict future values [7]. In other words, for the example of load forecasting, the future value of the load depends on its previously observed values [65]. This feature allows time series techniques such as the autoregressive integrated moving average (ARIMA) or exponential smoothing to make forecasts solely based on load data. Therefore, the main advantage of these techniques is that it can be non-reliant on the demand determinants for making reliable forecasts. This also leads to an underlying disadvantage of these techniques [2]. These techniques cannot hence be relied upon to gain insight on the electric load and its determinants for a specific utility and time frame. A load time series is a pattern of measured values of load, exhibiting daily, weekly, and seasonal periodicities [66]. There

are numerous techniques which deal with time series data. For example, the autoregressive and moving average (ARMA), and its variants, exponential smoothing technique, Grey–Markov models, structural time series models, and Holt–Winter techniques, etc. Some of these techniques have been frequently used in the literature and make time series forecasting one of the leading forecasting techniques in use [15].

3.4.1. ARMA/ARIMA/SARIMA

The autoregressive order and the moving average order, the two constituents of ARMA models, were used to forecast the electricity demand in ARMA [67]. In ARMA models, the current values of time series ($Y(t)$) are linearly expressed in terms of its previous values, ($y(t-1)$, $y(t-2)$, $y(t-3)$, …), and the current and previous values of white noise, ($a(t), a(t-1), a(t-2), …$) [68]. The mathematical representation of an ARMA model is given as below:

$$Y(t) = \Phi_t y(t-1) + \ldots + \Phi_p y(t-p) + \ldots + a(t-1) + \ldots + \Phi_q a(t-q) \tag{2}$$

Further extensions of the model include the autoregressive integrated moving average ARIMA, seasonal-ARIMA (SARIMA), autoregressive conditional heteroskedastic (ARCH) and generalized-ARCH (GARCH). For short term load forecasting, for example, multiplicative seasonal ARIMA models have been widely popular for years among forecasters [69]. Another generalization can also be found in the literature, which includes exogenous variables, as ARMAX models [2]. Moreover, these models are extensively used in a hybrid fashion with other forecasting techniques as well. For example, an ARIMA–ANN hybrid approach deals with both linear and non-linear correlations in a time series with a higher accuracy than any other model used in isolation [70].

ARIMA models have had a history of aiding researchers, forecasters, and policy makers in forecasting the ever-changing electricity demand at different consumption levels. These statistical models are useful when a dynamic series needs to be converted to a stationary form using the process of differentiation [71]. Utilizing the past data from 1992 to 2014, an energy forecast for Pakistan has been made from 2015 to 2035 using the ARIMA model [72]. An analysis of ARIMA, SARIMA, ARCH/GARCH for forecasting Pakistan's electricity demand renders ARIMA to be the most precise forecasting technique, comparatively [73]. In another comparative analysis, the electricity demand forecast for Pakistan over the period 2012–2020 has been made referring to ARIMA's significance for its use in Bangladesh [74]. In [75], the hydroelectricity consumption in Pakistan up to the year 2030 was forecasted, considering the GDP and population growth rates as demand determinants, using the ARIMA model. Similarly, an electricity demand forecast for Turkey has been provided using ARIMA with a co-integration analysis [76]. The impact of changing electricity prices and income levels on the electricity consumption levels in the future were investigated. In South Africa, the daily peak electrical load has been forecasted using SARIMA, SARIMA–GARCH, and regression-SARIMA–GARCH (reg-SARIMA–GARCH) [77]. Later, a comparison concluded that reg-SARIMA–GARCH showed the minimum mean absolute percentage error (MAPE). In [60], SARIMA is compared with reg-SARIMA while forecasting South Africa's daily peak electricity demand. Results show that the SARIMA model produces more accurate short term load forecasts. The accuracy of the seasonal ARIMA model for forecasting China's electricity demand has been improved by enhancing it with residual modification models [78]. A modified ARIMA model, with peak load predicting capabilities, was used for forecasting the hourly electricity load for an electric power network in Iran. The model takes previous load data and temperature data as input variables [79]. A hybrid forecasting model of a particle swarm optimization (PSO) algorithm, with moving average processes, is introduced while addressing seasonality effects [80]. The method, in comparison to SARIMA, showed a smaller MAPE; hence, it was more precise. Another hybrid model—ARIMA–SVM—is presented to simultaneously forecast the linear and non-linear parts of China's future electricity demand [81]. A model hybridizing ARIMA with ANN is presented to improve the forecasting accuracy [82]. In Malaysia, ARIMA in conjunction with a regression model

has been used to model the electricity demand forecast [61]. Using half-hourly data over the period of one year, a double SARIMA technique was used to forecast electricity demand [83]. A multiplicative SARIMA (MSARIMA) is compared with trend methods used by India's Central Electricity Authority. The comparison shows that MSARIMA outperforms the traditional trend analysis used for electrical load forecasting [84].

3.4.2. Exponential Smoothing

In addition to ARIMA models and its variants, another commonly used time series forecasting technique is called exponential smoothing. Compared to other popular methods, it requires less data for forecasting purposes [2]. Mathematically, exponential models can be expressed as below [68]:

$$Y(t) = \beta(t)^T f(t) + e(t) \tag{3}$$

where t—time, $Y(t)$—load at 't', $\beta(t)$—coefficient vector, $f(t)$—vector for fitting function, $e(t)$—white noise and T—operator for transpose.

Several exponential smoothing methods have appeared to be used in load forecasting applications in the literature. These methods have also been compared with other methods like discount weighted regressions, cubic splines, and a singular value decomposition [85]. The authors in [86] suggest a double seasonal Holt–Winters exponential smoothing method to be the one giving consistency and better results when compared to some other methods. It is simple and can be easily implemented. While dealing with multiple seasonalities in the data, the Holt–Winters exponential smoothing technique can be formulated to adapt to two seasonalities [87]. In [88], a double seasonal adaptation of the Holt–Winters' exponential smoothing method, once again, is suggested as the method outperforming other techniques. Using Pegels' exponential smoothing method, the electrical energy consumption in Brazil has been forecasted up to year 2050 [89].

3.4.3. Some Additional Time Series Techniques

With its vast applicability in forecasting, a time series approach offers several other forecasting techniques as well. For example, ARIMA and Holt–Winter models were tested and compared in [74] for forecasting the electricity demand for Pakistan. A comparison shows that the Holt–Winters model gives better and more robust results. Utilizing past load data from the government of Pakistan, the Holt–Winters technique was used to forecast the electricity demand for Pakistan over the period of 2015–2035 [72]. In [90], the authors forecasted the electricity demand for Malaysia using a Holt–Winters–Taylor technique, traditional Holt–Winters technique and Holt–Winters exponential smoothing technique. In a comparison made by the authors, the Holt–Winters–Taylor technique outperformed the latter two. A variation of the Grey Model GM (1, 1)—grey prediction with rolling mechanism—is used to predict India's electricity and coal consumption. Such models are beneficial when limited data is available for making a forecast [91]. With the application of a singular spectrum analysis (SSA) technique on time series data, the monthly load forecast for a Venezuelan region was produced [92]. Using data from China, two case studies were used to demonstrate an enhanced performance by merging the traditional grey prediction model GM (1, 1) with the trigonometric residual modification technique [93]. A comparison of the univariate time series model and an econometric model shows similar results while forecasting electricity demand for Pakistan [49]. In Turkey, a structural time series modeling approach was used to forecast its industrial electricity consumption [94]. Inclusive of seasonal effects, a functional time series (FTS) analysis was carried out for forecasting the electricity demand for Pakistan [95]. Taking into account the non-stationarity and annual periodicity, STLF for Iranian electric markets was produced using an SSA technique on load time series data [96].

It is, as of now, evident that time series models and techniques for forecasting electricity demand have vastly been used and, in some cases, enhanced by researchers from across the world. It is nearly impractical to give these methods a chronology based on their performance or forecasting accuracy.

Therefore, stating a technique better than another would just be an oversimplification for maintaining any performance hierarchy.

3.5. Artificial Intelligence-Based Techniques

As the computational power is increasing day by day, the use of machine learning and artificial neural networks (ANN) becomes more appealing. With their ability to predict errors before their occurrence, artificial intelligence provides its users leverage to enhance business profitability [97]. While making forecasts using ANNs, forecasters do not have to have knowledge of statistical modeling and data analysis techniques [2]. However, ANN models lack in providing the relationship between the electricity demand and its determinants. When used for forecasting the electrical demand, ANN models learn from given historical data patterns and develop relationships between the input variables and forecasted load. Generally, a neural network requires well spread data in feature space to yield a high accuracy [66]. These networks generally operate in three distinct layers, namely: the input layer, hidden layer, and output layer [11]. In load forecasting, ANNs are mostly used in STLF, but literature on long term forecasting using artificial intelligence-based techniques is also available [7]. While forecasting, different optimization techniques can also be used with ANNs to improve the forecast results.

Another machine learning approach for electricity demand forecasting is called fuzzy logic (FL). Unlike linear regression techniques, fuzzy logic (FL) determines a more vivid relationship between the dependent (e.g., electricity demand) and independent (e.g., GDP, temperature, etc.) variables [2]. It further assists in dealing with a scarce number of observations, hence it is compatible working with comparatively smaller data sets, and error distribution verification processes [2]. Fuzzy logic systems also come with the capability of drawing similarities in big data sets as well. These similarities in the data can be drawn with the help of various first and second order differences in the data as represented below [9].

$$V_k = (L_k - L_{k-1})/T \tag{4}$$

$$A_k = (A_k - A_{k-1})/T \tag{5}$$

where V_k—first order difference and A_k—second order difference.

While using soft computing techniques for load forecasting, hybridization can be a way forward to attain more accuracy and precision. It allows researchers to test and experiment with the combination of different techniques. Using a chaotic PSO with a support vector regression (SVP) can be one of many examples [98].

By using past load data and weather variables of Dalian city in China, STLF was produced by using generalized regression neural networks with a fruit fly optimization algorithm (FOA) [99]. A scenario-based long term forecast for Wuhan, China was carried out by using a particle swarm optimization–genetic algorithm–radial basis function (PSO–GA–RBA) model [100]. Daily electricity demands in smaller population areas of Colombia were forecasted by using a back-propagation (BP)-based ANN model [101]. Three approaches to forecasting electricity demand—simulated-based ANN, ANN, and conventional time series—are tested and compared. Based on lower MAPEs, ANNs turn out to be the most suitable approach for forecasting the monthly electricity demand for Iran [102]. For a day ahead load forecasting for a province in Argentina, different methods were applied using weather data, previous consumption data, and calendar days as demand determinants. Results show that, compared to other methods (MLR, feed-forward neural networks), radial basis function (RBF) neural networks perform better in the given case [103]. In another study, an RBF-based SVM regression performs with a better accuracy while forecasting the industrial electricity consumption in Russia [104]. On a load data set from a substation in Agra, India, STLF was carried out by using generalized neural networks (GNN) [105]. It is maintained that GNNs are advantageous compared to ANNs in terms of their structure related decisions, neuron selection, and the longer training times of ANN. Another comparison is made between BP–ANN and PSO–ANN models while computing the LTLF for Tamil

Nadu, India [106]. Emphasis, here, is made on PSO as a better optimization technique. Similarly, another LTLF for India uses k-mean clustering with ANNs by using 18 years of past load data as an input to the ANN model [107]. In Indonesia, STLF was carried out by using two different variants of ANN and FL on half-hourly and hourly load series data [108]. Using ANNs, a short term load forecasting model for a retail company in Russia was created using load data, weather data, and calendar days as demand determining variables [109]. By using historical load data, different variants of ANNs have been used and compared for Malaysia's electricity demand forecasts [110]. Considering twelve different economic indicators as model inputs, the long term electricity demand for an Iranian power grid was forecasted using ANNs and fuzzy networks [111]. STLF for South Africa's electrical load was modeled using an adaptive neuro fuzzy inference system (ANFIS) and was validated using the actual load data from utility [112]. In [113], ANN's performance superiority over ARIMA and MLR is presented while forecasting for Thailand's electricity demand. However, in [114], genetic programming and simulated annealing (GSA) was shown to produce more accurate results compared to ANNs while forecasting Thailand's long term electricity demand.

Socio-economic and climatic indicators are one of the significant demand determinants for electricity. Incorporating these indicators as descriptor variables, the long term electricity demand for Turkey was forecasted in [115]. Both ANN and MLR techniques were used and compared. Results of the forecast indicate that the unemployment percentage was insignificant in determining any changes in Turkey's future electricity demand. However, the inflation percentage had minor impacts on the electricity demand in Turkey. In another study, the monthly electricity demand for Turkey was forecasted by using four different seasonal ANNs [116]. When compared with SARIMA, ANN-based models showed more accurate forecasts. For the Moscow region, Russia, the daily electricity consumption was forecasted using past consumption data and calendar effects in an ANN-based forecasting model [117]. ANNs and a bagged regression tree (BRT)-based day ahead LF was carried out on 17 months of data provided by IESCO-Pakistan. Results show that the BRT with 96.66% accuracy is better than an ANN which has a slightly lower accuracy percentage of 96.28% [118]. A tree-based decision algorithm (XGBoost) using machine learning techniques has been used to forecast an hourly electric power load of an educational institution in Pakistan [119].

3.6. Additive Models

Additive models, for load forecasting, fall under the domain of statistical methods. These models are designed to incorporate non-linearity between dependent and independent variables [2]. Due to their flexibility, accuracy, and interpretability, there is an increasingly popular variation of additive models called generalized additive models (GAMs). These models have the following mathematical representation [120]:

$$y_{t+h} = l(m(x_t)) = \beta_o + a_1(x_{1t}) + \ldots + a_p(x_{pt}) \tag{6}$$

where l—link function, m—gh = σh = smooth functions, a_k—parametrically specified function/non-parametrically specified smooth function and x_{kt}—kth component of vector xt where $k = 1, \ldots, p$.

These models, when allowed to have non-linear and non-parametric terms in a regression framework, have shown to find complex relationships between the electric load and its determinants [121]. In GEFcom2014, quantGAM was ranked the best in terms of the probabilistic electric demand forecasting stream [122]. Besides that, functional additive models and boosted additive models have also been discussed in the literature on electricity demand forecasting [120,123].

In China, the electricity demand was forecasted using meteorological and economic factors as input variables for a semiparametric additive model [124]. Utilizing the hourly load data along with the national aggregated average temperature data, a medium term electric load forecast for South Africa was carried out using a GAM [125].

In this section, we have reviewed and analyzed various forecasting methodologies and have presented their advantages and limitations. However, the selection of these methodologies solely

depends on the available data and related constraints and not on their forecasting accuracy per se [2]. Therefore, it is nearly impossible to develop a hierarchy of these methodologies based on their forecasting performance.

4. Electricity Demand Forecasting Methodologies and Its Determinants—A Comparative Analysis

Electricity load forecasting studies were carried out on three majorly different forecasting horizons, i.e., LTLF, MTLF, and STLF. According to these forecasting horizons, different works we reviewed have used different sets of demand determinants and forecasting models/techniques. This section provides a comparative analysis of the major academic studies from Pakistan and some meaningful solutions on subject from our selected pool of LMICs. Since many articles used more than one model/technique for comparative purposes, it must be noticed that every such model/technique was separately counted and considered during our analysis. To facilitate this analysis, Table 2 below provides information related to the forecasting horizon, country of study, methodologies, demand determinants, publication years, and forecast periods.

According to different forecasting horizons, an overall contribution of the literature analyzed in this study is represented in Figure 5. Since a comparison is to be made between Pakistan and LMICs, our study set includes LTLF the most for the significance it carries regarding the long term policy implications for developing economies. In Pakistan, 87.5% of the academic studies carried out are on LTLF, therefore, we chose our LTLF study set for LMICs larger compared to MTLF and STLF for a fair comparison. Similarly, the second subset of the study set we reviewed comprises of STLF (31.8% of total studies). We have found that in Pakistan, studies on STLF utilizing indigenous data sets from within Pakistan are very limited. Considering the present and future impacts of climate change in Pakistan, it is imperative to carry out more STLF studies in Pakistan. What is also important is to make use of the relevant demand determinants such as the temperature, rainfall, humidity, etc., in these studies. MTLF contributes to our study set the least (14.4% of total studies). Despite the importance it carries regarding revenue assessment and energy trading, etc. [30], no such study has yet been carried out in Pakistan. Therefore, an overview for the MTLF studies is also provided for readers to help construct a vivid picture of medium term load forecasting for Pakistan in contrast to other LMICs.
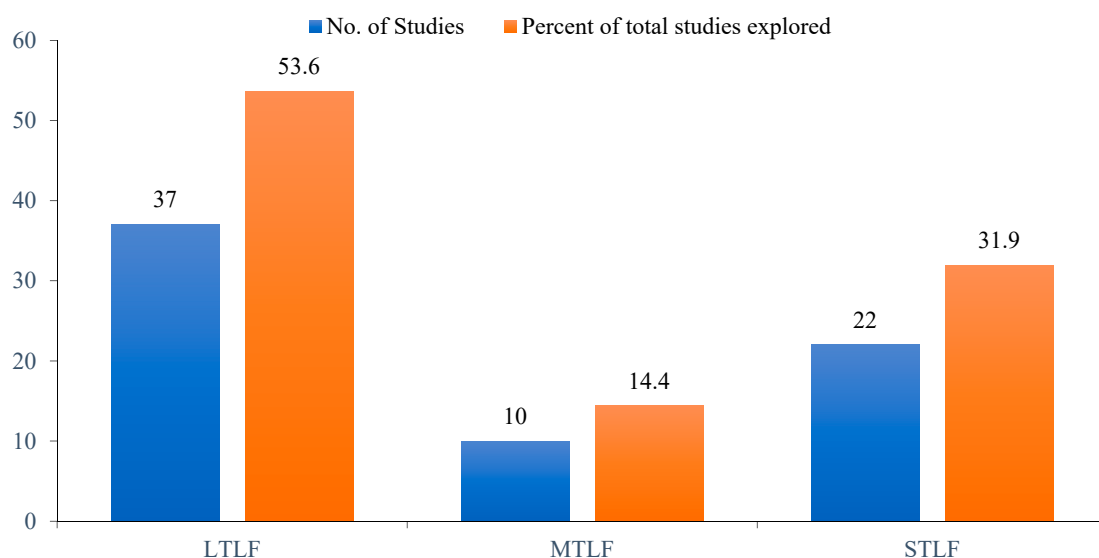

Figure 5. A forecast horizon-based categorization of the reviewed studies.

Table 2. Summary of the main features of the reviewed literature.

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
LTLF	Colombia	Long-range Energy Alternative Planning System (LEAP)	GDP, number of households, national vehicle fleet (vehicles per household)	2018	2015–2030 & 2015–2050	[42]
LTLF	China (Beijing)	Long-range Energy Alternative Planning System (LEAP)	Terminal energy needs, activity levels, energy intensity, departmental activity, terminal activity, energy equipment activity level, environmental emission, environmental emission factor	2019	2017–2035	[41]
LTLF	Turkey	Cointegration and ARIMA	Price, GDP per capita, consumption per capita	2007	2005–2014	[76]
LTLF	South Africa	ARMA, Neural networks and Neuro-fuzzy systems	Previous consumption data	2014	1985–2011	[67]
LTLF	Pakistan	Bottom up Approaches (LEAP Model)	Population, GDP, Electricity consumption per capita, GHG emissions	2019	2015–2035	[43]
LTLF	Pakistan		GDP, GDP growth, Population, Population growth, energy intensity growth rate	2015	2011–2030	[37]
LTLF	Pakistan		income, income growth rate, population, and population growth rate, number of households, household size and GDP	2018	2016–2040	[46]
LTLF	Pakistan		GDP growth trend, electricity consumers growth, fuel cost, Technology's lifetime, Plant Capacity Factor	2018	2015–2050	[39]
LTLF	Pakistan		Electric consumer growth, level of activities (number of consumers), final energy intensity (energy consumed per consumer), forecasted growth and other factors.	2014	2011–2030	[40]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
LTLF	Pakistan		Rate of urbanization, penetration of energy efficient devices, population growth control plan, economic growth, domestic consumption trends. Income growth.	2012	2005–2030	[44]
LTLF	Pakistan	ARIMA (3,1,2), SARIMA (2, 1, 2), SMA (12), ARCH (2), GARCH (1,1)	Socioeconomic Factors, Seasonal Variations.	2014	1990–2011	[73]
LTLF	Pakistan	ARIMA, Holt-Winter, LEAP	Not Discussed	2017	2015–2035	[72]
LTLF	Pakistan	Functional Time series (FTS)	Seasonal variations, economic growth, urbanization, population growth, industrialization	2015	2012–2021	[95]
LTLF	Pakistan	Ordinary Least Square technique using MDEE Model & multiple linear regression Index Model	GDP, population, electricity price, previous year's electricity demand, and the number of consumers	2012	2007–2030	[62]
LTLF	China	Trigonometric grey prediction approach	Not discussed	2006	1981–2001	[93]
LTLF	India	Grey-Markov, Grey	Not discussed	2009	2005–2015	[91]
LTLF	Turkey	structural time series analysis	Electricity prices	2011	2010–2020	[94]
LTLF	China	Econometric Model and System Dynamic Approach	Internet age, marketization reform, technological progress and consciousness of energy conservation and emission reduction.	2017	2000–2050	[52]
LTLF	Brazil	Spatial econometric approach using ARIMA model	Spatial Data, Past consumption, GDP, and population	2017	Not Provided	[51]
LTLF	Thailand	MLR/ANN	GDP, population	2015	2010, 2015,2020	[63]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
LTLF	India	Regression Techniques	Net State Domestic Product (NSDP), Sector-wise Domestic Savings Household sector, Consumers, Connected Load	2019	2006–2012	[59]
LTLF	Philippines	Multiple Linear Regression	Historical data, number of consumers for past 5 years, development plans (commercial, industrial etc.) for next 10 years	2017	2016–2025	[57]
LTLF	China	Hybrid self-adaptive Particle Swarm Optimization–Genetic Algorithm–Radial Basis Function	GDP, population, industrial energy intensity, average annual temperature	2014	2013–2020	[100]
LTLF	India	K-mean clustering and ANN	Load data and population	2018	2018–2026	[107]
LTLF	India	ANN-PSO Models	Population, consumers, per capita income/GDP	2017	2001–2015	[106]
LTLF	Thailand	Genetic Programming and Simulated Annealing (GSA) Model	Population, gross domestic product (GDP), stock index, and total revenue from exporting industrial products	2013	2004–2009	[114]
LTLF	Thailand	ANN, ARIMA, MLR	Population, stock exchange index, GDP and amount of export	2011	1986–2010	[113]
LTLF	Turkey	ANN	Population, GDP per capita, inflation percentage, unemployment percentage, average temperature	2015	2014–2028	[115]
LTLF	Pakistan	STAR (Smooth Transition Auto-Regressive) Model	GDP per capita, Electricity Prices	2014	1971–2012	[64]
LTLF	Brazil	Bottom-Up Approach	Previous load data (1995–2015), electric consumption by process, value added of different sectors, electricity price, production and value addition forecasts until 2050	2017	2015–2050	[33]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
LTLF	Pakistan	Winter Holt and ARIMA	Consumption Sectors: Household, Govt. Sector, Street Lights, Commercial, Industrial, Agriculture.	2015	2012–2020	[74]
LTLF	Pakistan	Univariate Time Series Model, Multiple Linear Regression based Econometric Model	GDP, Income per capita and Population	2011	2011–2025	[49]
LTLF	Pakistan	ARIMA	Hydroelectricity consumption data, GDP, population growth rates	2020	2018–2030	[75]
LTLF	Russian Federation	Regression Analysis AND Econometric Models	Elasticity of GDP, electricity intensity, GDP growth rate, income growth rate, electricity prices	2009	N/A	[48]
LTLF	Venezuela	Econometric Model	GDP, Electricity price, number of consumers, aluminum and iron price, population.	2006	2004–2024	[50]
LTLF	Mexico	Multiple Linear Regression	Number of establishments, number of employees, number of shipments, electricity prices, natural gas prices	2004	2002–2010	[58]
LTLF	Islamic Republic of Iran	ANN and FL	GDP, GDP without accounting for oil, (GNP), Iranian oil price, value added of manufacturing and mining group, oil income, population consumer price index, gas consumption, electricity, water and gas supply, exchange rate, gold price	2008	2008–2011	[111]
MTLF	China	Residual Modification of SARIMA	GDP, generation	2012	Apr2010–Sept 2010, 2011–2013	[78]
MTLF	India	MSARIMA	Previous loads	2012	April 2010–March 2011	[84]
MTLF	Malaysia	Holt-Winters Taylor (HWT), Holt-Winters, modified Holt-Winters exponential smoothing	Previous load data, seasonal patterns	2013	2005–2006	[90]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
MTLF	Thailand	MLR/ARIMA	Seasonal weather, national economic growth, monthly peak load	2006	2006–2007	[126]
MTLF	Turkey	Seasonal ANN	Load data and weather	2017	Monthly forecasts between 2015 to 2018	[116]
MTLF	China	SVR (support vector regression) with chaotic artificial bee colony algorithm	Past Load Data	2011	Monthly forecasts from Oct 2008 to April 2009	[127]
MTLF	South Africa	Generalized Additive Model	Temperature and load data	2017	Monthly predictions	[125]
MTLF	China	Semiparametric-based additive model	Meteorological and economic variables	2014	Monthly predictions between 2006–2011	[124]
MTLF	Russian Federation	ANN (Caterpillar-SSA Method)	Load data, calendar effects (days, week, month, years)	2017	-	[117]
MTLF	Venezuela	Singular Spectrum Analysis of Time Series Data	Load data	2013	-	[92]
STLF	Islamic Republic of Iran	ARIMA	Load data, temperature data	2001		[79]
STLF	Pakistan	ANN & Bagged Regression Tree	Weather, time factor, past load data	2018		[118]
STLF	South Africa	SARIMA, SARIMA-GARCH, Reg-SARIMA-GARCH	Previous consumption data, Seasonality, Day of the week, month, year	2011		[77]
STLF	South Africa	Regression-SARIMA	Previous consumption data	2012		[60]
STLF	China	Hybrid of ARIMA and SVMs	Previous loads, day of the week, weather	2012		[81]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
STLF	China	ARIMA-ANN	Previous loads	2004		[82]
STLF	Malaysia	Double SARIMA	Previous load data	2010		[83]
STLF	Malaysia	Holt-Winters Taylor (HWT), Holt-Winters, modified Holt-Winters exponential smoothing	Previous load data, seasonal patterns	2013		[90]
STLF	Indonesia	Multiple Linear Regression	Historical data, temperature data	2007		[56]
STLF	China	Decreasing step fruit fly optimization algorithm	Historical data, weather/temperature data	2017	Forecast periods for STLF are diverse and reveal no significant information. Therefore, these time periods are not provided.	[99]
STLF	Colombia	ANN	Historical load data	2015		[101]
STLF	India	FL and WNN	Past load data	2014		[105]
STLF	Indonesia	Singular spectrum analysis, fuzzy systems and neural networks	Load data	2019		[108]
STLF	Malaysia	ANN	Load data	2010		[110]
STLF	Philippine	Fast ANN	Load data, day timings (day of week, week of month)	2015		[128]
STLF	South Africa	Adaptive Neuro Fuzzy Inference System—ANFIS	Temperature, humidity, load data	2010		[112]
STLF	Pakistan	XGBoost Algorithm using NN	Load data, weather data	2019		[119]
STLF	Argentina	Radial Basis Function Neural Network, and Feed-forward Neural Network, Multi-Linear Regression	Load data, weather data (temperature etc.), days of the week/month	2017		[103]

Table 2. *Cont.*

Forecast Horizon	Country of Study	Forecasting Methodologies	Demand Determinants Involved	Study Year	Forecast Period	Ref. No.
STLF	Russian Federation	Long short-term memory ANN, SVM regression based on radial basis functions (RBF) SVM Regression linear and ARIMA.	Load Data	2019		[104]
STLF	Russian Federation	ANN	Load Data, calendar effects, temperature, wind speed	2018		[109]
STLF	Islamic Republic of Iran	ANN	Load data	2008		[102]
STLF	Islamic Republic of Iran	Singular Spectrum Analysis of Time Series Data	Load data	2011		[96]

Based on the forecasting methodologies these studies incorporated, another categorization is presented and analyzed here. Overall, a variety of forecasting models and techniques were used. However, we broadly constructed and compared six study groups based on the different forecasting methodologies they followed. Figure 6 gives an insight into how different studies adopted different forecasting approaches. Owing to an increasing computational power, artificial intelligence-based forecasting techniques have mostly (39.1% usage) been used by forecasters. Next to that, time series modeling finds its place as the second (31.8% usage) most used forecasting methodology. Additive models, with 2.9% usage only, seem to carry the least significance, comparatively.
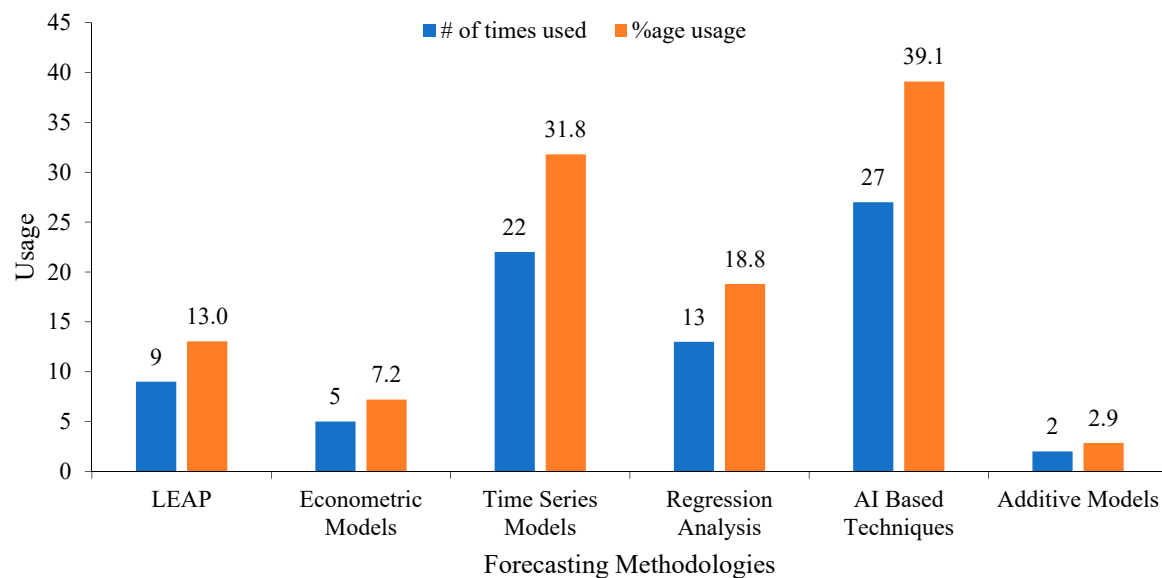
Figure 6. Use of different forecasting methodologies.

Figure 7 shows the usage of different forecasting methodologies over different forecasting horizons. For example, time series modeling has been majorly used while forecasting for long and medium terms (35% and 50%, respectively), whereas for STLF, 64% of the studies used machine learning-based techniques. LEAP and econometric models were used for only LTLF while additive models were used for MTLF only. Overall, time series models, regression analyses, and machine learning-based techniques found their applications in all three categories, i.e., LTLF, MTLF, and STLF.
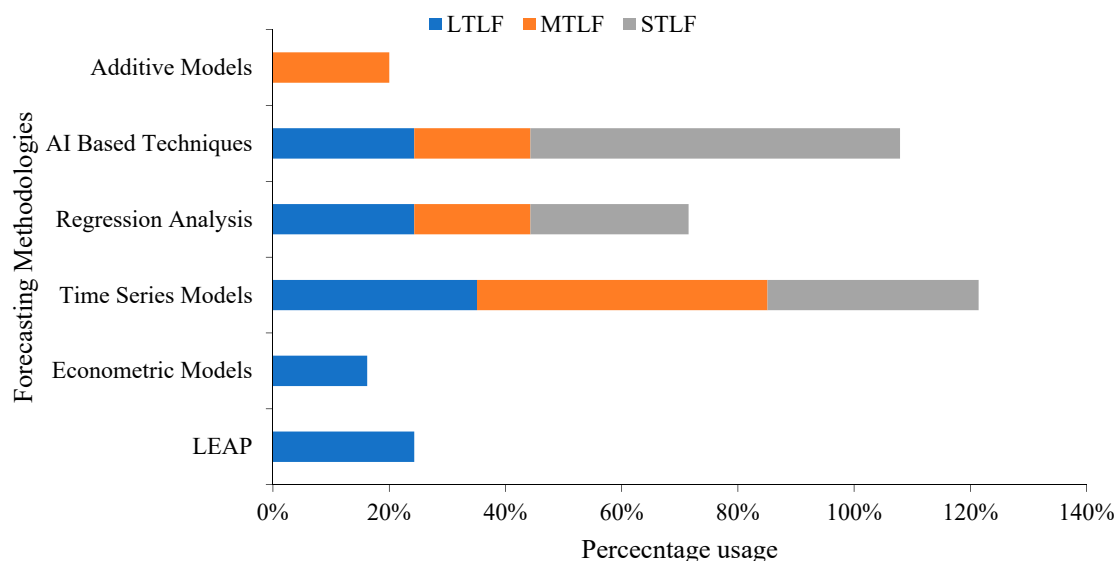

Figure 7. Use of forecasting methodologies over different time horizons.

While exclusively looking at the study set from Pakistan, we see that out of the sixteen studies we analyzed, only two studies were found to utilize data sets from Pakistan for STLF. These were the only articles we included under our STLF category for Pakistan. Fourteen studies were categorized as LTLF studies, whereas no study was found in the MTLF category.

Having said that, in Pakistan, forecasters seem to use LEAP (50%) and time series models (43%) the most while forecasting over long terms. Surprisingly, no long term study made use of machine learning techniques. However, for STLF, as shown in Figure 8, both the studies used machine learning-based techniques.
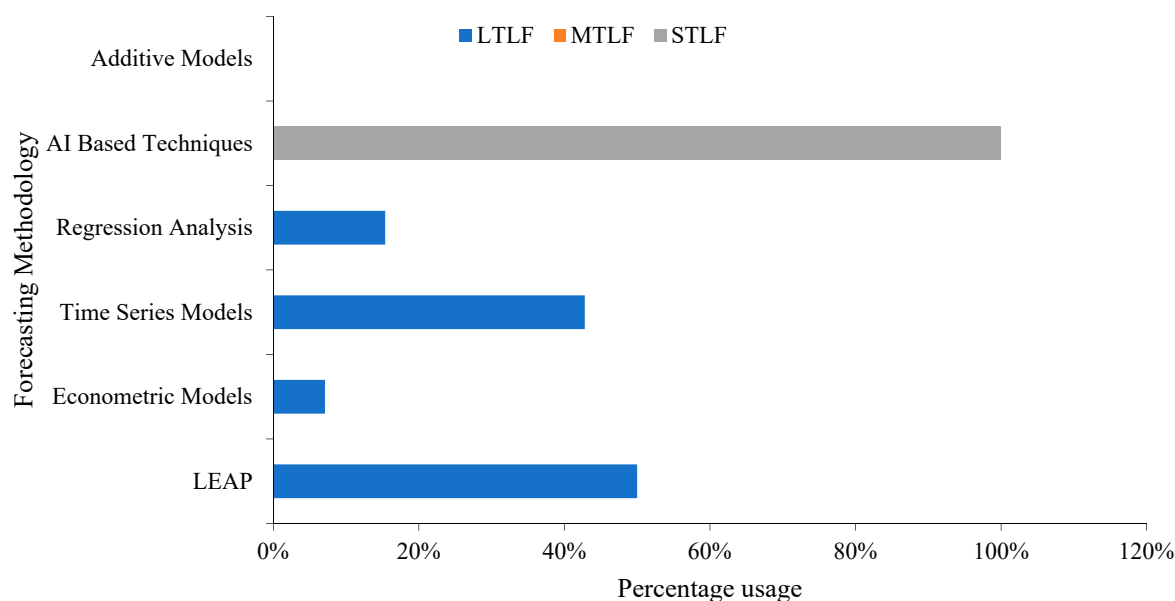
Figure 8. Usage of forecasting methodologies over different time horizons in Pakistan.

In the LMIC study set, it can be seen in Figure 9 that artificial intelligence-based forecasting techniques dominate the LTLF and STLF categories with a usage of 39% and 60%, respectively. For MTLF, time series models constitute a bigger chunk with a 50% usage. It can also be noticed that LEAP, which constituted the biggest chunk (50% usage) in the Pakistani study set, is one of the least used (9% usage) methodologies in the LMIC study set. Owing to their robustness and high computational power, AI-based forecasting methodologies have been frequently used in Pakistan's neighboring countries like China and India. Therefore, a paradigm shift is now indispensable for forecasters in Pakistan as well to adapt to these forecasting methodologies rather than sticking to previous and relatively older methods.

Electricity demand, as mentioned earlier, is driven by a variety of determinants. These determinants change in accordance with the changing forecasting horizons. Table 3 gives the frequency of occurrence of twenty-one demand determinants which showed up in our study sets from both Pakistan and LMICs. Determinants such as the GDP (29.0%), population (21.7%), previous load data (53.6%), and weather data (30.4%) were considered the most throughout our data set. Contrary to that, factors like energy conservation (1.4%), device/appliance efficiencies (1.4%), and urbanization (2.9%), etc., are amongst the least used variables for electric load forecasting studies. Other demand determinants such as the income/income growth rate/income per capita (8.7%), industrial development (7.2%), number of consumers/consumer growth rate (10.1%) and electricity prices (11.6%) were also not used often. It is worth mentioning that the energy efficiency measures, electrification rates, income levels, and industrialization are one of the main demand driving factors which need to be modeled while forecasting for Pakistan [1].
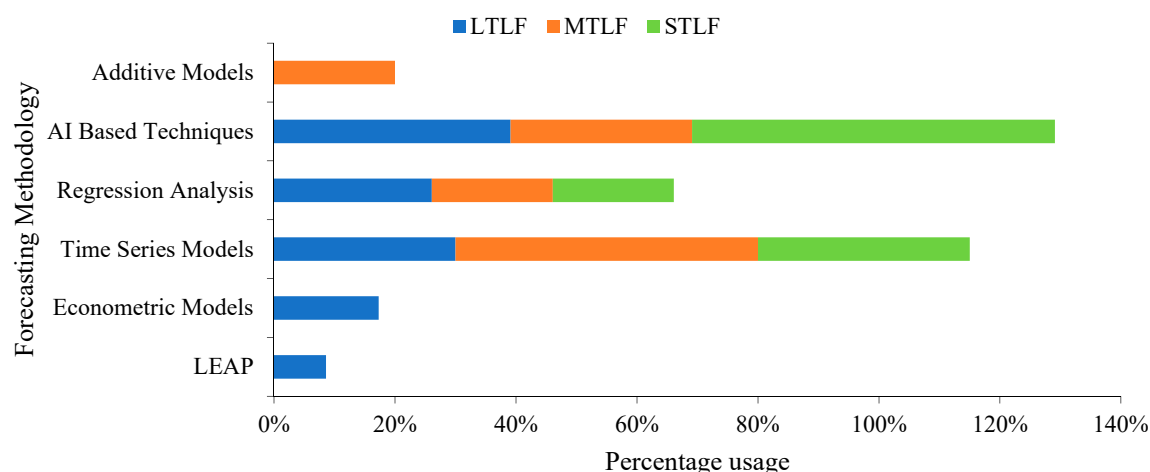
Figure 9. The usage of forecasting methodologies over different time horizons in low and middle income countries (LMICs).

Table 3. Usage of different electricity demand determinants.

Electricity Demand Determinants	Frequency of Occurrence	%Age Usage Over Total Studies Reviewed
GDP/Economic growth	20	29.0
GDP growth rate	3	4.3
GDP/capita	3	4.3
Population	15	21.7
Population growth rate	5	7.2
Consumption per capita/Energy intensity	4	5.8
Energy intensity/Energy intensity growth rate	6	8.7
Income/Income growth rate/Income per capita	6	8.7
Weather (temperature, humidity, rain levels etc.)	21	30.4
Electricity prices	8	11.6
Number of consumers/consumer growth rate	7	10.1
Previous load data	37	53.6
Household size/household growth rate/number of households	2	2.9
Urbanization	2	2.9
Stock exchange index	2	2.9
Spatial data	1	1.4
Socioeconomic factors	1	1.4
Energy conservation	1	1.4
Device or appliance efficiency	1	1.4
Industrial development	5	7.2
Calendar Effects	4	5.7

The percentage usage of different demand determinants over all three forecast horizons is shown in Figure 10. For LTLF, the GDP, population and industrial development have been mostly used. Of all the LTLF studies we reviewed, 40.5% studies used the GDP and 48.6% used population data as demand driving variables. These studies also used previous load data (21.6%), number of consumers/consumer growth rate (18.9%), energy intensity/energy intensity growth rate (13.5%), income/income growth rate/income per capita (13.5%), electricity prices (10.8%), and industrial development (8.1%) as demand driving variables in their analysis. Inclusion of these variables in LTLF studies shows their relevance and importance as demand determinants for long term forecasts. Meanwhile, looking at MTLF and STLF study sets, neither of the two had industrial development or electricity prices as demand determinants. Only 30% of the MTLF studies we reviewed considered the GDP as an electricity demand determinant. Contrary to the significant use of GDP and population data for LTLF, MTLF and STLF, studies incorporated weather variables and previous load data most frequently. In the MTLF

study set, 40% of the studies used weather variables and 80% of studies used previous load data as demand determinants. Similarly, in the STLF study set, 41% of studies used weather related variables and almost all the studies used previous load data as their major demand determinants. A portion of the STLF studies (13.6%) also took into account the calendar effects. In the LTLF study sets, inclusion of these variables seems comparatively quite a lot less. Only 8.1% of the studies used weather variables and 21.6% of the studies used previous load data as one of the demand determinants. It is interesting to note that 80% of the demand determinants we identified were only used for LTLF. The only variable which was used in both MTLF and STLF, but not in LTLF, was the calendar effects. Determinants like weather variables and previous load were incorporated in all the three categories of long, medium and short term forecasts.
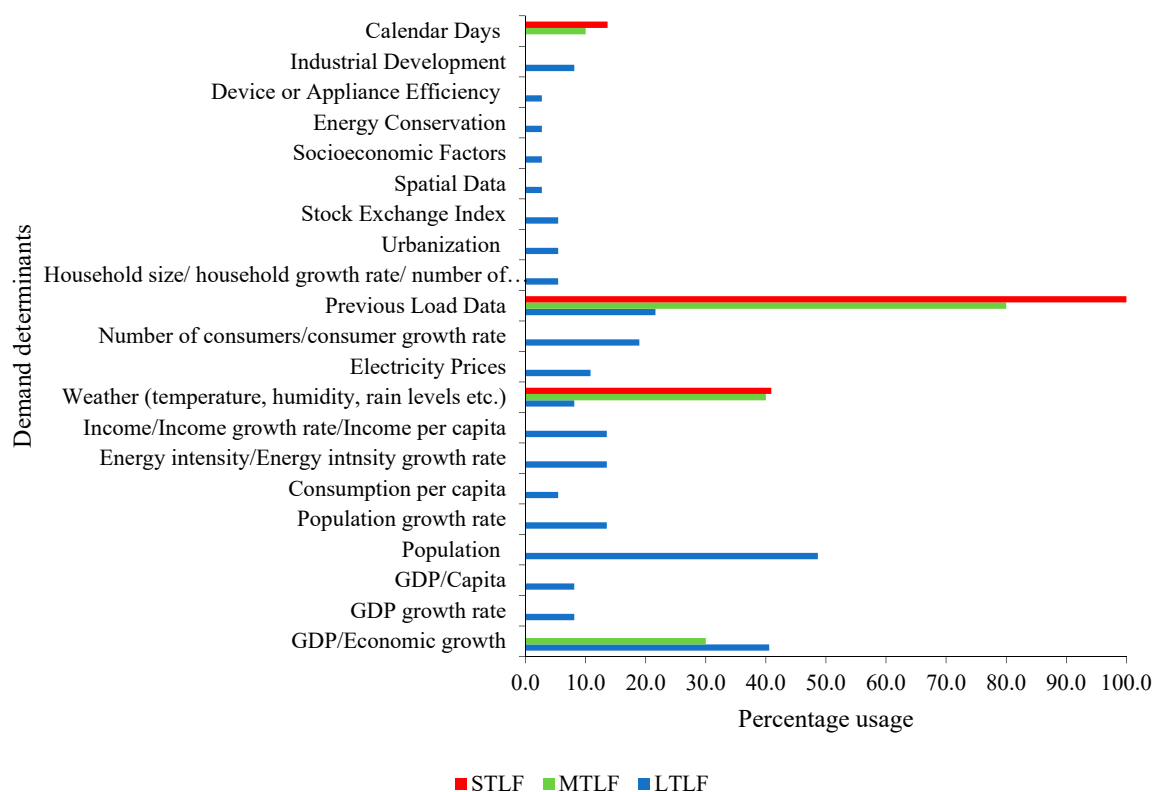
Figure 10. Electricity demand determinants over different forecasting horizons.

It can be noted in Table 4 that for different countries, the nature of electricity demand determinants generally changes according to the country's economic, demographic, and climatic dynamics. Therefore, prior to developing a forecast model for a region, the demand determinants of that particular region must be carefully examined.

Table 4. The electricity demand determinants in selected countries.

Country Name	Variables Most Frequently Used in Forecast Models
China	Terminal energy needs, energy intensity, environmental emission factors, technological progress, energy conservation, GDP, population, weather variables, generation, load data, calendar effects,
India	Net State Domestic Product, sector-wise domestic savings, consumers, connected load, load data, population, consumers, per capita income/GDP
Pakistan	Population, GDP, per capita consumption, GHG emissions, energy intensity growth rate, income related variables, household variables, electricity consumers growth, fuel cost, technology's lifetime, plant capacity factor, urbanization rate, energy efficiency, population growth control plan, electricity price, hydroelectricity consumption data, weather variables
Islamic Republic of Iran	GDP, Iranian oil price, value added of manufacturing and mining group, oil income, population consumer price index, gas consumption, electricity, water and gas supply, exchange rate, gold price, load data, weather data
Russian Federation	Elasticity of GDP, electricity intensity, GDP growth rate, income variables, electricity prices, load data, calendar effects, weather variables.
Colombia	GDP, household variables, national vehicle fleet, load data
Turkey	Electricity price, GDP per capita, electricity consumption per capita, load data, weather variables, population, inflation percentage, unemployment percentage, weather variables.
South Africa	Load data, weather variables, calendar effects
Argentina	Load data, weather variables, calendar effects
Philippine	Load data, calendar effects, number of consumers, development plans.
Thailand	Population, GDP, stock index, total revenue from exporting industrial products, stock exchange index, weather variables, load data
Venezuela	Load data
Malaysia	Load data, calendar effects
Indonesia	Load data, weather variables
Mexico	Number of establishments, number of employees, number of shipments, electricity prices, natural gas prices
Brazil	Load data, electric consumption by process, value added of different sectors, electricity price, production and value addition forecasts, spatial data, GDP, and population

This indicates that a forecast model developed for one region might not work equally well for another region [129]. Moreover, this variation in demand determinants can also be seen at sub-regional levels within a country itself. We now see how demand determinants have been used in Pakistan in contrast to other LMICs. As mentioned earlier, most of the studies carried out in Pakistan on load forecasting fall in the LTLF category. Therefore, the demand determinants for LTLF have aptly been used. Determinants like the GDP, population, population growth rate, incomes, and electricity consumers seem to have strong correlation with the electricity demand in Pakistan. These determinants, as illustrated in the Figure 11, have been fairly used by forecasters in Pakistan. In contrast to the LMIC study set, determinants like weather variables, long term climatic impacts, previous load trends, and calendar effects were comparatively less frequently used in Pakistan. A less frequent use of the STLF related determinants (weather and load data) is because of the fact that studies on STLF in Pakistan, incorporating Pakistani data sets, are very limited. This limitation comes due the reason

that the availability of high resolution data for the aforementioned variables in Pakistan is still a major challenge.
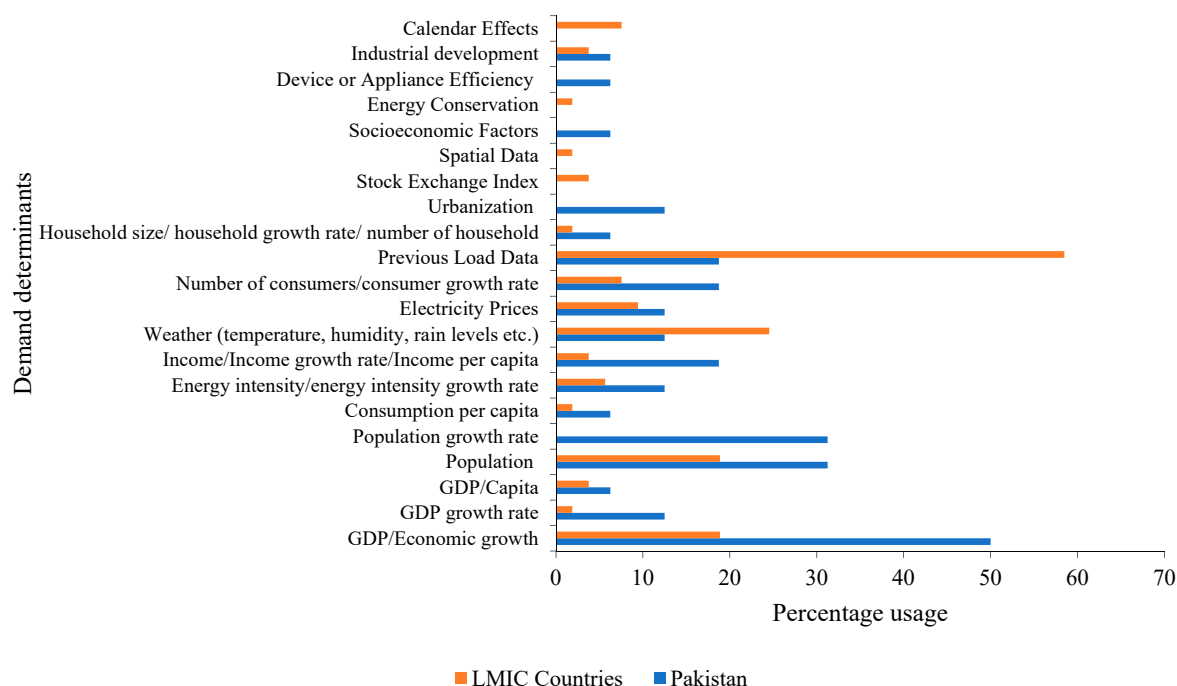
Figure 11. Percentage usage of demand determinants in Pakistan and other LMICs.

It can also be noticed that determinants like the stock exchange index, spatial factors, consciousness of energy conservation, and calendar effects have not been used in Pakistan yet. Therefore, researchers can consider the inclusion of these determinants while making forecasts for Pakistan in future. Another interesting finding is that in contrast to other LMICs, forecasters in Pakistan made an apt use of certain demand determinants. These determinants include the population growth rate, consumption per capita, income/income growth rate/income per capita, urbanization, socio-economic factors, and device/appliance efficiency. While producing MTLF for Pakistan, it is also suggested that variables such the GDP, previous load data and weather data must be necessarily incorporated in its forecast models.

In general, determinants like local calendar effects, weather information, and processed load data are indispensable while making short term forecast models. Economic activity, load and weather information for medium term along with economic activity, local demography, and energy conservation for long term forecasts are promising determinants to consider. Similarly, for short term forecasts in particular, and medium or long in general, neural nets and AI-based models appear to be a preferable choice and must be adopted by electric distribution companies. For long term forecasts, econometric models are preferred owing to their inclusivity for economic variables.

Apart from forecasting horizons and demand determinants, another aspect of load growth in these countries is the penetration of RES in the overall electricity generation. Such penetration levels have initiated a rapid change in power grids. With the introduction of RES and microgrids, load projections have to be made using net-load forecasting techniques instead of simple forecasting methods [130]. In Figure 12, we have shown, in a gradient blur color, our selected group of countries on world map. For instance, while looking at it, it can be seen that the share of electricity production by RES varies from 2.2% in South Africa to 73.9% in Brazil [131].

The production of electricity by RES has since been increasing in these countries and is signaling an even higher penetration of these resources in the future as well [132]. This increasing trend highlights the importance of net-load forecasting in the future. Moreover, it also imposes challenges on

grid operators to match the production from intermittent resources and net-load of microgrids and customers [130].
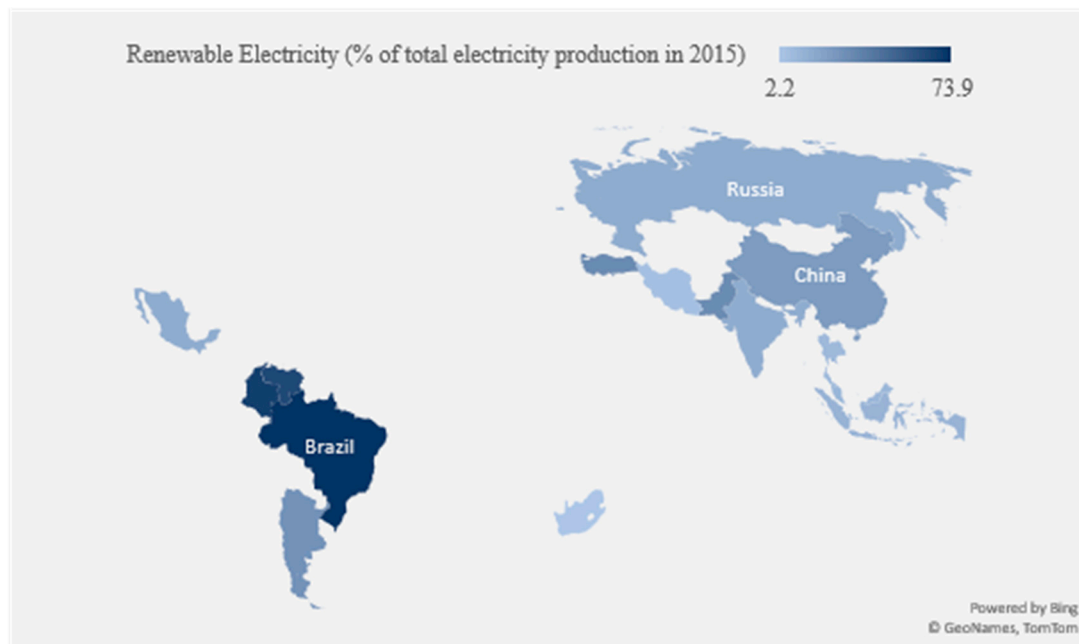
Figure 12. Share of renewable electricity in total electricity generation.

5. Conclusions

In this paper, we have reviewed electricity demand forecasting practices (methodologies and determinants) in a group of LMICs and used Pakistan as a reference country for comparison. Numerous studies were found combining different techniques and approaches in attempts to enhance forecasting accuracies. We identified that the selection of forecasting techniques and demand determinants depends on the forecasting horizons and regional dynamics. For LTLF and MTLF, time series modeling was found to be extensively used by researchers. On the other hand, AI-based techniques were mostly used while forecasting for short term (STLF). Similarly, for LTLF, the GDP, population, and previous load data were the most commonly used demand determinants. For MTLF, the GDP, weather data, and previous load data appeared to be more relevant demand determinants. For STLF, only weather data and past load data were significant.

Amongst the most meaningful studies we considered from Pakistan, 87.5% were on LTLF. When compared with those from LMICs, it was found that no LTLF study from Pakistan used AI-based techniques and only a few used econometric models. Therefore, it is recommended that advanced and more inclusive methodologies (such as AI and econometric modeling techniques) must be used by the forecasters while making forecasting models for Pakistan. The literature on STLF is very limited, with no study found on MTLF, in contrast to LMICs, raising another concern for forecasters in Pakistan to tap on these potential research gaps.

In the end, electricity demand determinants from Pakistan and LMICs were reviewed, analyzed and compared. It was found that when compared to LMICs, LTLF related demand determinants were quite fairly used in literature from Pakistan. In LMICs, STLF studies extensively incorporated determinants related to weather and load data. However, due to challenges associated with the data availability, very limited literature is available in Pakistan which incorporates these data sets. Since no meaningful study on MTLF has yet been produced in Pakistan, it was also suggested that MTLF related demand determinants must be used while producing medium term forecasts for Pakistan. Finally, with the rise of RES in the country's energy mix, it is also concluded that forecasters in Pakistan must adapt to net-load forecasting techniques instead of the usual forecasting methods in future.

Authors have reviewed and compared forecasting practices in Pakistan within the context of developing countries. We have explored the different dimensions of electricity load forecasting, including electricity forecasting horizons, methodologies and demand determinants. For the country selection process, we used a robust criterion and finally selected four different parameters as a basis for comparison. However, this criterion can be made stricter in future by introducing additional parameters to those already used. This will result in more precise results and hence a deeper insight into the subject as well. Moreover, any future extension of this work may also include comparing forecasting practices in a developed/developing country with or within other developed/developing countries.

References

1. IEA. *World Energy Outlook 2019*; IEA: Paris, France, 2019. Available online: https://www.iea.org/reports/world-energy-outlook-2019 (accessed on 16 November 2019).

2. Hong, T.; Fan, S. Probabilistic electric load forecasting: A tutorial review. *Int. J. Forecast.* **2016**, *32*, 914–938. [CrossRef]

3. Web of Science [v.5.34]-Web of Science Core Collection Result Analysis. Available online: https://wcs.webofknowledge.com/RA/analyze.do?product=WOS&SID=D1nlmkZp7gsWRfth3WV&field=PY_PublicationYear_PublicationYear_en&yearSort=true (accessed on 23 January 2020).

4. Son, H.; Kim, C. A deep learning approach to forecasting monthly demand for residential-sector electricity. *Sustainability* **2020**, *12*, 3103. [CrossRef]

5. Liu, D.; Sun, K.; Huang, H.; Tang, P. Monthly load forecasting based on economic data by decomposition integration theory. *Sustainability* **2018**, *10*, 3282. [CrossRef]

6. Low & Middle Income. Available online: https://data.worldbank.org/income-level/low-and-middle-income (accessed on 26 March 2020).

7. Suganthi, L.; Samuel, A.A. Energy models for demand forecasting-A review. *Renew. Sustain. Energy Rev.* **2012**, *16*, 1223–1240. [CrossRef]

8. Ahmed, S.; Nayyar, S.; Mirjat, H.; Shabbir, W.; Gordhan, K.; Walasai, D.; Sattar, A. Electricity Demand Forecasting: A Pakistans Perspective. *Asian J. Eng. Sci. Technol.* **2017**, *2*, 1–7.

9. Alfares, H.K.; Nazeeruddin, M. Electric load forecasting: Literature survey and classification of methods. *Int. J. Syst. Sci.* **2002**, *33*, 23–34. [CrossRef]

10. Swan, L.G.; Ugursal, V.I. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1819–1835. [CrossRef]

11. Hernandez, L.; Baladron, C.; Aguiar, J.M.; Carro, B.; Sanchez-Esguevillas, A.J.; Lloret, J.; Massana, J. A survey on electric power demand forecasting: Future trends in smart grids, microgrids and smart buildings. *IEEE Commun. Surv. Tutor.* **2014**, *16*, 1460–1495. [CrossRef]

12. Yildiz, B.; Bilbao, J.I.; Sproul, A.B. A review and analysis of regression and machine learning models on commercial building electricity load forecasting. *Renew. Sustain. Energy Rev.* **2017**, *73*, 1104–1122. [CrossRef]

13. Khan, A.R.; Mahmood, A.; Safdar, A.; Khan, Z.A.; Khan, N.A. Load forecasting, dynamic pricing and DSM in smart grid: A review. *Renew. Sustain. Energy Rev.* **2016**, *54*, 1311–1322. [CrossRef]

14. Qamar, M.; Khosravi, A. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renew. Sustain. Energy Rev.* **2015**, *50*, 1352–1372. [CrossRef]

15. Kuster, C.; Rezgui, Y.; Mourshed, M. Electrical load forecasting models: A critical systematic review. *Sustain. Cities Soc.* **2017**, *35*, 257–270. [CrossRef]

16. Kyriakides, E.; Polycarpou, M. Short term electric load forecasting: A tutorial. *Stud. Comput. Intell.* **2006**, *35*, 391–418. [CrossRef]

17. Sangrody, H.; Zhou, N. An initial study on load forecasting considering economic factors. In Proceedings of the 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 17–21 July 2016; pp. 1–5. [CrossRef]

18. Ortega-Vazquez, M.A.; Kirschen, D.S. Economic impact assessment of load forecast errors considering the cost of interruptions. In Proceedings of the 2006 IEEE Power Engineering Society General Meeting, Montreal, QC, Canada, 18–22 June 2006. [CrossRef]

19. Hafeez, A. *Circular Debt in Power Sector of Pakistan: Impacts; Causes and Solutions*; Amjad Hafeez MPhil in ESD University of Cambridge BSc Electrical Engineering UET Lahore: Cambridge, UK, 2019.

20. Jamil, F.; Ahmad, E. The relationship between electricity consumption, electricity prices and GDP in Pakistan. *Energy Policy* **2010**, *38*, 6016–6025. [CrossRef]

21. Mirza, F.M.; Fatima, N.; Ullah, K. Impact of China-Pakistan economic corridor on Pakistan's future energy consumption and energy saving potential: Evidence from sectoral time series analysis. *Energy Strateg. Rev.* **2019**, *25*, 34–46. [CrossRef]

22. Qamar Uz Zaman, C. *Climate Change Profile of Pakistan (ASIAN DEVELOPMENT BANK)*; Asian Development Bank: Mandaluyong, Philippines, 2017; ISBN 9789292577216.

23. Personal, M.; Archive, R. *Electricity Demand Analysis Using Cointegration and ARIMA Modelling: A Case Study of Turkey*; Munich Personal RePEc Archive: Munich, Germany, 2009.

24. IEA Energy Atlas. Available online: http://energyatlas.iea.org/#!/tellmap/-1118783123/1 (accessed on 30 January 2020).

25. GDP per Capita (current US$)-Pakistan. Available online: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?end=2018&locations=PK&start=2000 (accessed on 30 January 2020).

26. National Transmission & Despatch Company Limited (NTDC) Pakistan. Available online: https://www.ntdc.com.pk/transmission (accessed on 17 May 2020).

27. Ali, M.; Iqbal, M.J.; Sharif, M. Relationship between extreme temperature and electricity demand in Pakistan. *Int. J. Energy Environ. Eng.* **2013**, *4*, 1–7. [CrossRef]

28. Rahman, S. Global climate change: Impact on pakistan's political economy. *ISSRA Pap.* **2010**, *2*, 24–36.

29. Khan, Z.A.; Jayaweera, D. Approach for forecasting smart customer demand with significant energy demand variability. In Proceedings of the 2018 1st International Conference on Power, Energy and Smart Grid (ICPESG), Mirpur Azad Kashmir, Pakistan, 9–10 April 2018; pp. 1–5.

30. Al-Alawi, S.M.; Islam, S.M. Principles of electricity demand forecasting. Part 1: Methodologies. *Power Eng. J.* **1996**, *11*, 91–95. [CrossRef]

31. Hong, T. *Short Term Electric Load Forecasting*; North Carolina State University: Raleigh, NC, USA, 2010.

32. Simpson, W. *Standard Approaches to Load Forecasting and Review of Manitoba Hydro Load Forecast for Needs For and Alternatives To (NFAT)*; University of Manitoba: Winnipeg, MB, Canada, 2014.

33. Silva, F.L.C.; Souza, R.C.; Cyrino Oliveira, F.L.; Lourenco, P.M.; Calili, R.F. A bottom-up methodology for long term electricity consumption forecasting of an industrial sector-Application to pulp and paper sector in Brazil. *Energy* **2018**, *144*, 1107–1118. [CrossRef]

34. Herbst, A.; Toro, F.; Reitze, F.; Jochem, E. Introduction to Energy Systems Modelling. *Swiss J. Econ. Stat.* **2012**, *148*, 111–135. [CrossRef]

35. SEI A short history of LEAP. Available online: https://energycommunity.org/Help/Concepts/History_of_LEAP.htm (accessed on 2 October 2019).

36. SEI LEAP description from SEI. Available online: https://www.energycommunity.org/default.asp?action=introduction (accessed on 2 October 2019).

37. Perwez, U.; Sohail, A.; Hassan, S.F.; Zia, U. The long-term forecast of Pakistan's electricity supply and demand: An application of long range energy alternatives planning. *Energy* **2015**, *93*, 2423–2435. [CrossRef]

38. Worldbank. *Pakistan-Proposed World Bank Climate Change and Environment Program 2010–2015 (Anglais)*; Worldbank: Washington, DC, USA, 2012.

39. Mirjat, N.H.; Uqaili, M.A.; Harijan, K.; Walasai, G.D.; Mondal, M.A.H.; Sahin, H. Long-term electricity demand forecast and supply side scenarios for Pakistan (2015–2050): A LEAP model application for policy analysis. *Energy* **2018**, *165*, 512–526. [CrossRef]

40. Perwez, U.; Sohail, A. Forecasting of Pakistan's net electricity energy consumption on the basis of energy pathway scenarios. *Energy Procedia* **2014**, *61*, 2403–2411. [CrossRef]

41. Chi, Y.; Yuan, L.; Li, H.; Zhang, Y.; Bai, G. Using LEAP model to predict energy consumption of beijing under the constraint of low-carbon economy. *Ekoloji* **2019**, *28*, 1205–1211.

42. Nieves, J.A.; Aristizábal, A.J.; Dyner, I.; Báez, O.; Ospina, D.H. Energy demand and greenhouse gas emissions analysis in Colombia: A LEAP model application. *Energy* **2019**, *169*, 380–397. [CrossRef]

43. Mengal, A.; Mirjat, N.H.; DasWalasai, G.; Khatri, S.A.; Harijan, K.; Uqaili, M.A. Modeling of future electricity generation and emissions assessment for Pakistan. *Processes* **2019**, *7*, 212. [CrossRef]

44. Gul, M.; Qureshi, W.A. Long term electricity demand forecasting in residential sector of Pakistan. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–7. [CrossRef]

45. Sohail, S. Federal Bureau of Statistics. In *Pakistan Statistical Year Book*; Government of Pakistan: Islamabad, Pakistan, 2010.

46. Hussain, A.; Shahid, M. The Long-term Forecast of Gilgit Baltistan (GB)'s Electricity Demand. In Proceedings of the 2018 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), Islamabad, Pakistan, 10–12 September 2018; pp. 1–5. [CrossRef]

47. Shabbir, R.; Ahmad, S.S. Monitoring urban transport air pollution and energy demand in Rawalpindi and Islamabad using leap model. *Energy* **2010**, *35*, 2323–2332. [CrossRef]

48. Malakhov, V.A. Approaches to forecasting electricity demand in Russia. *Stud. Russ. Econ. Dev.* **2009**, *20*, 153–157. [CrossRef]

49. Gul, M.; Qa, S.A. Incorporating Economic and Demographic Variables for Forecasting Electricity Consumption in Pakistan. In Proceedings of the 2011 2nd International Conference on Electric Power and Energy Conversion Systems (EPECS), Sharjah, United Arab Emirates, 15–17 November 2011. [CrossRef]

50. Franco, M.; Blanco, D.; Blequett, W.; Guglia, M.; Alvarado, E. Cointegration methodology and error correction model used to forecast the electricity demand of the Venezuelan electric system-Period 2004–2024. In Proceedings of the 2006 IEEE/PES Transmission & Distribution Conference and Exposition: Latin America, Caracas, Venezuela, 15–18 August 2006; pp. 1–8. [CrossRef]

51. Cabral, J.D.A.; Legey, L.F.L.; Cabral, M.V.D.F. Electricity consumption forecasting in Brazil: A spatial econometrics approach. *Energy* **2017**, *126*, 124–131. [CrossRef]

52. He, Y.; Jiao, J.; Chen, Q.; Ge, S.; Chang, Y.; Xu, Y. Urban long term electricity demand forecast method based on system dynamics of the new economic normal: The case of Tianjin. *Energy* **2017**, *133*, 9–22. [CrossRef]

53. Mbamalu, G.A.N.; El-Hawary, M.E. Load forecasting via suboptimal seasonal autoregressive models and iteratively reweighted least squares estimation. *IEEE Trans. Power Syst.* **1993**, *8*, 343–348. [CrossRef]

54. Chen, B.J.; Chang, M.W.; Lin, C.J. Load forecasting using support vector machines: A study on EUNITE Competition 2001. *IEEE Trans. Power Syst.* **2004**, *19*, 1821–1830. [CrossRef]

55. Hong, T.; Pinson, P.; Fan, S. Global energy forecasting competition 2012. *Int. J. Forecast.* **2014**, *30*, 357–363. [CrossRef]

56. Amral, N.; Özveren, C.S.; King, D. Short term load forecasting using multiple linear regression. In Proceedings of the 2007 42nd International Universities Power Engineering Conference, Brighton, UK, 4–6 September 2007; pp. 1192–1198. [CrossRef]

57. Supapo, K.R.M.; Santiago, R.V.M.; Pacis, M.C. Electric load demand forecasting for Aborlan-Narra-Quezon distribution grid in Palawan using multiple linear regression. In Proceedings of the 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Manila, Philippines, 1–3 December 2017; pp. 1–6.

58. Flores, C.E.; Phelan, P.E.; Mou, J.I.; Bryan, H. Forecasting the electricity consumption of the Mexican border states maquiladoras. *Int. J. Energy Res.* **2004**, *28*, 641–660. [CrossRef]

59. Wani, T.A.; Shiraz, M. *Advances in Energy and Built Environment*; Springer Singapore: Singapore, 2020; Volume 36, ISBN 978-981-13-7556-9.

60. Chikobvu, D.; Sigauke, C. Regression-SARIMA modelling of daily peak electricity demand in South Africa. *J. Energy S. Afr.* **2012**, *23*, 23–30. [CrossRef]

61. Miswan, N.H.; Said, R.M.; Anuar, S.H.H. ARIMA with regression model in modelling electricity load demand. *J. Telecommun. Electron. Comput. Eng.* **2016**, *8*, 113–116.

62. Uqaili, M.A.; Harijan, K. Energy, environment and sustainable development. *Energy Environ. Sustain. Dev.* **2012**, 1–349. [CrossRef]

63. Panklib, K.; Prakasvudhisarn, C.; Khummongkol, D. Electricity Consumption Forecasting in Thailand Using an Artificial Neural Network and Multiple Linear Regression. *Energy Sources Part B Econ. Plan. Policy* **2015**, *10*, 427–434. [CrossRef]

64. Nawaz, S.; Iqbal, N.; Anwar, S. Modelling electricity demand using the STAR (Smooth Transition Auto-Regressive) model in Pakistan. *Energy* **2014**, *78*, 535–542. [CrossRef]

65. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural networks for short-term load forecasting: A review and evaluation. *IEEE Trans. Power Syst.* **2001**, *16*, 44–55. [CrossRef]

66. Madani, S.S. Electric load forecasting using an artificial neural network. *Middle East J. Sci. Res.* **2013**, *18*, 396–400. [CrossRef]

67. Marwala, L.; Twala, B. Forecasting electricity consumption in South Africa: ARMA, neural networks and neuro-fuzzy systems. In Proceedings of the 2014 International Joint Conference on Neural Networks (IJCNN), Beijing, China, 6–11 July 2014; pp. 3049–3055. [CrossRef]

68. Moghram, I.; Rahman, S. Analysis and Evaluation of Five Short-Term Load Forecasting Techniques. *IEEE Power Eng. Rev.* **1989**, *9*, 42–43. [CrossRef]

69. Taylor, J.W.; de Menezes, L.M.; McSharry, P.E. A comparison of univariate methods for forecasting electricity demand up to a day ahead. *Int. J. Forecast.* **2006**, *22*, 1–16. [CrossRef]

70. Zhang, P.G. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing* **2003**, *50*, 159–175. [CrossRef]

71. Singh, A.K.; Ibraheem; Khatoon, S.; Muazzam, M.; Chaturvedi, D.K. Load forecasting techniques and methodologies: A review. In Proceedings of the 2012 2nd International Conference on Power, Control and Embedded Systems, Allahabad, India, 17–19 December 2012; pp. 1–10. [CrossRef]

72. Ur Rehman, S.A.; Cai, Y.; Fazal, R.; Walasai, G.D.; Mirjat, N.H. An integrated modeling approach for forecasting long-term energy demand in Pakistan. *Energies* **2017**, *10*, 1868. [CrossRef]

73. Yasmeen, F.; Sharif, M. Forecasting Electricity Consumption for Pakistan. *Int. J. Emerg. Technol. Adv. Eng.* **2014**, *4*, 496–503.

74. Hussain, A.; Rahman, M.; Memon, J.A. Forecasting electricity consumption in Pakistan: The way forward. *Energy Policy* **2016**, *90*, 73–80. [CrossRef]

75. Jamil, R. Hydroelectricity consumption forecast for Pakistan using ARIMA modeling and supply-demand analysis for the year 2030. *Renew. Energy* **2020**, *154*, 1–10. [CrossRef]

76. Erdogdu, E. Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. *Energy Policy* **2007**, *35*, 1129–1146. [CrossRef]

77. Sigauke, C.; Chikobvu, D. Prediction of daily peak electricity demand in South Africa using volatility forecasting models. *Energy Econ.* **2011**, *33*, 882–888. [CrossRef]

78. Wang, Y.; Wang, J.; Zhao, G.; Dong, Y. Application of residual modification approach in seasonal ARIMA for electricity demand forecasting: A case study of China. *Energy Policy* **2012**, *48*, 284–294. [CrossRef]

79. Amjady, N. Short-term hourly load forecasting using time-series modeling with peak load estimation capability. *IEEE Trans. Power Syst.* **2001**, *16*, 798–805. [CrossRef]

80. Zhu, S.; Wang, J.; Zhao, W.; Wang, J. A seasonal hybrid procedure for electricity demand forecasting in China. *Appl. Energy* **2011**, *88*, 3807–3815. [CrossRef]

81. Nie, H.; Liu, G.; Liu, X.; Wang, Y. Hybrid of ARIMA and SVMs for short-term load forecasting. *Energy Procedia* **2012**, *16*, 1455–1460. [CrossRef]

82. Lu, J.-C.; Niu, D.-X.; Jia, Z.-Y. A study of short-term load forecasting based on ARIMA-ANN. In Proceedings of the 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No.04EX826), Shanghai, China, 26–29 August 2004; pp. 26–29. [CrossRef]

83. Mohamed, N.; Ahmad, M.H.; Ismail, Z. Short term load forecasting using double seasonal ARIMA model. *World Appl. Sci. J.* **2010**, *15*, 57–73.

84. Rallapalli, S.R.; Ghosh, S. Forecasting monthly peak demand of electricity in India-A critique. *Energy Policy* **2012**, *45*, 516–520. [CrossRef]

85. Taylor, J.W. Short-term load forecasting with exponentially weighted methods. *IEEE Trans. Power Syst.* **2012**, *27*, 458–464. [CrossRef]

86. Taylor, J.W.; Mcsharry, P.E.; Member, S. Short-Term Load Forecasting Methods: An Evaluation Based on European Data. *IEEE Trans. Power Syst.* **2007**, *22*, 2213–2219. [CrossRef]

87. Taylor, J.W. Short-term electricity demand forecasting using double seasonal exponential smoothing. *J. Oper. Res. Soc.* **2003**, *54*, 799–805. [CrossRef]

88. Taylor, J.W. An evaluation of methods for very short-term load forecasting using minute-by-minute British data. *Int. J. Forecast.* **2008**, *24*, 645–658. [CrossRef]

89. Medina MacAira, P.; Castro Sousa, R.; Cyrino Oliveira, F.L. Forecasting Brazils electricity consumption with Pegels Exponential Smoothing Techniques. *IEEE Lat. Am. Trans.* **2016**, *14*, 1252–1258. [CrossRef]

90. Abd Jalil, N.A.; Ahmad, M.H.; Mohamed, N. Electricity load demand forecasting using exponential smoothing methods. *World Appl. Sci. J.* **2013**, *22*, 1540–1543. [CrossRef]

91. Kumar, U.; Jain, V.K. Time series models (Grey-Markov, Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. *Energy* **2010**, *35*, 1709–1716. [CrossRef]

92. Briceño, H.; Rocco, C.M.; Zio, E. Singular spectrum analysis for forecasting of electric load demand. *Chem. Eng. Trans.* **2013**, *33*, 919–924. [CrossRef]

93. Zhou, P.Ã.; Ang, B.W.; Poh, K.L. A trigonometric grey prediction approach to forecasting electricity demand. *Energy* **2006**, *31*, 2839–2847. [CrossRef]

94. Dilaver, Z.; Hunt, L.C. Industrial electricity demand for Turkey: A structural time series analysis. *Energy Econ.* **2011**, *33*, 426–436. [CrossRef]

95. Yasmeen, F.; Sharif, M. Functional Time series (FTS) Forecasting of Electricity Consumption in Pakistan. *Int. J. Comput. Appl.* **2015**, *124*, 15–19. [CrossRef]

96. Afshar, K.; Bigdeli, N. Data analysis and short term load forecasting in Iran electricity market using singular spectral analysis (SSA). *Energy* **2011**, *36*, 2620–2627. [CrossRef]

97. Solyali, D. A Comparative Analysis of Machine Learning Approaches for Short- / Long-Term Electricity Load Forecasting in Cyprus. *Sustainability* **2020**, *12*, 3612. [CrossRef]

98. Hong, W.C. Chaotic particle swarm optimization algorithm in a support vector regression electric load forecasting model. *Energy Convers. Manag.* **2009**, *50*, 105–117. [CrossRef]

99. Hu, R.; Wen, S.; Zeng, Z.; Huang, T. A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm. *Neurocomputing* **2017**, *221*, 24–31. [CrossRef]

100. Yu, S.; Wang, K.; Wei, Y.M. A hybrid self-adaptive Particle Swarm Optimization-Genetic Algorithm-Radial Basis Function model for annual electricity demand prediction. *Energy Convers. Manag.* **2015**, *91*, 176–185. [CrossRef]

101. Gil-Vera, V.D. Forecasting Electricity Demand for Small Colombian Populations. *Cuderno Act.* **2015**, *7*, 111–119.

102. Azadeh, A.; Ghaderi, S.F.; Sohrabkhani, S. A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. *Energy Policy* **2008**, *36*, 2637–2644. [CrossRef]

103. Adrian, V.; Fernando, D.; Investigación, G.D.; Avanzadas, I. *Short-Term Load Forecasting for Low Voltage Distribution Lines in Tucumán, Argentina*; Consejo Nacional de Investigaciones Científicas y Técnicas: Buenos Aires, Argentina, 2017.

104. Babich, L.; Svalov, D.; Smirnov, A.; Babich, M. Industrial Power Consumption Forecasting Methods Comparison. In Proceedings of the 2019 Ural Symposium on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT), Yekaterinburg, Russia, 25–26 April 2019; pp. 307–309. [CrossRef]

105. Chaturvedi, D.K.; Sinha, A.P.; Malik, O.P. Short term load forecast using fuzzy logic and wavelet transform integrated generalized neural network. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 230–237. [CrossRef]

106. Anand, A.; Suganthi, L. Forecasting of Electricity Demand by Hybrid ANN-PSO Models. *Int. J. Energy Optim. Eng.* **2017**, *6*, 66–83. [CrossRef]

107. Bhanot, S. Long term load forecasting using K-mean clustering and ANN approach. *Int. J. Adv. Res. Ideas Innov. Technol.* **2018**, *4*, 2217–2222.

108. Sulandari, W.; Subanar; Lee, M.H.; Rodrigues, P.C. Indonesian electricity load forecasting using singular spectrum analysis, fuzzy systems and neural networks. *Energy* **2020**, *190*, 116408. [CrossRef]

109. Potapov, V.; Khamitov, R.; Makarov, V.; Gritsay, A.; Tyunkov, D.; Chervenchuk, I. Short-Term Forecast of Electricity Load for LLC Omsk Energy Retail Company Using Neural Network. In Proceedings of the 2018 Dynamics of Systems, Mechanisms and Machines (Dynamics), Omsk, Russia, 13–15 November 2018; pp. 1–5. [CrossRef]

110. Mohamed Othman, M.S.; Johari, D.; Musirin, I.; Abdul Rahman, T.K.; Nik Ismail, N.F. Artificial neural network-based forecast for electricity consumption in Malaysia. In Proceedings of the 2010 IEEE International Conference on Power and Energy, Kuala Lumpur, Malaysia, 29 November–1 December 2010; pp. 24–28. [CrossRef]

111. Dalvand, M.M.; Azami, S.B.Z.; Tarimoradi, H. Long-term load forecasting of iranian power grid using fuzzy and artificial neural networks. In Proceedings of the 2008 43rd International Universities Power Engineering Conference, Padova, Italy, 1–4 September 2008. [CrossRef]

112. Yuill, W.; Kgokong, R.; Chowdhury, S.; Chowdhury, S.P. Application of adaptive neuro fuzzy inference system (ANFIS) based short term load forecasting in south african power networks. In Proceedings of the 45th International Universities Power Engineering Conference UPEC2010, Cardiff, Wales, UK, 31 August–3 September 2010; pp. 1–5.

113. Kandananond, K. Forecasting electricity demand in Thailand with an artificial neural network approach. *Energies* **2011**, *4*, 1246–1257. [CrossRef]

114. Mostafavi, E.S.; Mostafavi, S.I.; Jaafari, A.; Hosseinpour, F. A novel machine learning approach for estimation of electricity demand: An empirical evidence from Thailand. *Energy Convers. Manag.* **2013**, *74*, 548–555. [CrossRef]

115. Günay, M.E. Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey. *Energy Policy* **2016**, *90*, 92–101. [CrossRef]

116. Hamzaçebi, C.; Es, H.A.; Çakmak, R. Forecasting of Turkey's monthly electricity demand by seasonal artificial neural network. *Neural Comput. Appl.* **2019**, *31*, 2217–2231. [CrossRef]

117. Ivanov, V.V.; Kryanev, A.V.; Osetrov, E.S. Forecasting the daily electricity consumption in the Moscow region using artificial neural networks. *Phys. Part. Nucl. Lett.* **2017**, *14*, 647–657. [CrossRef]

118. Khan, A.R.; Razzaq, S.; Alquthami, T.; Moghal, M.R.; Amin, A.; Mahmood, A. Day Ahead Load Forecasting for IESCO using Artificial Neural Network and Bagged Regression Tree. In Proceedings of the 2018 1st International Conference on Power, Energy and Smart Grid (ICPESG), Mirpur Azad Kashmir, Pakistan, 9–10 April 2018; pp. 1–6. [CrossRef]

119. Kharal, A.Y.; Mahmood, A.; Ullah, K. Load forecasting of an educational institution using machine learning: The case of nust, islamabad. *Pak. J. Sci.* **2019**, *71*, 252–257.

120. Taieb, S.B.; Huser, R.; Hyndman, R.J.; Genton, M.G. Probabilistic Time Series Forecasting with Boosted Additive Models: An Application to Smart Meter Data. Available online: https://robjhyndman.com/publications/kdd2015/ (accessed on 26 March 2020).

121. Fan, S.; Hyndman, R.J. Short-term load forecasting based on a semi-parametric additive model. *IEEE Trans. Power Syst.* **2012**, *27*, 134–141. [CrossRef]

122. Gaillard, P.; Goude, Y.; Nedellec, R. Additive models and robust aggregation for GEFCom2014 probabilistic electric load and electricity price forecasting. *Int. J. Forecast.* **2016**, *32*, 1038–1050. [CrossRef]

123. Raña, P.; Vilar, J.; Aneiros, G. On the Use of Functional Additive Models for Electricity Demand and Price Prediction. *IEEE Access* **2018**, *6*, 9603–9613. [CrossRef]

124. Shao, Z.; Yang, S.L.; Gao, F. Density prediction and dimensionality reduction of mid-term electricity demand in China: A new semiparametric-based additive model. *Energy Convers. Manag.* **2014**, *87*, 439–454. [CrossRef]

125. Sigauke, C. Forecasting medium-term electricity demand in a South African electric power supply system. *J. Energy S. Afr.* **2017**, *28*, 54–67. [CrossRef]

126. Bunnoon, P.; Chalermyanont, K.; Limsakul, C. Mid term load forecasting of the country using statistical methodology: Case study in thailand. In Proceedings of the 2009 International Conference on Signal Processing Systems, Singapore, 15–17 May 2009; pp. 924–928. [CrossRef]

127. Hong, W.C. Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm. *Energy* **2011**, *36*, 5568–5578. [CrossRef]

128. Velasco, L.C.P.; Villezas, C.R.; Palahang, P.N.C.; Dagaang, J.A.A. Next day electric load forecasting using Artificial Neural Networks. In Proceedings of the 2015 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Cebu City, Philippines, 9–12 December 2015; pp. 1–6. [CrossRef]

129. Pao, H.T. Comparing linear and nonlinear forecasts for Taiwan's electricity consumption. *Energy* **2006**, *31*, 2129–2141. [CrossRef]

130. Kaur, A.; Nonnenmacher, L.; Coimbra, C.F.M. Net load forecasting for high renewable energy penetration grids. *Energy* **2016**, *114*, 1073–1084. [CrossRef]

131. Renewable Electricity Output (% of Total Electricity Output)-Low & Middle Income. Available online: https://data.worldbank.org/indicator/EG.ELC.RNEW.ZS?locations=XO (accessed on 21 May 2020).

132. Renewable, I.; Agency, E. *Renewable Energy Statistics2019 Statistiques D' Énergie Renouvelable 2019 Estadisticas Dd Energia*; International Renewable Energy Agency: Masdar City, UAE, 2019; ISBN 9789292601379.