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A Smart Analysis and Visualization of The Power Forecasting in Pakistan

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Abstract: Over the last decade, the energy sector has experienced a significant modernization cycle. Its network is undergoing accelerated upgrades. The instability of production, demand and markets is far less stable than ever before. Also, the corporate concept is profoundly questioned. Many decision-making processes in this competitive and complex setting depend on probabilistic predictions to measure unpredictable futures. In recent years, the interest in probabilistic energy forecasting analysis has rapidly begun, even though many articles in the energy forecasting literature focus on points or single-valuation forecasting. In Pakistan, the bulk of early studies require various kinds of econometric modeling. However, the simulation of time series appears to deliver more reliable results, given the projected economic and demographic parameters usually deviate from the achievements. The machine learning technique "ARIMA" and deep learning technique Long Short-Term Memory "LSTM," are used to calculate Pakistan's future primary energy demand from 2019 to 2030. In this paper, it is accessed that the dataset of the electricity sector for forecasting purposes from the hydrocarbon development institute of Pakistan "HDIP."The dataset of HDIP is from 1999 to 2019 with different attributes like Electricity Installed Capacity (Hydel Thermal (WAPDA), Thermal (K-Electric), Thermal (IPPs), Nuclear), Energy Consumption by Sector (Domestic, Commercial), Resource Production (Oil, Gas, Coal, Electricity), and Resource Consumption (Oil, Gas, Coal, Electricity). It is visualized and forecasted the energy demand of each attribute until 2030. Predicting overall primary energy demand using machine learning appears to be more accurate than summing up the individual forecasts.

Keywords: Power Forecasting, Machine Learning Techniques, Power Consumption, ARIMA, LSTM

1. Introduction

Energy is of vital social, economic, and environmental significance for the growth of any society. The impact on manufacturing and agricultural goods, environment, environment, health, economy, employment, and the standard of human existence is marvelous. Since energy is a significant contributor to the country's industrial component, energy demand rises with increased industrial activity. Rapid technological and economic developments have a direct impact on electricity use. Energy usage, thus, is a critical economic factor reflecting a region or country's economic growth [1]. There will be several changes in energy use and the kind of future (the year 2030) according to the International Energy Agency study. Global energy demand increased exponentially over the past decade as a consequence of population and economic development. Over the last decade, energy demand management has become very critical for economic development, protection of the climate, and adequate preparation of capital contributing to self-reliance and economic growth centered on widespread energy use growth [2]. Various methods for controlling electricity demand have also been used to forecast potential energy demands reliably. Energy forecasts are, however, challenging since they are affected by fast economic development, infrastructure, and decision-making by governments, and others. Concerning energy forecasting, in developing countries such as Iran in particular, the lack of data is a significant forecasting problem. Also, a lack of standards and a reliable and useful data collection method posed many challenges in these nations [3].

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The increase in GDP and lifestyle, especially in developed countries are related to each other's demand for electricity [4]. Reported that developed countries reflected the accurate connection picture and listed the ties between energy use, income, and value-added output. In Pakistan, the energy demand grew dramatically as a consequence of steady 6-per-cent annual GDP growth between 2002 and 2007. With no adequate power-sector preparation, the nation suffered significant power cuts leading to a 2.5% GDP loss, 0.535 million factory workers unemployment, and $1.3 billion in export loss [5]. In the future, energy policy recommendations are focused on several environmental, economic, and policy factors that are affected by the type of technology to be employed to meet the future energy demand. For addressing this scarcity, power systems with higher output and lower running costs must be designed to address the cuts in power and circular debt in Pakistan's power sector [6]. Among these reasons, Pakistan has some problems with electricity stability and developing facilities for a stable power supply, which would also influence potential energy policies [7].

Pakistan's electricity market relies mainly on non-renewable fuels. Overall, fossil fuels have a significant 62% share of electricity production, while 31.5% and 30.5% supply natural gas and furnace oil. Hydropower, which is 33.5% of the overall output, is accompanied by fossil fuels. Throughout the domestic economy, livestock, manufacturing, sector, and other resources are five end-consumers [8]. Nearly 80% of energy consumers in Pakistan are in the domestic market, which makes power production very complicated and impossible at peak hours to tackle charge control. Consumers in the domestic and manufacturing industries increased by 4.7% to 5.75% a year on average over the last ten years. Of manufacturing, commerce, and other utilities, consumer electric development is 5.3%, 5.86%, and 5.32%, respectively. Therefore, for the growth and potential of jobs, a future Pakistani economy will focus on manufacturing, commerce, and company. With the planned rapid expansion of the electricity generating potential in these industries, rising demand for power would have to be met [9].

Four significant entities are operating under Pakistan's energy supply sector: WAPDA, PPIB, Pakistan Electric Power Companies (PEPCO), and privatization of the 2005-initiated Karachi Electronic Supply Company (KESC). WAPDA is, therefore, potentially a hydroelectric corporation, and the public policy introduced in 1994, PPIB relations with independent generators (IPP) are likely to contribute to a particular emphasis on thermal generation. The Pakistan Electric Power Corporation (PEPCO), including 4 GENCO, 9 Discos, and the Karachi Electric Supply Corporation, a vertical power production and distribution enterprise for Karachi as a whole, are two other power suppliers [10, 11].

An autoregressive moving average model (ARMA) is generalized by ARIMA. Both models are adapted to time series data to understand better or predict data. In some cases, ARIMA models are used when data show no stationary characteristics [12].

The RA factor of ARIMA reveals that at lagging (i.e., previous) values themselves, through the component of concern is regressed. The MA segment shows that regression error is a constant mixture of error factors, whose profits have sometimes been added in different periods [13].

ARIMA models are commonly referred to as ARIMA(p, d, q)(P, D, Q)m, in which m refer to the seasonal number, and the autoregressive, distinct, or shifting standard terms of the annual part are referenced in High Case P, D and Q [14].

The deep learning architecture of the artificial recurrent neural network (RNN) is long-term shorter memory. LSTM has input links, as opposed to traditional neural networks, for feed-forward. The entire sequence of data is processable not only by individual data points (e. g. images) [14] but also. An LSTM model unit has a container, an entry door, an escape door, and an escape screen. Arbitrary time values are recorded in the cell and the three gates track movement. In conventional RNN training, LSTMs were built for the question of the absence of gradient [15].

The emphasis of this research is on the current situation of power waste in Pakistan, concentrating on identifying the main recycling sites, existing and potential domestic energy waste production, unknown flows, and energy waste imports. Political measures required and possible government actions to be taken to avoid the growing problem of electricity waste in the country are discussed. Our findings show that there is still a general lack of reliable data, inventories, and research studies on the environmental and human health issues of power waste in Pakistan. The global information base, which will draw on the study experience of other countries with comparable circumstances in the past, also needs to be improved critically. Additional work in Pakistan into these problems is deemed necessary for advising potential policies/control mechanisms that have already been applied effectively in other countries [16].

As it is known, the use of power is a major issue all over the world. In Pakistan, this issue is more extensive. So, this research will help the manufacturer and users all over Pakistan that how to save and use electricity. As in the current situation in Pakistan. it is being faced every day, so this research will tell the condition of electricity till 2030.

2. Literature Review:

The electricity supply of Pakistan is highly dependent on imports of fossil fuels. Pakistan's electricity industry uses this to research and estimates electricity demand in every region. The findings show that the enterprise generates five times as much energy as the sun, wind, and hydrogen as a typical scenario. Clean energies should be promoted to improve their electricity penetration in the Pakistani energy planning companies and developing countries in general, says the paper. The goal of this theory is to determine the best policy choice to increase the measures of renewable energy in Pakistan in the power mix [9].

Nearly 40 million tons of energy are usable in Pakistan before 2018. The electricity generation potential with the use of crop biomass is estimated at approximately 11,000MW for 2018. Pakistan's Province of Punjab, an agricultural region, has combined resources up to 7000 MW to finance waste-driven power stations [10].

Different approaches to machine learning have been widely used to forecast short-term solar energy. The goal of this analysis is to analyze various models and selection methods quantitatively. In particular, the machine learning approach includes Random Forest, Artificial Neural network, and Extreme Gradient Boosting [12].

The goal is to provide a reliable model for the monthly electricity demand forecast. The success was measured with the metrics MAPE, MAE, RMSE, MBE, and UPA. The ability to predict the short-term electricity demand will help suppliers of energy systems and market participants make rational decisions on energy procurement and stable customer electricity supply, the authors say. The proposed method is more advantageous than previous methods as it determines the variables that are appropriate and necessary for automatic forecasting. It is expected to lead to more reliable estimates of Short-term energy demand in the residential sector [3].

Oil prices are considered to be a potential driver of renewable energy spread. The study uses an extended model of logistic growth to examine this issue. Results indicate that RPP levels have a more significant effect than the feed-in tariff in the energy market in South Korea. The study concludes that the Government plays a key role in the first phase of the transition to renewable energy [13].

Electricity has become a commodity sold and purchased in the market. A short-term forecast of energy loading is made 24 hours a day in this study. Dual approaches for the forecasting process are used by the Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) In the learning phase, PSO updates the weights ofANN. 4-year loading data are considered on an hourly basis [14].

The electricity supply of Pakistan is highly dependent on imports of fossil fuels. The national exchequer importing these fuels is subject to tremendous financial pressure. The paper examines five situations on the supply side to determine the strongest market rival. The findings show that the enterprise generates five times as much energy as the sun, wind, and hydrogen as a typical scenario. Clean energies should be promoted to improve their electricity penetration in the Pakistani energy planning companies [17]. The electricity generation potential with the use of crop biomass is estimated at approximately 11,000MW for 2018. Pakistan's Province of Punjab, an agricultural region, has combined resources up to 7000MW to finance waste-driven power stations. Financial, technological, legislative, and political obstacles are the difficulties of producing renewable power from biomass [18].

One-quarter of the overall electricity generation in Pakistan supplies water. Water is one of the cheapest and clean energy sources in the country. Hydroelectricity demand was projected by 2030 based on the established forecasting equation [19].

Los Angeles County has a population of 9.7 million and aging in a large area of city development. Population forecasts indicate that by 2060 LCA will accommodate an additional 1.2–3.1 million people. It is expected that peak demand will increase by 0.4–1GW in northern Palmdeli, Lancastri, and Santa Clarita [20]

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3. METHODOLOGY AND DATA COLLECTION:

The dataset is collected from the electricity sector for forecasting purposes from the hydrocarbon development institute of Pakistan (HDIP). The dataset of HDIP is from 1999 to 2019 with different attributes like Electricity Installed Capacity (Hydel Thermal (WAPDA), Thermal (K-Electric), Thermal (IPPs), Nuclear), Energy Consumption by Sector (Domestic, Commercial), Resource Production (Oil, Gas, Coal, Electricity), and Resource Consumption (Oil, Gas, Coal, Electricity). Subsequently, the energy demand forecast of all these sectors of the economy for each fuel using each ARIMA, and LSTM methodology was undertaken.

A. Autoregressive Integrated Moving Average (ARIMA)

The abbreviation ARIMA was extracted from two statistical models, Autoregressive (AR) and Moving

Average (MA). In this analysis, the ARMA technique has been used to model a stationary time series with a reasonable number of p and q lags. Instead of developing single or parallel equation models, ARMA centers attention on the stochastic or probabilistic properties of the economic time series. The model considers stochastic error terms and is based on past or lagged values. When the pattern of ARMA (p, q) is written as ARIMA (p, d, q), the sequence would be rendered stationary by "d" intervals. It is important because the ARIMA model is used in a stationary sequence, or because a specific order of difference is used such that it is stationary for forecasting.

B. Long Short-Term Memory (LSTM)

Long short-term memory networks (LSTM) are a changed variant of repetitive neural networks that encourages memory retrieval of previous results. The absence of the RNN gradient problem is solved here. LSTM is useful for classifying, storing, and forecasting time sequences, despite uncertain time lags. The model is conditioned through back-propagation. There are three gates in the LSTM network, as shown in "Fig. 1".

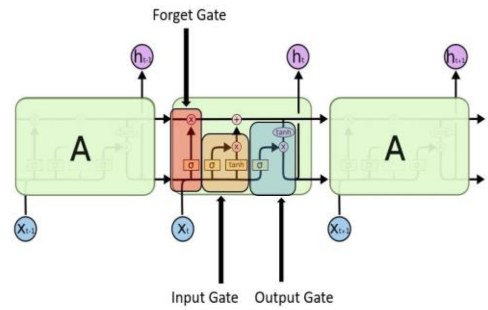


Figure 1. The concept of the LSTM gates [21]

As in this methodology, The dataset is collected from the electricity of the electricity sector for forecasting purposes from the hydrocarbon development institute of Pakistan (HDIP) because the dataset of the electricity sector is not available publicly online. The dataset of HDIP is from 1999 to 2019, with different attributes of power usage.

The raw dataset that was used in the un-stationary format has been updated the dataset in the stationary format. One machine learning and one deep learning technique were selected for the analysis and visualization of the results. The selected tool for analysis in Python with Co-lab IDE for the analysis where implement this algorithm is performed for analysis, as shown in "Fig. 2".

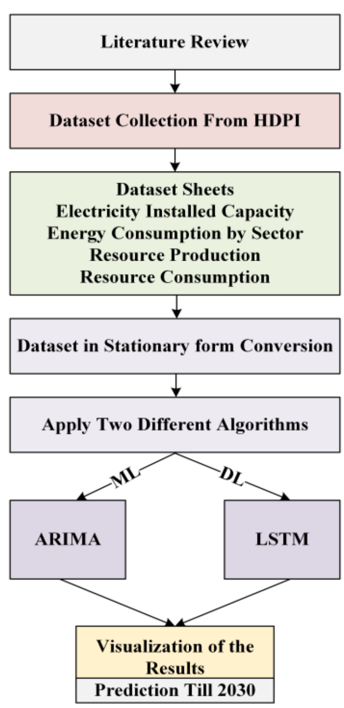


Figure 2. Flowchart of the analysis and visualization of the power forecasting in Pakistan

C. Dataset Stationary Conversion

For getting better and clear data, the dataset was converted in a stationary form. "Table. 1" shows the sample value of the electricity installed capacity in year-wise format; then "Table. 2" shows the stationary behavior of the data in the month-wise form.

TABLE I. THE SAMPLE VALUE IN THE YEAR WISE FORMAT

Year	Hydel	Thermal (WAPDA)	Thermal (K-Electric)	Thermal (IPPs)	Nuclear
1999	4,826	5,131	1,690	3,879	137

TABLE II. THE SAMPLE VALUES OF THE DATA IN THE MONTH WISE FORMAT

Year	Hydel	Thermal (WAPDA)	Thermal (K-Electric)	Thermal (IPPs)	Nuclear
01-01-99	402	428	141	323	11
01-02-99	402	428	141	323	11
01-03-99	402	428	141	323	11
01-04-99	402	428	141	323	11
01-05-99	500	550	250	450	25
01-06-99	500	550	250	450	25
01-07-99	500	550	250	450	25
01-08-99	500	550	250	450	25
01-09-99	500	550	250	450	25
01-10-99	402	428	141	323	11
01-11-99	402	428	141	323	11
01-12-99	402	428	141	323	11

4. RESULTS AND DISCUSSION

Over the last decade, the energy sector has experienced a major modernization cycle. Its network is undergoing accelerated upgrades. The instability of production, demand and markets is far less stable than ever before. After having analyzed and visualized the power using the Autoregressive moving average, which is one of the most widely employed strategies for time-series forecasting known as ARIMA. The notation ARIMA (p, d, q) denotes ARIMA types, the seasonality, dynamics, and noise in data compensate for these three parameters. Long Short Memory (LSTM) is a recurring artificial architecture of the neural network (RNN) in deep learning applications. Unlike regular neural networks, LSTM has input connections. The evaluated results of the models are given below:

D. The Evaluated Results of The ARIMA Model

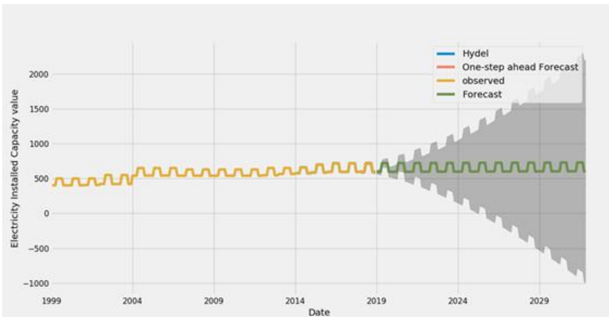
In this paper, the dataset of the electricity sector was accessed for forecasting purposes from the hydrocarbon development institute of Pakistan "HDIP." The dataset of HDIP is from 1999 to 2019 with different attributes like Electricity Installed Capacity (Hydel Thermal (WAPDA), Thermal (K-Electric), Thermal (IPPs), Nuclear), Energy Consumption by Sector (Domestic, Commercial), Resource Production (Oil, Gas, Coal, Electricity), and Resource Consumption (Oil, Gas, Coal, Electricity)." The evaluated graph was visualized, respectively, from "Fig. 3" to "Fig. 6".

E. The Evaluated Results of ARIMA Model

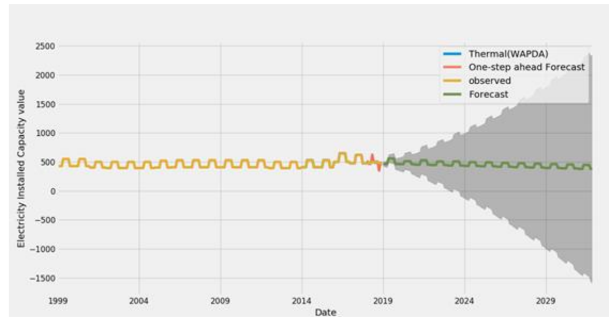
Work was done with a univariate series for a single variable, so the number of features is one. The input is the amount that is selected for the split-sequence function as a justification for our dataset. In the input shape statement for the first secret layer description, the input form for each sample is defined. The model is supposed to have a dimension or form for the training data input variable, there were almost always multiple samples: samples, timesteps, features, split-sequence) (function with shape [samples, timesteps] in the previous section, so that X can be reshaped conveniently to have additional dimensions for one element. A model of 50 LSTM units and a laying of output predicting a single numerical value are defined in the hidden layer. The model fits with the efficient stochastic gradient downward version of Adam and is optimized with the average square error or 'MSE' losing function.

```
# fit model
model.fit(X, y, epochs=200, verbose=0)
```

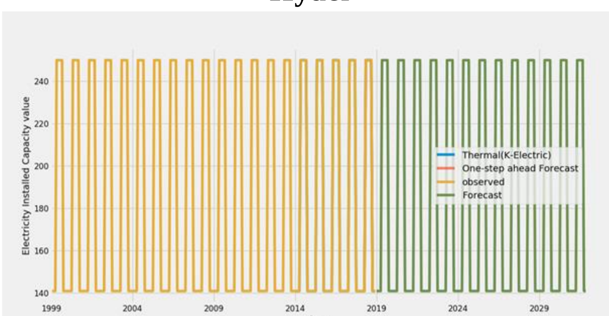
this model was used to predict after it's correct. By providing the data, it can predict the next sequence number. Example running prepares the details, fits the model, and predicts. With the stochastic existence of the algorithm, the results can differ. The forecasted value of the like Electricity Installed Capacity (Hydel Thermal (WAPDA), Thermal (K-Electric), Thermal (IPPs), Nuclear), Energy Consumption by Sector (Domestic, Commercial), Resource Production (Oil, Gas, Coal, Electricity), and Resource Consumption (Oil, Gas, Coal, Electricity) is shown from “Table. 3” to “Table. 6”. Also, the bar chart visualization of these results, as shown in “Fig. 7”.



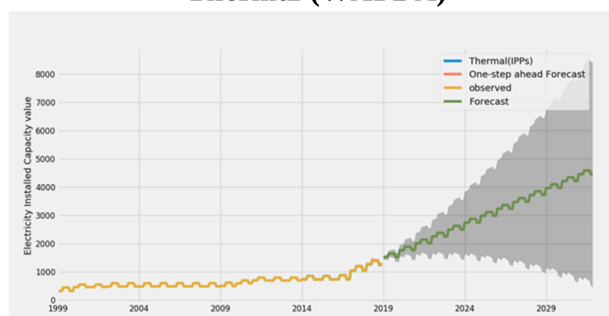
Hydel



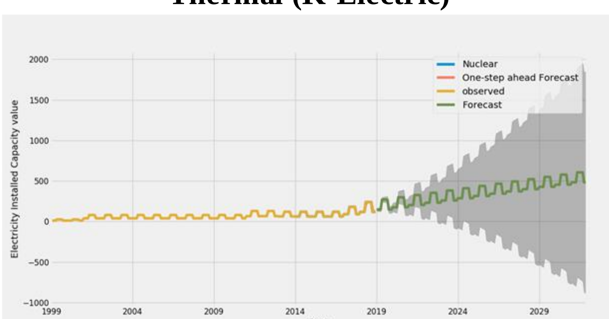
Thermal (WAPDA)



Thermal (K-Electric)

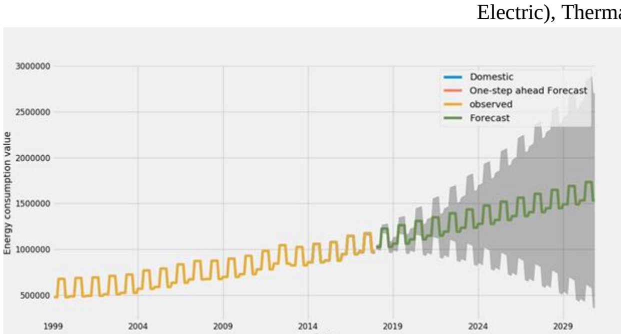


Thermal (IPPs)

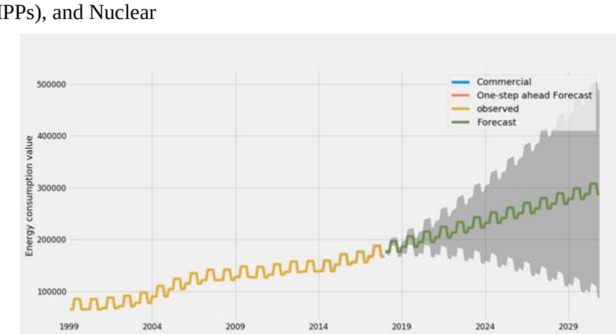


Nuclear

Figure 3. The Visualization of The Forecasted Graph till 2030 for Electricity Installed Capacity with Hydel, Thermal (WAPDA), Thermal (K-Electric), Thermal (IPPs), and Nuclear

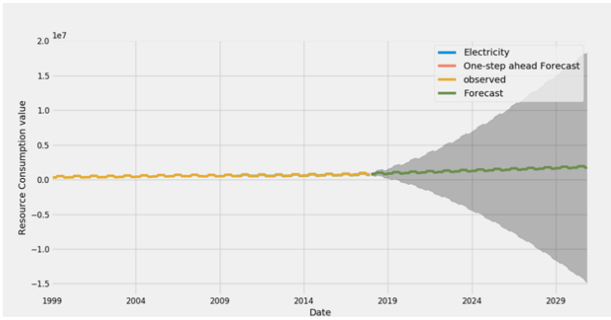


Domestic

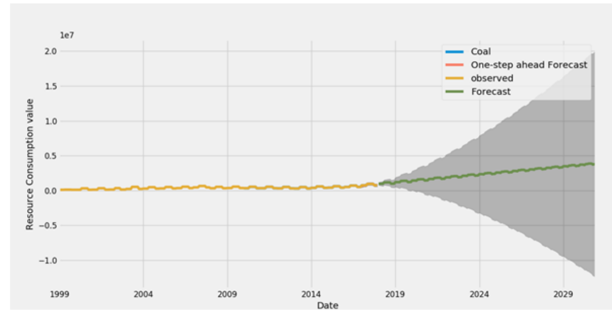


Commercial

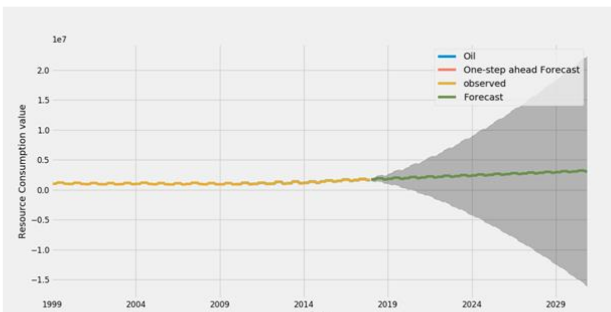
Figure 4. The Visualization of The Forecasted Graph until 2030 for Energy Consumption by Sector with Domestic, and Commercial



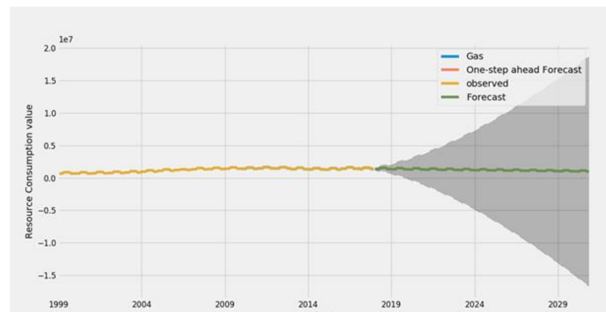
Electricity



Coal

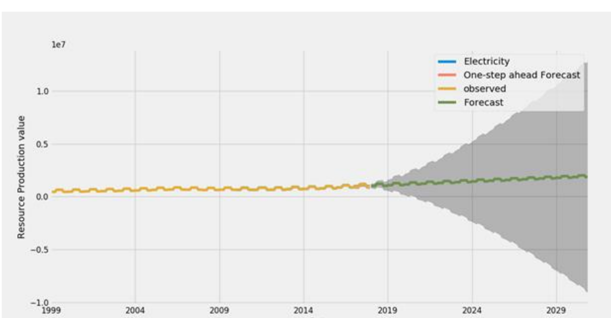


Oil

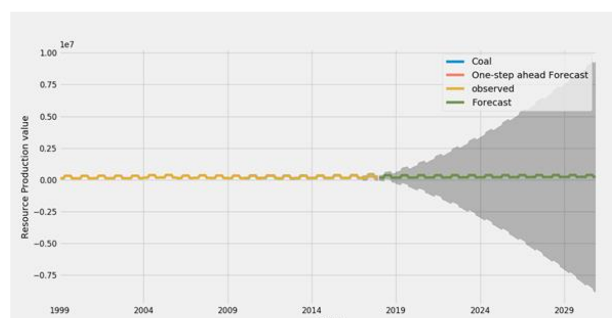


Gas

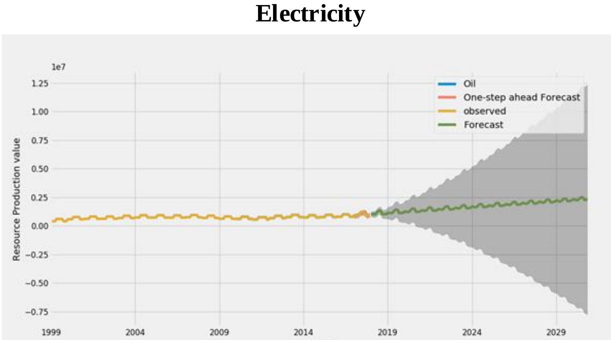
Figure 5. The Visualization of The Forecasted Graph until 2030 for Resource Domestic, and Commercial with Electricity



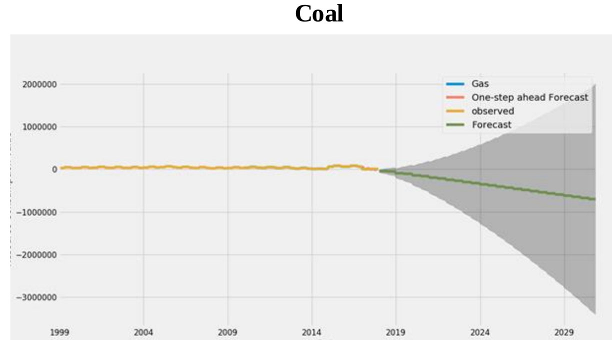
Electricity



Coal



Oil



Gas

Figure 6. The Visualization of The Forecasted Graph until 2030 for Resource Production with Electricity, Oil, Gas, and Coal

TABLE III. THE STATISTICAL EVALUATION OF THE ELECTRICITY INSTALLED CAPACITY TILL 2030

Year	Hydel	Thermal (WAPDA)	Thermal(K-Electric)	Thermal (IPPs)	Nuclear
01-01-19	698	469	245	1263.972	226.883
01-01-20	734.6028	600.7351	235.2896	1356.866	216.629
01-01-21	724.8972	586.8711	245.8401	1344.379	224.3242
01-01-22	698	571.9722	250.1881	1261.811	225.7201
01-01-23	731.1243	536.5438	210.3974	1165.853	231.048
01-01-24	737.2788	517.1022	208.8518	1383.494	232.2158
01-01-25	687.6271	522.3052	254.87	1403.914	206.8409
01-01-26	741.2982	523.0894	218.2888	1349.225	207.0252
01-01-27	756.6824	559.2158	270.2826	1311	225.7458
01-01-28	730.6592	573.8325	273.1617	1333.926	220.0691
01-01-29	745.5831	622.2249	226.1507	1452.014	213.4868
01-01-30	717.0546	569.1343	234.7632	1424.008	242.1858

TABLE IV. THE STATISTICAL EVALUATION OF THE ENERGY CONSUMPTION BY SECTOR TILL 2030

Year	Domestic	Commercial
01-01-18	1094624.8	147945.94
01-01-19	1289661.8	193761.92
01-01-20	1074860.8	193134.9
01-01-21	1144598.4	196320.62
01-01-22	1321975.5	196295.84
01-01-23	1056263.6	196367.62
01-01-24	1068891.5	180142.05
01-01-25	1073266.4	195329.42
01-01-26	1080704	195114.22
01-01-27	1072046	197381.66
01-01-28	1070111.4	212704.02
01-01-29	1093119.8	194323.69
01-01-30	869348.75	196817.73

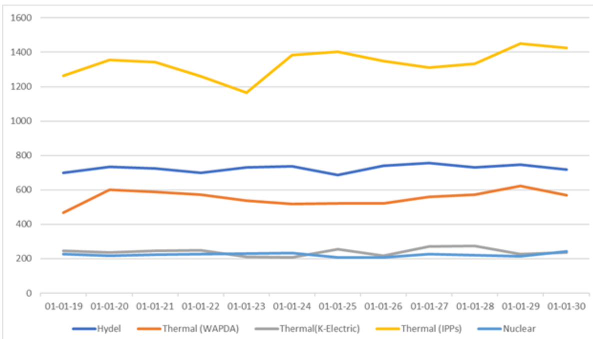
TABLE V. THE STATISTICAL EVALUATION OF THE RESOURCE CONSUMPTION TILL 2030

Year	Oil	Gas	Coal	Electricity
01-01-18	1487412.9	1369123.5	597765.2	696615.75
01-01-19	1468182.1	1382751.6	632903.56	671400.7
01-01-20	1,500,278	1354808.5	609033.9	682762.5
01-01-21	1,491,928	1350552.9	648158	629818.2
01-01-22	1,470,593	1365829.9	680731.56	645967.94
01-01-23	1,487,803	1347613.8	586805.4	696807.6
01-01-24	1,469,105	1328416.5	699096.8	669123.7
01-01-25	1471524.5	1393234.8	632670.5	675690.6
01-01-26	1453211.4	1390102.8	769830.56	642982.56
01-01-27	1,499,358	1379412.2	631563.9	678401.25
01-01-28	1,486,142	1385258.2	732479.75	656274.06
01-01-29	1,474,995	1381132.6	624878.44	661955.5
01-01-30	1,484,344	1365312.8	706125.44	683005.25

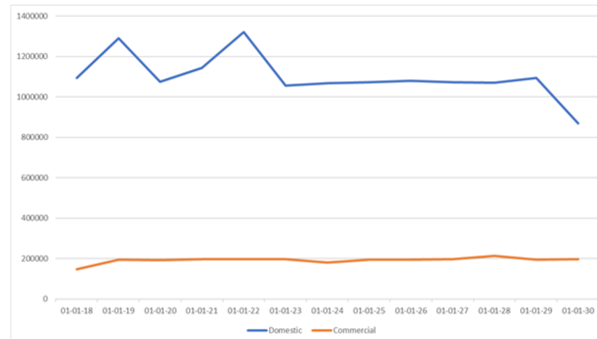
TABLE VI. THE STATISTICAL EVALUATION OF THE RESOURCE PRODUCTION TILL 2030

Year	Oil	Gas	Coal	Electricity
01-01-18	842566.75	48744.39	151919	899348.7
01-01-19	819951.56	47759.266	148760.8	850785.1
01-01-20	816585.25	56019.32	159252.1	885113.8
01-01-21	847870.3	59116.758	152147	839522.5
01-01-22	863988.3	36464.715	130456.6	904907.2
01-01-23	818898.6	47326.406	144499.9	886907.6
01-01-24	818069.9	47589.613	157448.6	854785.06
01-01-25	858786	38783.93	149107.5	879217.44
01-01-26	834361.94	70534.46	145548.8	840268.2
01-01-27	825088.25	53646.867	160221.6	897749.5

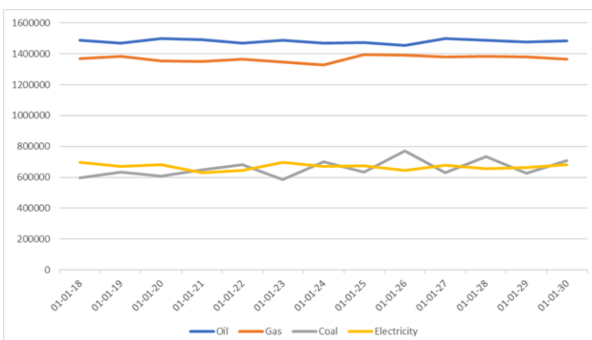
01-01-28	830094.3	54253.965	141995.4	895720.56
01-01-29	826256.44	56793.973	149487.8	1.5877314
01-01-30	873870.56	62611.293	136004.1	874215.6
01-01-31	840909	48604.207	140404.1	958545.5



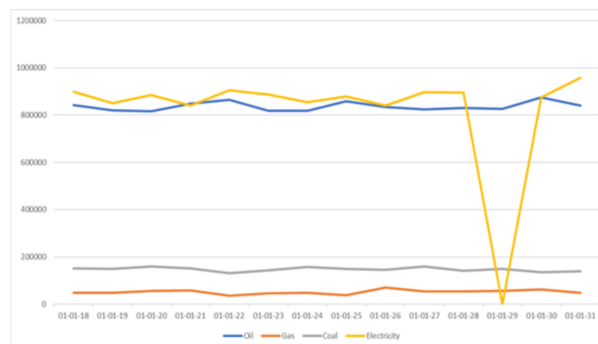
Electricity Installed Capacity



Energy Consumption



Resource Consumption



Resource Production

Figure 7. The Bar Chart Visualization of Electricity Installed Capacity, Energy Consumption, Resource Production, Resource Consumption, Until 2030

5. Conclusion and Future Work

F. Conclusion

Over the last decade, the energy sector has experienced a major modernization cycle. Its network is undergoing accelerated upgrades. The instability of production, demand and markets is far less stable than ever before. We've seen in before our research authors focus on single-valued forecasts. Most researchers have come to the econometric modeling of energy demand in Pakistan's history. The value of the demographic and economic parameters might, however, deviate from the factor of realizations. In this case, the simulation of the time series is providing better results for a variance. In this study, ARIMA, a machine learning model was used to estimate Pakistan's future primary energy demand from 2018 through 2030. Dataset used in the study was from the electricity sector for forecasting purposes from Pakistan's Hydrocarbon Development Institute (HDIP), as the electricity sector dataset is not publicly available online. HDIP's dataset will be from 1999 to 2018 with different sheets such as electricity installed capacity, sector-by-sector energy consumption, resource output, and resource consumption. Using machine learning techniques will help to do the foresting of the energy demand of each sheet attribute before 2030. Predicting overall primary energy demand using machine learning seems to be more accurate than summing up the individual predictions. Studies have shown that different energy sources average annual growth rates.

G. Future work

Further on, different techniques of generative adversarial neural networks (GANN) or (GAN) can be used, which consist of the multi-layer perceptron as the discriminator, and to forecast power, LSTM also acts as the generator. To architect this model, LSTM base generator developed, will be used to forecast the power from the available data of electricity and produce the data in the exactly similar distribution. On the other hand, the discriminator, which is consists of multi-layer perceptron

(MLP) purpose of distinguishing the power forecasting data and produced data by the generator. There are plenty of other methods and variants of ANN and deep learning-based RNN models that can be incorporated to predict the time series data regarding power forecast.

REFERENCES

[1] D. Hussain and A. A. Khan, "Machine learning techniques for monthly river flow forecasting of Hunza River, Pakistan," Earth Science Informatics, pp. 1-11, 2020.

[2] W. Ahmad et al., "Towards Short Term Electricity Load Forecasting Using Improved Support Vector Machine and Extreme Learning Machine," Energies, vol. 13, no. 11, p. 2907, 2020.

[3] H. Son and C. Kim, "Short-term forecasting of electricity demand for the residential sector using weather and social variables," Resources, conservation and recycling, vol. 123, pp. 200-207, 2017.

[4] M. C. R. BATAC, M. J. V. GUNO, C. CAPARAS-DE CASTRO, K. GUTIERREZ-SANTOS, and A. TANDOC, "Effects of a probiotic formula on measles, mumps and rubella IgG production and on anthropometric measurements of infants aged 11-15 months in a tertiary hospital," Santo Tomas journal of medicine, vol. 52, no. 4, pp. 124-130, 2005.

[5] V. Bianco, O. Manca, S. Nardini, and A. A. Minea, "Analysis and forecasting of nonresidential electricity consumption in Romania," Applied Energy, vol. 87, no. 11, pp. 3584-3590, 2010.

[6] C. Chakraborty, "Chronic wound image analysis by particle swarm optimization technique for tele-wound network," Wireless Personal Communications, vol. 96, no. 3, pp. 3655-3671, 2017.

[7] H. K. Ozturk and H. Ceylan, "Forecasting total and industrial sector electricity demand based on genetic algorithm approach: Turkey case study," International journal of energy research, vol. 29, no. 9, pp. 829-840, 2005.

[8] M. M. Nezhad, A. Heydari, D. Groppi, F. Cumo, and D. A. Garcia, "Wind source potential assessment using Sentinel 1 satellite and a new forecasting model based on machine learning: A case study Sardinia islands," Renewable Energy, 2020.

[9] B. Zeng, Y. Tan, H. Xu, J. Quan, L. Wang, and X. Zhou, "Forecasting the Electricity Consumption of Commercial Sector in Hong Kong Using a Novel Grey Dynamic Prediction Model," Journal of grey system, vol. 30, no. 1, 2018.

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

[11] J. K. R. Nair et al., "Radiogenomic Models Using Machine Learning Techniques to Predict EGFR Mutations in Non-Small Cell Lung Cancer," Canadian Association of Radiologists Journal, p. 0846537119899526, 2020.

[12] J. Contreras, R. Espinola, F. J. Nogales, and A. J. Conejo, "ARIMA models to predict next-day electricity prices," IEEE transactions on power systems, vol. 18, no. 3, pp. 1014-1020, 2003.

[13] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," Neurocomputing, vol. 50, pp. 159-175, 2003.

[14] S. C. Hillmer and G. C. Tiao, "An ARIMA-model-based approach to seasonal adjustment," Journal of the American Statistical Association, vol. 77, no. 377, pp. 63-70, 1982.

[15] H. Sak, A. W. Senior, and F. Beaufays, "Long short-term memory recurrent neural network architectures for large scale acoustic modeling," 2014.

[16] M. Iqbal et al., "Emerging issue of e-waste in Pakistan: a review of status, research needs and data gaps," Environmental pollution, vol. 207, pp. 308-318, 2015.

[17] M. Shahid, K. Ullah, K. Imran, I. Mahmood, and A. Mahmood, "Electricity supply pathways based on renewable resources: A sustainable energy future for Pakistan," Journal of Cleaner Production, p. 121511, 2020.

[18] M. Kashif et al., "Untapped renewable energy potential of crop residues in Pakistan: Challenges and future directions," Journal of Environmental Management, vol. 256, p. 109924, 2020.

[19] R. Jamil, "Hydroelectricity consumption forecast for Pakistan using ARIMA modeling and sup[]ply-demand analysis for the year 2030," Renewable Energy, 2020.

[20] D. Burillo, M. V. Chester, S. Pincetl, E. D. Fournier, and J. Reyna, "Forecasting peak electricity demand for Los Angeles considering higher air temperatures due to climate change," Applied Energy, vol. 236, pp. 1-9, 2019.

[21] A. Mittal. (Oct 12, 2019). Understanding RNN and LSTM. Available: https://towardsdatascience.com/understanding-rnn-and-lstm-f7cdf6dfc14e

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