Forecasting Energy Production from Coal, Gas and Coal Sources in Pakistan by Using Machine Learning Models

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Abstract

For energy planning and policymaking, forecasting energy production is significant. Pakistan's energy production through oil, gas, and coal sources over the next ten years was predicted using data from 1971 to 2015. The forecasting procedure is carried out with the help of the autoregressive integrated moving average (ARIMA) model, Holt-Winter Exponential Smoothing model, Artificial Neural Networks (ANNs), and Hybrid Model. The ARIMA (1,1,0) and NN (2,2) are determined for the data. The annual electricity production from oil, gas, and coal sources will be 58% to 65% (of the total production) in the next ten years. This research holds enormous significance for Pakistan's energy landscape. Dependable and exact energy creation conjectures are fundamental for policymakers, energy organizers, and partners in making informed choices on asset designation and infrastructure development. By guaranteeing the manageability, dependability, and productivity of Pakistan's energy framework, these forecasts assume an imperative part in supporting economic growth and satisfying the population's energy needs. Furthermore, the study investigates a scope of modeling methods, including ARIMA, Holt-Winter Exponential Smoothing, and ANNs, and presents a Hybrid model. The hybrid approach, which combines the qualities of different models, offers a promising answer for upgrading forecasting accuracy. By considering the complex elements of electricity production from various sources, this exploration benefits Pakistan and adds to the more extensive energy forecasting field.

Keywords: Forecasting, ARIMA, Holt-Winter Exponential Smoothing model, Artificial Neural Network, Hybrid model, Electricity production, Pakistan, Energy Planning.

Introduction

Predicting power generation is a crucial responsibility for energy planning and resource management. A reliable and adequate energy supply depends on accurate electricity production estimates from natural gas, coal, and oil resources. Forecasting power output is significant in the case of Pakistan, a nation that depends mainly on these energy sources.

The main objective of this study is to forecast Pakistan's energy generation using various modeling methods, including ARIMA, Holt-Winters exponential smoothing, artificial neural networks (ANN), and a hybrid model. Each model has distinct skills and techniques for capturing the underlying dynamics and patterns of the data on electricity production time series.

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To capture dependencies and trends in the data, the ARIMA model, which is based on the Autoregressive Integrated Moving Average approach, combines the ideas of autoregression, differencing, and moving averages. It is a well-liked option for estimating power generation because it can handle non-stationary time series.
The Holt-Winters exponential smoothing model is a potent technique that considers the data's seasonality and trend components. It can produce precise forecasts by giving previous observations the proper weights using exponential smoothing methods.
A flexible and adaptive modeling strategy is provided by artificial neural networks (ANN). They can understand intricate correlations between input variables and output predictions through connected layers of artificial neurons. ANNs are effective at collecting nonlinear trends in data on electricity output and have demonstrated promising outcomes in various forecasting applications.
A hybrid approach is suggested to increase predicting accuracy even more. Combining the forecasts from the ARIMA, Holt-Winters, and ANN models, this model combines the benefits of several different approaches. The hybrid model tries to use these methodologies' complementing qualities to generate more reliable and precise predictions.
Policymakers, energy planners, and other stakeholders in Pakistan's energy sector may find the study's findings helpful in assisting them in making decisions on resource allocation, infrastructure development, and energy management tactics. Accurate predictions of electricity output can support Pakistan's energy system's sustainability, reliability, and efficiency while promoting economic growth and satisfying the population's energy requirement.

Literature Review

The field of energy forecasting is rich with assorted approaches and models; each custom-fitted to address the one-of-a-kind difficulties of various regions and sectors. These methodologies include many statistical and computational procedures, offering bits of knowledge and techniques to upgrade the precision and accuracy of energy production forecasts.
Adom and Bekoe (2012) analyzed two methodologies, ARDL and PAM, to forecast electrical energy utilization prerequisites in Ghana by 2020. Their study featured the meaning of choosing proper models for determining energy needs and the significance of considering dynamic conditional factors in the forecasting system. The decision of modeling procedure was uncovered to fundamentally affect the precision of energy forecast, reflecting the requirement for an appropriate methodology in Pakistan's energy landscape.
Badmus and Ariyo (2011) applied an ARIMA model to forecast the development region and production of maize in Nigeria. Their study exhibited the materialness of time series examination in predicting agricultural results, underlining the flexibility of ARIMA models. Such modeling procedures could be adjusted to address forecasting difficulties in the energy area, revealing insight into the capability of these models in Pakistan's specific circumstances.
Djakaria and Saleh (2021) investigated the utilization of Holt-Winters exponential smoothing to forecast the direction of Coronavirus cases. While the context varied, their study displayed the power of exponential smoothing procedures in catching seasonality and trends. This model could address similar patterns in energy production time series information, giving significant knowledge into how to behave during the electricity age in Pakistan.
Ozturk and Ozturk (2018) applied an ARIMA model to forecast the energy utilization of Turkey. Their research featured the adequacy of ARIMA models in foreseeing energy utilization, supporting the pertinence of such models in tending to energy forecasting challenges in Pakistan.

Sako et al. (2022) investigated the utilization of neural networks for financial time series forecasting, exhibiting the force of artificial neural networks in catching complex connections within data. This approach has promising implications for energy forecasting, particularly in Pakistan, where the energy scene is dynamic and complex.
Hybrid approaches, as concentrated by Suhartono et al. (2017) offer the possibility of joining the qualities of different forecasting models. Their research showed how hybrid models can deal with time series information with trend, seasonality, and schedule variety designs. Using hybrid models for energy production forecasting in Pakistan might further develop forecasting accuracy by harnessing the qualities of ARIMA, exponential smoothing, and artificial neural networks.

Data and Methodology

Autoregressive Integrated Moving Average (ARIMA)

This research investigates Pakistan's annual electricity generation from coal, oil, and natural gas between 1971 and 2015. The data on electricity production is obtained from the World Bank. ARIMA models are built using statistical tools to analyze this data. More specifically, the Autoregressive Integrated Moving Average (ARIMA) model proposed by Box and Jenkins in 1976 is used. The Moving Average (MA) model and the Autoregressive (AR) model are combined in the ARIMA model. The AR component, which incorporates a random variable, considers the correlation between current and previous values. The link between the present value and the historical residuals, on the other hand, is captured by the MA component. If it is determined that the data is not stationary, differencing is used to convert it to a stationary form. The ARIMA (p, d, q) model's general statement is as follows.

$$\Phi_p\,(B)(1-B)^d Z_t = \boldsymbol{\theta}_q(B)\boldsymbol{a}_t$$

Where p is the AR model order, q is the MA model order and d is the differencing order. Moreover

$$\Phi_p\,(B) = 1 - \Phi_1\,B\text{-}\,\Phi_2\,B^2 - \cdots - \Phi_p\,B^p$$

$$\boldsymbol{\theta}_q(B) = 1 - \boldsymbol{\theta}_1\,B\text{-}\,\boldsymbol{\theta}_2 B^2 - \cdots - \boldsymbol{\theta}_q\,B^q$$

The first step is to do model identification, The Augmented Dickey-Fuller (ADF) test is used to check whether the variable of interest is stationary. If the Q Statistics' p-value is low (typically below a predetermined significance level), it suggests that the tested model does not adequately account for the autocorrelation in the data. Analysts should consider creating a brand-new or altered model that addresses the autocorrelation problem in such instances. The investigation should continue until the discovery of a good model that accurately reflects the autocorrelation patterns in the data.
The selected econometric approach, which uses Auto-Regressive Integrated Moving Average (ARIMA) models, firmly aligns with the exploration's center targets. The ARIMA models act as the logical spine for surveying and forecasting electricity from Pakistan's oil, gas, and coal sources. This strategy empowers us to catch and break down the complex fleeting examples and conditions present in the energy creation information; it is precise and dependable to guarantee our expectations. By choosing the fitting ARIMA model request (p, d, q) through thorough measurable rules, we tailor the investigation to the particular attributes of the dataset, representing auto-regression, differencing, and moving average components. This careful methodology guarantees the strength of our display and considers a far-reaching assessment of estimating execution through different measurements and approval strategies. The econometric system established in ARIMA supports the review's ability to give significant experiences and information-driven estimates, filling in as an essential starting point for energy arranging and strategy improvement in Pakistan.

Holt-Winter Exponential Smoothing

A well-known forecasting strategy, Holt's double exponential smoothing method is particularly effective at capturing trends and seasonality in time series data. Smoothing constants, alpha, and beta, are two weighting parameters incorporated into it. The first smoothing constant, alpha, determines the weight assigned to the most recent observation. A higher alpha value indicates that current comments are more significant in predicting future discounts. Thanks to this parameter, the method can quickly adapt to changes in the underlying data pattern. The data's trend component is estimated using the beta, the second smoothing constant. It gives the trend calculated weight, allowing the forecast to adjust for any upward or downward series movement. The forecast is more sensitive to changes in the data trend when the beta value is higher because it places a greater emphasis on the direction.

There are three main equations in Holt's method. The first equation updates the level component, which is the data's overall average or baseline. The trend component, which represents the series direction and rate of change, is updated in the second equation. The forecast for the subsequent period is produced by combining the level and trend components in the third equation.

Smoothing: $S_t = \alpha X_t + (1-\alpha)(S_{t-1} + b_{t-1})$

Smoothing trend: $b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1}$

Forecast: $F_{t+m} = S_t + b_t(m)$

Artificial Neural Networking (ANNs)

At the point when the limitations on the model structure are loose, countless nonlinear designs can be utilized to portray and figure out time series information. An excellent nonlinear model can capture some of the data's nonlinear patterns. One such modeling strategy, Artificial Neural Networks (ANNs), can accurately approximate various data's nonlinear relationships. Flexible computational frameworks known as ANNs are frequently utilized for modeling various nonlinear problems. Compared to other types of nonlinear models, ANNs have a significant advantage because they can act as universal approximators, accurately representing a wide range of functions. It is because they can process information from the input data in parallel. During the process of building a model, ANNs, in contrast to other models, do not necessitate a priori assumptions regarding the model's form. Instead, the data's characteristics heavily influence the network architecture.

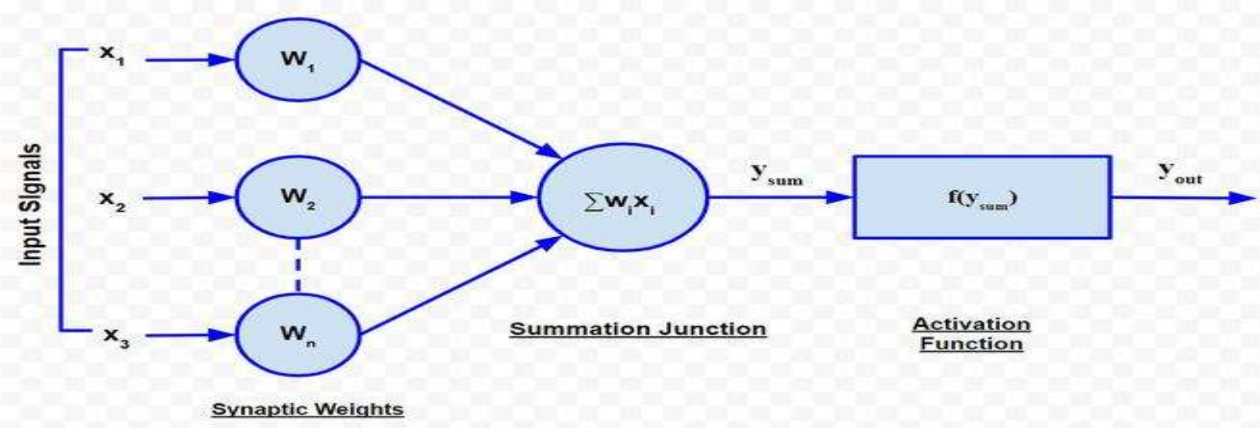
The relationship between the independent and dependent variables has the following mathematical representation.

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + e_t \qquad (1)$$

Where alpha and beta are the model parameters known as connection weight; p and q are the number of input nodes and hidden nodes respectively. The ANN model is the functional mapping from past observations to future values, i.e.,

$$y_t = f(y_{t-1}, y_{t-2} \ldots \ldots \ldots . y_{t-p}, \text{w}) + e_t$$

Where w is a vector of all parameters and function f is determined by the network structure and connection weights. As the number of hidden nodes (q) grows, the simple network described by Equation 1 becomes surprisingly powerful and can approximate a wide range of functions. However, a network structure with fewer hidden nodes frequently produces satisfactory results for out-of-sample forecasting. The problem of overfitting, which is common in modeling neural networks, is to blame for this. While an overfitted model works well with the data used to build the model, it can't be used to generalize to new data. There is no established method for determining this parameter because q depends on the data.



In ANN modeling of time series data, selecting the number of lagged observations (p) is as important as choosing the correct number of hidden nodes. This parameter determines the time series' (nonlinear) autocorrelation structure. The network is ready for training, which entails estimating the model parameters, once the form of the network (p, q) has been specified. However, there is no theoretical guideline for determining the value of p. As a result, experiments are frequently carried out to identify a suitable value for both p and q. The parameters are estimated using practical nonlinear optimization algorithms to minimize an overall accuracy criterion like the mean squared error, just like in the ARIMA model-building process.

Hybrid Model

A hybrid model combines linear and nonlinear models to improve forecast accuracy. It is the combination of linear and nonlinear models, such as

$$y_t = l_t + n_t + e_t$$

Where l_t is a linear component, it is a nonlinear component, and it is the model's error term. In this paper, ARIMA is used for modeling the linear part, and ANN is used for modeling the nonlinear component.

Results and Discussions

Autoregressive Integrated Moving Average (ARIMA)

The maximum production of electricity in Pakistan through oil, gas, and coal sources was 71.83% of the total in 2000 and the minimum output was 38% of the total in 1978.

In the model specification, we look at the plot of time series (Fig 1), Autocorrelation function (ACF) for electricity production from oil, gas, and coal sources (Fig 2), and partial autocorrelation function (PACF) for electricity production from oil, gas, and coal sources (Fig 3). The ACF indicated the order of the MA (q), and the PACF noted the order of AR.

The time series plot [Fig 1] showed an increasing trend, which means it is non-stationary. The first difference from the initial series was taken to check the subsequent stationery. The first difference in the series is more stationary than the original one. t. The histogram (Fig 5) and QQ plot (Fig 6) tell us that our data become normal after taking the first difference. The autocorrelation function of the series correlogram revealed that the autocorrelation function finally falls after lag 0; consequently, the parameter "q" values were chosen to be 0.

Parameter "p" was determined using the PAC function of the series. We chose p to be 1. As a result, ARIMA (1, 1, 0) gives us better results.

Figure 1: Time series plot of electricity production in Pakistan in the period ranging from 1971 to 2015.

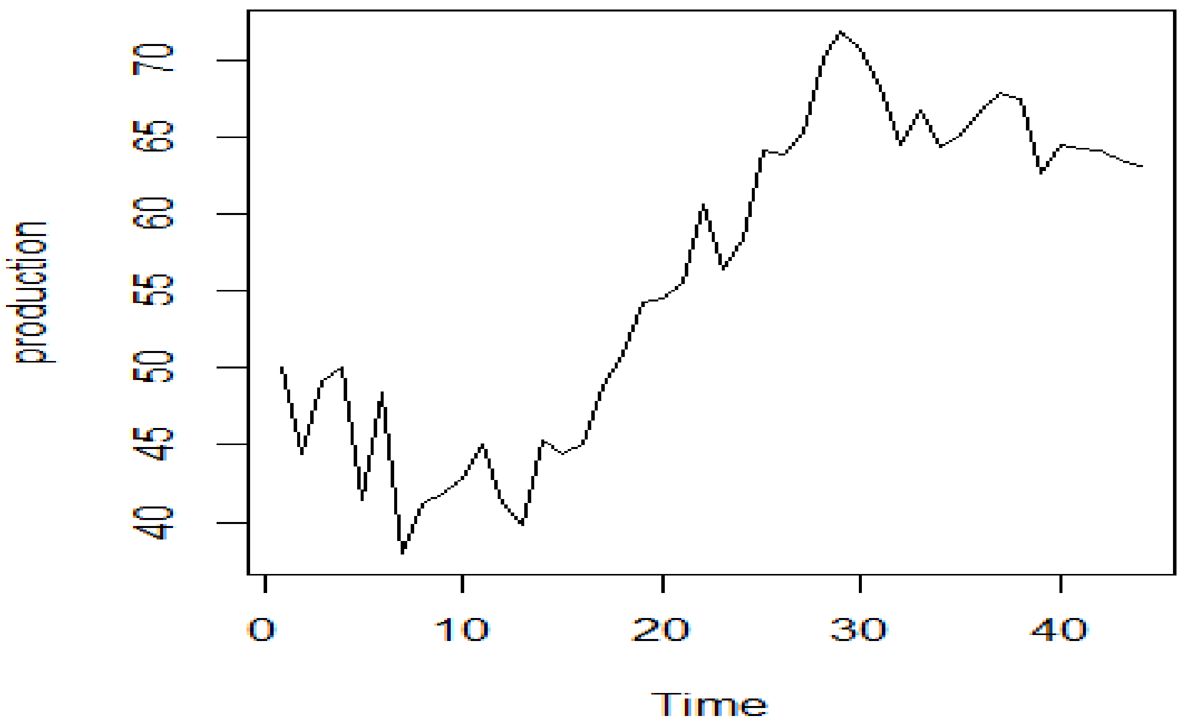


Figure 2: Autocorrelation function (ACF)

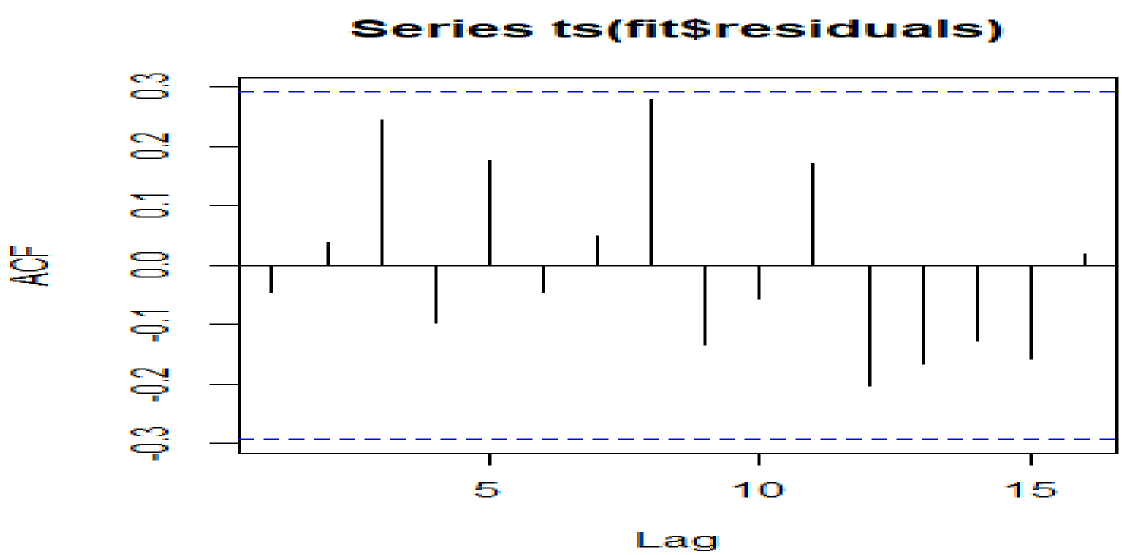


Figure 3: Partial Autocorrelation Function (PACF)

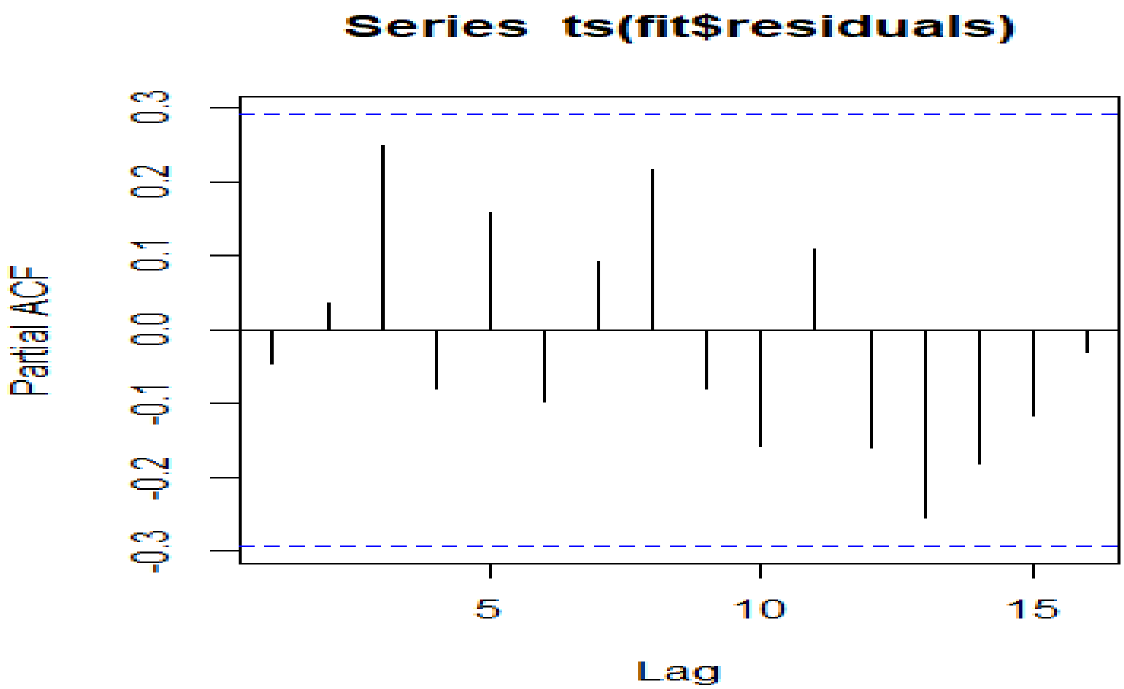


Figure 4: Time series plot of electricity production in Pakistan in the period ranging from 1971 to 2015 after differencing

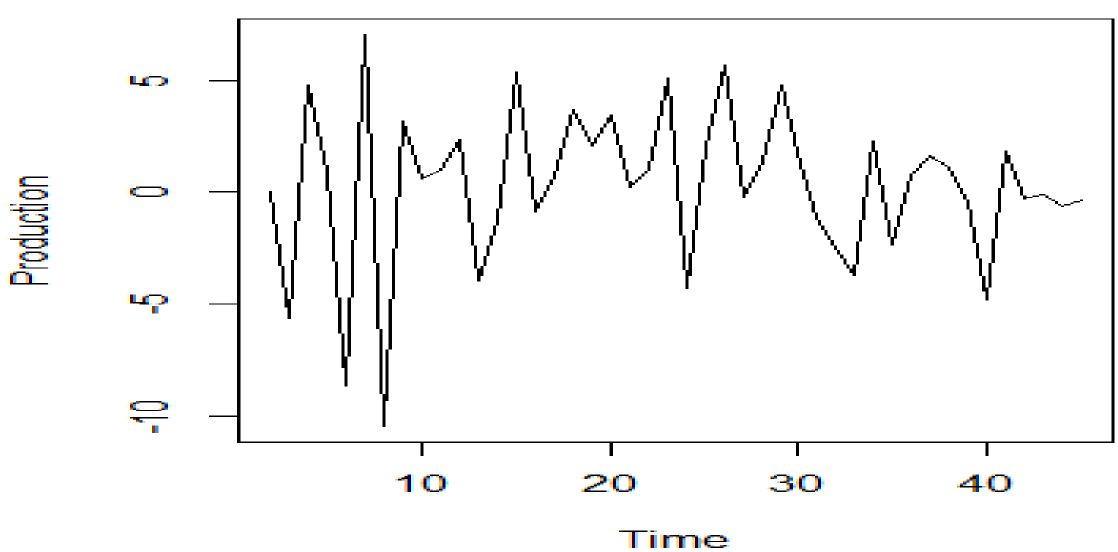


Figure 5: Histogram of Electricity production in Pakistan in the period ranging from 1971 to 2015 after differencing

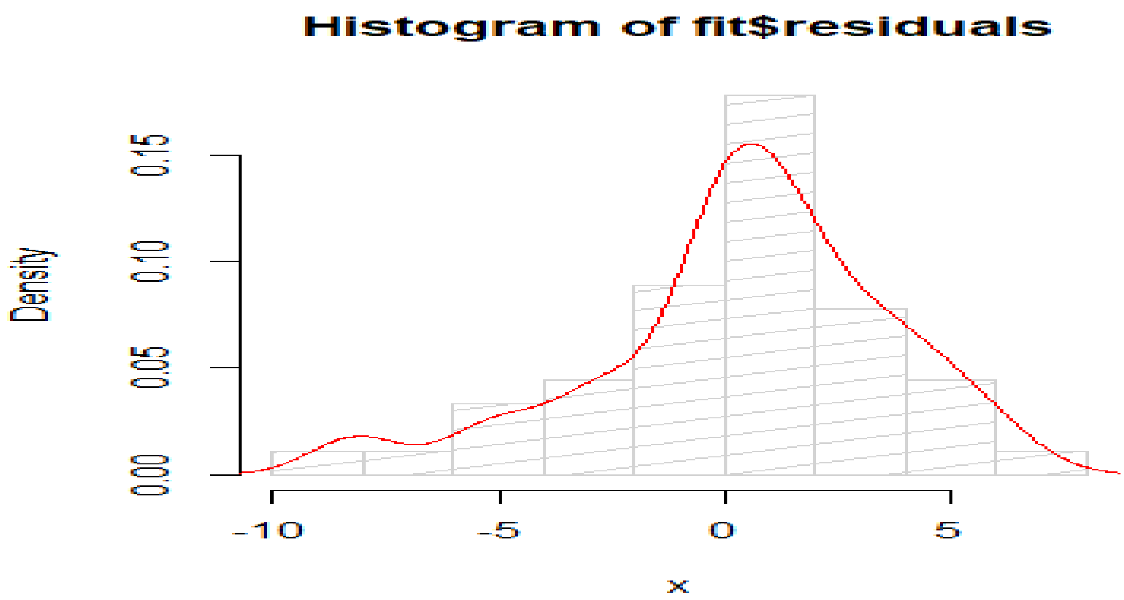
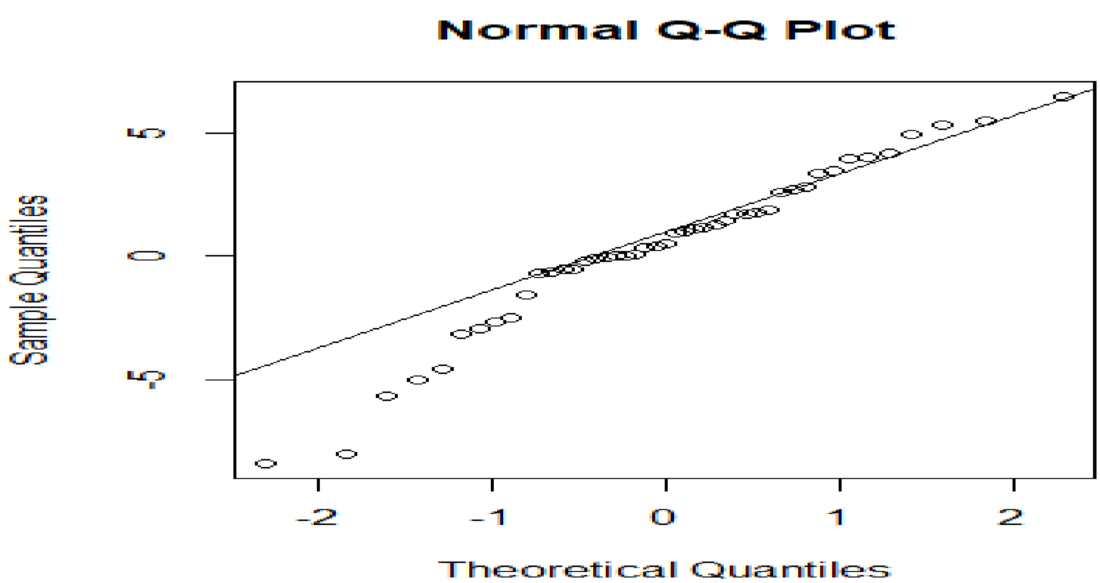


Figure 6: QQ plot of electricity production in Pakistan in the period ranging from 1971 to 2015 after differencing



One other way to select the best fitted ARIMA model is by calculating Akaike information criterion (AIC). The best fitted ARIMA model is the one that has the smallest AIC value. Table 1 shows us some ARIMA (1,1,0) is the best-fitted model.

Table 1: ARIMA Models

Model	Lag L	AIC*
(1,1,0)	**-115.34**	**232.68**
(1,1,1)	-115.31	234.62
(1,1,2)	-114.29	234.58
(1,1,3)	-113.43	234.85
(0,1,0)	-118.35	236.69
(0,1,1)	-115.77	233.55
(0,1,2)	-114.47	232.94
(0,1,3)	-114.11	234.23
(1,1,1)	-115.31	234.62
(2,1,2)	-113.91	235.82
(3,1,3)	-114.47	232.94

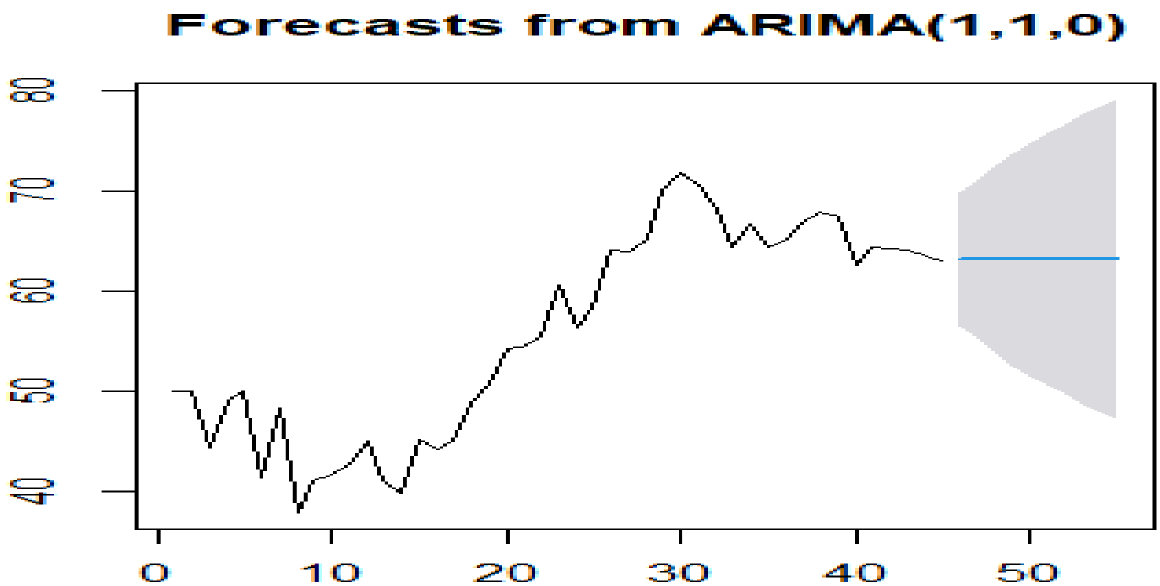
The residual production data's time series plot revealed erratic trends; as a result, residual analysis models were correctly fitted. The Shapiro-Wilk test was employed for the normality check. The test was significant, and the assumption of normality was accepted. The model fits the data well since the fitted series displays normalcy.

Table 2 and Figure 7 provide projections for production with 95% confidence interval values using ARIMA (1,1,0) for a 10-year horizon. According to Table 2 and Figure 7, 63 to 64% of the electricity produced in the next 10 years will come from coal, gas, and oil sources.

Table 2: Forecasting values by using ARIMA Model

Time	Forecast	Lower limit 95%	Upper limit 95%
2016	63.22327	56.63491	69.81164
2017	63.17517	55.32906	71.02128
2018	63.19216	53.84340	72.54093
2019	63.18616	52.68051	73.69181
2020	63.18828	51.59811	74.77846
2021	63.18753	50.62003	75.75503
2022	63.18780	49.70906	76.66654
2023	63.18770	48.85708	77.51833
2024	63.18774	48.05259	78.32288
2025	63.18772	47.28888	79.08657

Figure 7: Forecasted and actual values of electricity production using ARIMA (1,1,0)



Holt Exponential Smoothing

Holt exponential smoothing method, as stated above, uses two parameters. Therefore, several forecasting models will be obtained using different parameters. We use MAPE value to decide which model is best for forecasting electricity production through oil, gas, and coal sources. The model which has the lowest MAPE value is the best one. So, we get α=0.622 and β=0.362, and the MAPE accuracy is 5.57.

Figure 8: Holt-Winter exponential smoothing time series plot

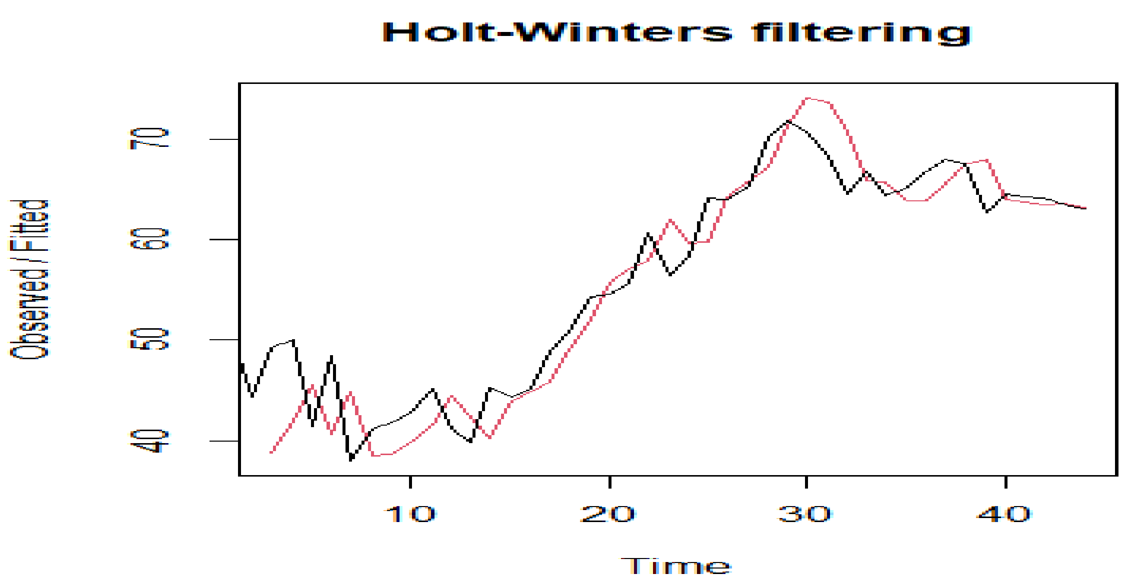
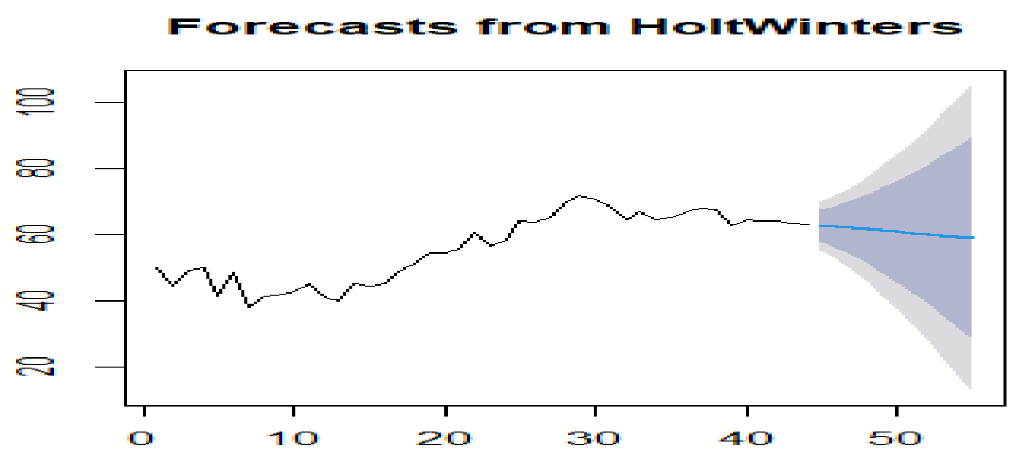


Table 3 and Figure 9 provide projections to produce electricity with 80% and 95% confidence interval values using the Holt-Winter Exponential Smoothing model for a 10-year horizon. According to Table 3 and Figure 9, 58 to 63% is the forecasted value of the electricity produced in the next 10 years will come from coal, gas, and oil sources.

Table 3: Forecasted values by Holt-Winter Exponential Smoothing model

Time	Forecast	Lower limit 80%	Upper limit 80%	Lower limit 95%	Upper limit 95%
2016	62.72582	57.86794	67.58370	55.29634	70.15531
2017	62.35105	55.98331	68.71879	52.61243	72.08966
2018	61.97627	53.74783	70.20471	49.39196	74.56059
2019	61.60149	51.23460	71.96838	45.74670	77.45628
2020	61.22672	48.48939	73.96404	41.74666	80.70678
2021	60.85194	45.54167	76.16221	37.43690	84.26698
2022	60.47717	42.41164	78.54269	32.84833	88.10600
2023	60.10239	39.11402	81.09076	28.00345	92.20133
2024	59.72761	35.66009	83.79514	22.91951	96.53572
2025	59.35284	32.05885	86.64682	17.61029	101.09538

Figure 9: Forecasted and actual values of electricity production using the Holt-Winter Exponential model

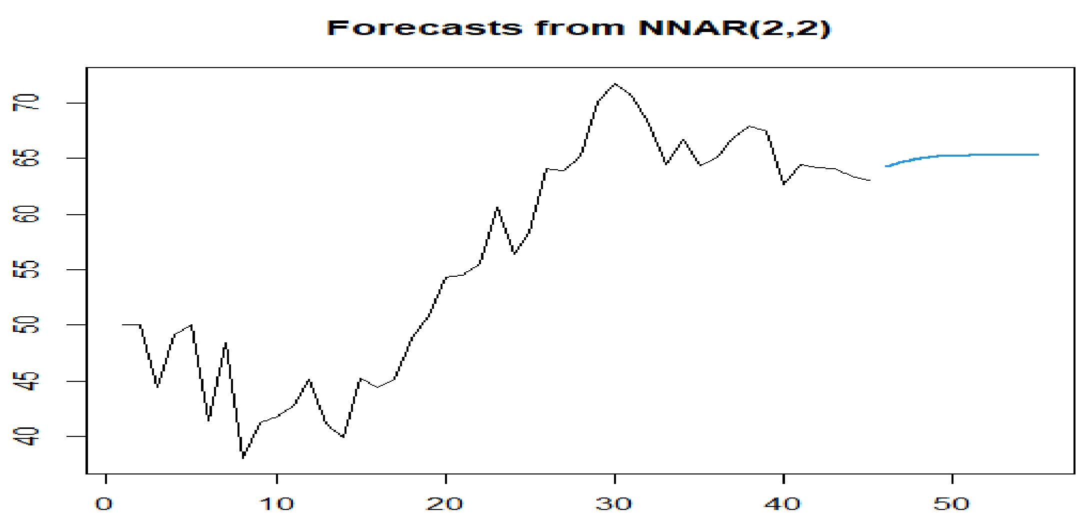


Artificial Neural Networking (ANNs)

This study's time series dataset consists of data points representing the annual electricity production from oil, gas, and coal sources. A single hidden layer feed-forward neural network was utilized for the forecasting task. The logistic function served as the activation function for the hidden layer in the network architecture, which had two remote nodes. Based on data from the previous year, the model tried to predict electricity production from oil, gas, and coal sources for the next ten years. The model had an MAE of 2.28 on the test set and a MAPE of 4.50. The low MSE and MAE values indicate the model's reasonably accurate forecasts. The training and validation loss curves demonstrate the model's good generalization performance and lack of significant overfitting.

The accuracy of the ANN model is superior to that of conventional time series forecasting methods like exponential smoothing and ARIMA when compared to their performance. The ability of the ANN to capture nonlinear trends and complex relationships in time series data gives it an advantage over linear models.

Figure 10: Forecasted and actual values of electricity production using the ANNs



Hybrid Model

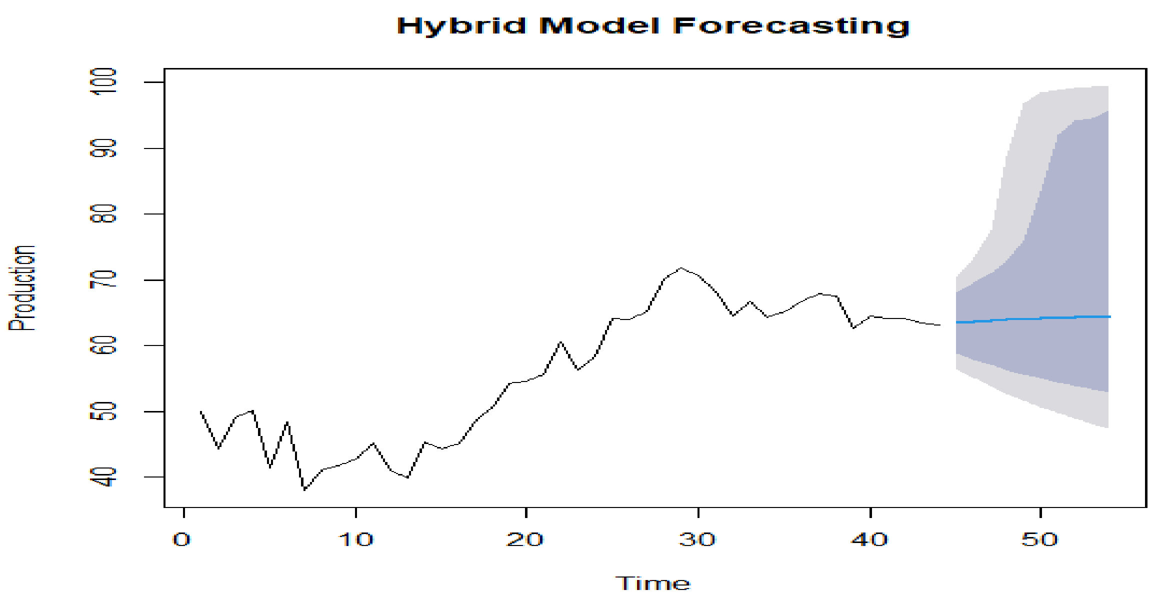
We use two steps to estimate the hybrid model. The linear component is modeled in the first step to obtain residuals; a nonlinear model is then applied to these residuals to handle the nonlinear component in the second step.

Table 4 and Figure 11 provide projections to produce electricity with 80% and 95% confidence interval values using the Hybrid model for a 10-year horizon. According to Table 5 and Figure 11, 63 to 65% is the forecasted value of the electricity produced in the next 10 years will come from coal, gas, and oil sources.

Table 4: Forecasted values by using Hybrid Model

Time	Forecast	Lower limit 80%	Upper limit 80%	Lower limit 95%	Upper limit 95%
2016	63.53625	58.86957	68.15441	56.54205	70.48193
2017	63.68601	57.90817	69.63415	55.07171	73.70088
2018	63.82066	57.09427	71.23087	53.82771	79.90711
2019	63.92279	56.34625	73.04790	52.72341	91.00972
2020	64.01148	55.64586	75.17010	51.65076	97.31054
2021	64.09048	55.01403	81.40644	50.68502	97.38831
2022	64.16484	54.42466	92.11291	49.78345	98.31197
2023	64.23640	53.87350	93.34283	48.94060	98.30549
2024	64.30653	53.35283	94.68411	48.14427	98.59660
2025	64.37587	52.85847	95.40380	47.38822	98.43360

Figure 10: Forecasted and actual values of electricity production using the Hybrid model



Conclusion

This study explored the forecasting of electricity production in Pakistan using various models, including ARIMA, Holt-Winters exponential smoothing, artificial neural network (ANN), and a hybrid model. Each model offers distinct features and approaches to capture electricity production's underlying patterns and dynamics from natural gas, coal, and oil resources.

This study has discovered through research that the ARIMA (1,1,0) model showed promise in capturing relationships and trends in the data. The ARIMA model produced accurate forecasts, including autoregressive, differencing, and moving average components. It worked well for handling non-stationary time series data, giving it a good option for Pakistani power generation forecasting. In the data on electricity output, the Holt-Winters exponential smoothing model (α=0.622, β=0.362) demonstrated its capacity to identify trend components. The model generated precise forecasts by giving past observations the proper weights. The ability of artificial neural networks (ANN) to recognize complicated relationships in the data demonstrated their adaptability and versatility. ANNs might recognize non-linear patterns and make precise predictions by learning from connected layers of artificial neurons. The ANN model showed promise for increasing forecasting precision, especially when working with complex and dynamic data on power generation. This study suggested a hybrid model that included the forecasts from the ARIMA, Holt-Winters, and ANN models to improve forecasting accuracy further. The mixed strategy attempted to use these models' complementary traits and produce more reliable and precise forecasts by combining their strengths. The hybrid model, which drew on the advantages of each distinct model, provided a thorough and well-rounded forecasting solution.

The ARIMA, Holt-Winters, ANN, and hybrid models discussed in this work offer proper instruments for predicting Pakistan's energy generation. It is projected that between 2015 and 2025, natural gas, coal, and oil resources will be used to generate 60 to 65 percent of all electricity. Policymakers and energy planners can build strategies that support a steady, effective, and sustainable energy supply by taking advantage of the advantages of these models.

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