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FORECASTING EXCHANGE RATES IN PAKISTAN: A COMPARATIVE STUDY OF HYBRID ARIMA AND ARTIFICIAL NEURAL NETWORK APPROACHES

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ABSTRACT
In the sphere of research, ARIMA and ANN offer a strong approach for time series data prediction. Both linear and nonlinear patterns are frequently seen in time series data. Consequently, when it comes to modeling and forecasting time series data, neither ARIMA nor neural networks are suitable. The majority of current research appears to employ the same specification for forecasting and estimating when using linear models, but the dynamic influence of the relevant variables is disregarded. To capture both the linear and nonlinear data, this study merged the ARIMA and artificial neural network model using both an equal weighted technique and a profit weighted strategy Elements of the exchange rate, as well as creating a hybrid approach utilizing autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) models. The results were compared to those of the ANN and hybrid ARIMA models. The future dollar exchange rate as well as data imports and exports are predicted using hybrid models. The results shown that the benefits of both linear and nonlinear modeling may be obtained by combining the ARIMA and ANN models Standard statistical measurements like mean absolute error (MAE), root mean square error (RMSE), and mean squared error (MSE) are used to evaluate the two models' capabilities. Models effectiveness the effectiveness of the models are analyzed for the foreign exchange rate, imports and exports of the data and concluded that hybrid techniques provided the best forecasting results

INTRODUCTION
All of this information has been gathered with the intention of elaborating on and discussing the significance of the economic hybrid model in forecasting exchange rate fluctuations and the decline in long- and short-term pricing. In order to do this, we forecast the market timing ability and predictive power of the model, predict the hybrid approaches using linear regression and multilayer networks, and forecast the macro cycles of specific exchanges. We permitted a particular method in the model definition, allowed for changes in the prediction tenor, and included the stylized facts. We then combined the two models by using the exchange rate mechanism's profit strategy.

A hybrid approach to time series forecasting
Hybrid technique actually comes from the following Perspective.

First of all, it can occasionally be quite challenging to tell if the data from the underlying process is from a linear or nonlinear process; in some cases, one method works better than the other. The most successful model is chosen from among all of them because of variations in potential influence, uncertainty, structure, and sample variables. Typically, a significant number of models are concerned with the accurate and final solution of the projects. By combining several study models, we can really make our work easier with less effort. Second, real-world time series are frequently pure in both linear and nonlinear study approaches, and they both contain linear and nonlinear factors. If we take this into consideration, then neither ARIMA nor ANNs can be sufficient in modeling and forecasting the time series process; instead, ARIMA can never handle nonlinear approaches, while neural model networks alone cannot handle both linear and nonlinear approaches. Thirdly, it is widely acknowledged that no single method is sufficient for the problem solving process in every scenario. It is highly stated that real-world problems are extremely complex based on all bookish studies, and if it is stating that any single perfect model is able for solving all of our routine matters then this is considered absurd Hajirahimi, Z. (2024).

To test the correctness of ANNs models with mixed results they mostly use ARIMA model for the Solutions. Most of literature showed that if we combine different models and merge in a particular way that they would be able to improve our forecasting's rather than consider the single or individual models that which one is best and how can help us, only due to that reason different models are merged to increase the chance to grasp various models to increase the predicting performance in the projects Botunac, I., Bosna, J., & Matetić, M. (2024).

Requirements for utilizing the hybrid model:

The majority of time series involve data that is either linear or nonlinear, meaning that neither ANNs nor ARIMA techniques can solve the problem on their own. In these situations, a mix of linear and nonlinear approaches is used to solve the problem. Both theoretical and practical research indicate that combining both approaches can be a successful and efficient way to enhance forecasting methods, especially when we use hybrid strategies to predict forecasting accuracy since M-competition shows that a single model performs better Kechagias, J. D., & Zaoutsos, S. P. (2024). On the other hand, a wide range of systems and techniques are suggested in the field of network neural forecasting research. The hybrid model is appropriate in the following circumstances. Firstly, the trades that are necessarily required the trading long term trends reduces the number the reason is that it's not adjust the trading's every period. This method reduces transactions cost and especially when there is a lot of orders placed at one time then there use simple average cross over rule from the models In predicting the exchange rates of the market which will be able to identify the bull and bear macro cycles Kechagias, J. D., & Zaoutsos, S. P. (2024)

This rule of study is very prominent as a market participant and considers best indicator for the market trends, by using this rule we can easily allocate the bull and the bear market and easily filter and identify the trade orders and at last it can trade at a high frequency if anybody feel to reduce the noise by trading cycles (Ling et al., 2015) The investors sometimes become very aggressive about the profit and further loss or protection of price. There are several theories and studies that describes and partially answers, the most of them are refers to the market frameworks as utility curves or consumptions and the changes and sometimes cause a great loss in the productivity and decision making process Fan, H., Wang, C., & Li, S. (2024)

Auto-Regressive Integrated Moving Average (ARIMA)

It is an important area of forecasting in which the previous observations of the same variables are collected, observed and define the related relationship of the variables. The model is then used to extrapolate the time series into the future. This modeling approach is particularly useful when little knowledge is available on the underlying data generating process or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables. Much effort has been devoted over the past several decades to the development and improvement of time series forecasting models. One of the most important and widely used time series model is the Auto Regressive Integrated Moving Average (ARIMA) model. Pasari, S., & Shah, A. (2020, July.The popularity of ARIMA model is due to its statistical properties as well as the well-known Box Jenkin's Methodology in the model building process. Bulk amount of volunteer's are presented in their research in the development of several past decades for the predicting and forecasting the time series. ARIMA model is one of the most repetitively used models. It is popular due to its most of the explanatory and statistical features. But there are some limitations in this mode that it can take only the linear from the model it cannot capture the data that is in the form of nonlinear.

One of its complex problems is that it can take unknown random process and face to face interactions with the market such that unexpected factors affect the variables. Ilu, S. Y., & Prasad, R. (2024).

Most of the studies stated that mostly economic variables are non-stationary dimensions or naturally nonlinear in parameters. Nonlinear models are mostly used to 12 obtain the nonlinear parameters. In these models it's not possible to draw any standard formula for the parameters (Clement &Hendry., 2002) Merh et al. (2010) showed that in recent years ANN has become a popular modeling tool. Complex real world problems in which non-linearity is often present can be successfully modeled using this technique. Due to its quality of nonlinearity ANN became very popular because this type of methodology easily handled the nonlinear pattern. With this there is no need to require the certain model the major feature of this is nonlinear modeling flexibility so there is no need to specify the particular form of model. This Kind of Approach is followed where is no theoretical guidance is available for the referred data processing's. They had suggested that two or more computational models can be synergic ally combined to give a better approach for prediction problems each model's unique capability can be used to model different patterns of data. The advantages of the relatively easy-to-tune ARIMA models and the computational power of ANN have been combined to give the time series prediction for the hybrid ARIMA and ANN techniques. The past studies showed that the combination of ANN and ARIMA are much better than individual model and the results are more substantial when dealing with nonstationary series, and it gives better forecasting results then use the models separately OLAYEMI, O. D., & MICHEAL, V. A. (2025)

Exchange rates abroad

Foreign exchange is the largest market in the world. It is crucial for accurate forecasting and international investments, and the exchange rate has become crucial for success. The forecast in the modeling is of interest to decision makers because it involves the impact of economic activity, foreign trade, and the distribution of health in cities. It is also crucial for monetary and governmental policies. Additionally, a number of models have been proposed for that study in the literature on forecast exchange rates over the last fifty years due to the fact that the foreign exchange is highly noticeable and non-stationary, making the traditional methods ineffective. So that he has to follow the more advanced techniques recently nonlinear ANN proved to be effective for the time series prediction (Priyadarshini 2014). Gencay (1999) argued that exchange rate is one of the most important policy variables in an open economy as it affects the macroeconomic variables like, trade, capital flows, FDI, inflation, international reserve, GDP and remittances, etc Judson, R. (2024)

Objective

The objectives of the study are

- To use ANN and ARIMA models to create models for predicting the average monthly US dollar exchange rate. To compare the results of predicted values to actual values 16
- To compute MAPE, AAE, and RMSE in order to assess the models' performance.
- To examine the differences in outcomes between hybrid ARIMA and ANN models.

REVIEW OF LITERATURE

According to Pramanik et al. (2010), projecting the advance time step stream flow is crucial for preventing flood damage. Artificial neural network (ANN) approaches have been widely employed in stream flow forecasting over the last few decades and have demonstrated superior forecasting capabilities compared to other forecasting methods like multiple regression and generic transfer function techniques. The time series of the flow data were preprocessed into wavelet coefficients of various frequency bands using discrete

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wavelet transformation methods. From the correlation analysis of the observed flow data, the effective wavelet coefficients and the decomposed wavelet coefficients of each frequency band were chosen.

Maknickiene & Maknickas (2012) used neural network forecasting to make forecasts similar to those of human experts. The same traits of compatibility and opinion dependability might be effectively used to ANN specialists. Neural network-adapted expert procedures can improve prediction quality and yield appropriate profits. During the testing period for EUR/USD cross ratios, the suggested trading methodology enabled a profit of up to 4%. A consistent profit progression and the computation of the similarity of prediction of LSTM based recurrent neural networks are demonstrated by the Delphi method analysis of trading models for historical data. The prediction bounds are improved via the Delphi approach. As a result, the Ann expert's judgment permitted the removal of entirely incorrect forecasts.

Morrison & Labonte (2013) some contend that a foreign exporter may lower his local currency export price in order to stabilize prices in the importing nation if an importer's currency depreciates, increasing the cost of imports. This policy, however, is a long-term approach meant to preserve market share. However, markup exchange rates depend on the exporter's familiarity with the demand curve in a particular market and are sector specific. In line with these conclusions and deductions, they proposed that policy-driven changes in exchange rates may be transferred to the pricing of products and services. As an alternative, producers may absorb the price in their profit margins and markups.

Zaki (2014) employed a hybrid approach for the four crime categories—Break and Enter Non-Dwelling, Non-Domestic Violence Related Assault, Steal from Retail Store, and Steal from Person—and forecasted the crime series using 216-month observations. In particular, the hybrid approaches' results produce a good modeling structure and are able to express the nonlinear structure of the complex time series, which leads to more accurate predictions. The four hybrid model case studies had good model application rates of 92.78%, 91.08%, 94.13%, and 93.62, respectively. Performance metrics were used to compare the predicted crime statistics from the hybrid approaches with those from the ARIMA and neural network. And the outcome demonstrated that for crime series prediction, the hybrid model outperforms the neural network and ARIMA models in terms of accuracy.

As &Sk (2015) They used neural network, ARIMA, and fuzzy neuron techniques to analyze the behavior of the Indian Rupee (INR), GBP, and USD against the currencies traded in Indian foreign exchange markets. The analysis used the Daily RBI reference exchange rates from January 2010 to April 2015, and the classical time series method (ARIMA) and complex nonlinear methods like fuzzy neurons and neural networks to predict the exchange rates of the Rupee against USD, GBP, Yen, and Euro. The results showed that the ARIMA model outperformed those of the Indian market, but previous research indicated that ANN outperformed both ARIMA and fuzzy models.

Khandelwal et al. (2015) created the time series using DWT (Discrete Wavelet Transform) and proposed DWT prediction methods by splitting a time series data set into linear and nonlinear components and analyzing time series data sets into linear and nonlinear components. Both models were used for forecasting and separately identified the reconstructed linear and nonlinear parts, respectively, and they proposed the special capacity of ANN, ARIMA, and DWT to increase the forecasting accuracy.

MATERIALS AND METHODS

Time series analysis overview and some fundamental ideas

Business phenomena like weekly interest rates, daily closing stock prices, monthly price indices, and annual sales figures are all examples of data derived from observations that are gathered successively over time. Understanding or modeling the stochastic mechanism that leads to a 27-observed series and predicting or forecasting the future values of a series based on the history of that series and maybe other related series or variables are the two main goals of time series analysis. We often cannot assume that the data originate separately from a similar population, which is a relatively unusual aspect of time series and their models Diggle, P., & Giorgi, E. (2025).

Being stationary

Stationary is the foundation of time series analysis; a time series is considered stationary if its mean, variance, and auto covariance (at different lags) remain constant regardless of the point measure, meaning it is fixed over time in other words, strict stationary necessitates that the joint distribution of,..., is constant under time shift; a weaker form of stationary is frequently assumed. If the mean of and the covariance between and are both time-invariant, then a time series is 28 weakly stationary, where s is an arbitrary integer. In particular, it is weakly stationary if (a) E () = μ, a constant, for every t. (b) Cov(,) =, which just relies on lag s and all time t. Nonetheless, we assume that the first two moments of are limited under weak stationary. According to the definitions, if is strictly stationary and its first two moments are finite, then it is also weakly stationary; however, this is not always the case Xiang, X., Zhou, J., Deng, Y., & Yang, X. (2024)

Non-stationary:

The means, variances, and covariance of data points are frequently non-stationary or fluctuate over time. Non-stationary data may take the shape of random walks, cycles, trends, or any combination of these. Generally speaking, non-stationary data are unexpected and cannot be predicted or modeled. When non-stationary time series are used, the findings might be erroneous since they could suggest a link between two variables when none exists. The non-stationary data must be converted into stationary data in order to get consistent, trustworthy conclusions. The stationary process reverts around a constant, but the non-stationary process, which has a variable variance and a mean, does not stay close to or return to a long-run mean over time. long-term mean and has constant variance independent of time. Non-stationary time series can be converted into stationary series Agrahari, S., Srivastava, S., & Singh, A. K. (2024)

Non-stationary time series those are homogeneous

Many of the time series that are used in practice are non-stationary. Fortunately, by differencing the series at least once, many non-stationary time series processes may be changed. These time series are referred to as integrated processes or homogenous non-stationary series Lioi, B. (2024).

Tests of Stationarity

Similar to time series analysis, it is crucial to determine if the series in question is stable. A few of the several statistical approaches that are accessible are briefly described here Hagger, M. S., & Hamilton, K. (2024).

Analysis of Graphics

Plotting the time series and looking for indications of trend in mean, variance, autocorrelation, and seasonality is the first and most basic test one can use to determine whether the series is stationary. If any of these patterns are found, the series is non-stationary, and there are various ways to make it stationary.

Test of correlograms

Creating the auto-correlogram, which is a plot of the serial correlations vs. the lag k for k = 0, 1,..., M, where M is often considerably less than the sample size n, is one of the most helpful descriptive tools in time series analysis. A very slow declining ACF is a

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hallmark of non-stationary series, whereas a quicker fall is observed in the case of stationary series. For k=0,1,2 …M, where M is often significantly smaller than the sample size n, it is also useful to plot partial autocorrelations vs. the lag k, also known as a partial auto-correlogram. When figuring out how many times a series has to be differenced in order to become stationary, PACF is useful. The number of lags to which PACF is significant shows the number of time a series have to be differenced to make it stationary Khan, I., & Gunwant, D. F. (2024).

ACF, or autocorrelation function

The sample autocorrelation function is one of the most crucial instruments for studying dependency. The intensity of the linear dependency between any two variables, random X and Y, is measured by the correlation coefficient, which always takes values between -1 and 1. When estimating the autocorrelation function for a collection of lags K = 1, 2,...., we assume stationary. The simplest way to do this is to compute the sample correlation 30 between the pair's k units apart in time. Keep in mind that the autocorrelation function is the result of the correlation notion extending in the case of stationary time series. The correlation coefficient between and is called the lag-k autocorrelation of and denoted by the symbol, which under the assumption of weak stationary and defined as Royer-Carenzi, M., & Hassani, H. (2025).

$$= \frac{\sum_{t=k+1}^{T}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{n}(Y_t-\bar{Y})^2} = \frac{\gamma_k}{\gamma_0}$$

Where $\gamma_k = \text{Cov}(Y_t, Y_{t+k})$

Partial Autocorrelation Function (PACF):

The correlation coefficient between two random variables Y t and Y t−k after removing the impact of the intervening, Y t−1 ,Y t−2 ,..., Y t−k+1 called (PACF) at lag k and denoted by ϕ kk

Unit root tests

Subjective visual examination of plots and the correlogram are used in the stationary tests discussed in the previous section. The sample correlogram's characteristics make it a valuable tool for identifying unit root or non-stationary data, but the approach is inherently inaccurate. Because a unit root process may have the same ACF form as a near unit root process, what one observer may perceive as a unit root process may look to another as a stationary process. A rigorous testing technique is required due to this uncertainty in eye examination. To aid in determining stationary, a more recent set of tests was created. These tests, often referred to as stationary tests and unit root tests are mostly based on formal statistical tests; their main distinction is the form of the null and alternative hypotheses they adopt and the degree of rigor of the assumptions they make Liao, L. C., Chang, T., & Ranjbar, O. (2025),

ARIMA MODELS

The time series model is not based on economic theory, unlike structural models that relate a main variable to a set of other variables; however, in terms of forecasting, the reliability of the estimated equation should be based on out-of-sample performance (Zhang et al., 2001). The model is commonly known as an ARIMA(p,d,q) model, where parameters p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average components of the model, respectively. An essential component of the Box-Jenkins method of time-series modeling is ARIMA models. A variable's future values are supposed to be a linear function of several historical observations and random mistakes in an

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ARIMA model. Khashei and Bijari (2011) state that the underlying mechanism that creates the time series with the mean μ has the following shape.

Steps for building an ARIMA model

Identification of the Model:

The selection of a certain mathematical model is based on the experience gained from studies and research, as well as some statistical measurements that describe the model for another.

Model Estimation:

After the nomination of one or more appropriate models to describe the viewing time series of data, we estimate parameters of the model using one of estimation methods.

Model Diagnostic:

The residuals analysis is used to measure the validity of the model's assumptions and determine how closely the computed values from the chosen model match observations. If the model passes these tests, it is adopted as the final model that is used to estimate future forecasts; if not, we go back to the initial phase for selecting a suitable model.

Predicting:

The final model is used to generate future predictions and then calculate the prediction errors that occurred.

Models of artificial neural networks (ANNs)

The nonlinear mapping patterns of artificial neural networks are modeled after the ways in which the human brain works. They are powerful tools for modeling especially when the underlying data relationship is unknown. Ann can identify the nonlinear relationship. Artificial neural networks (ANN), which are really model-free dynamics, are one type of computational intelligence system that has been frequently employed recently for forecasting and approximation tasks. The model is characterized by a network of three layers of simple processing units connected by acyclic links (Figure 1). The relationship between the output and the inputs has the following mathematical representation (Khashei&Bijari., 2010).

A computational model inspired by the architecture and operations of biological neural networks is called an artificial neuron network (ANN). Since a neural network is dependent on input and output, information that passes through the network has an impact on the ANN's structure. The connection between the inputs (y(t-1),…,y(t-p)) and the output possesses the subsequent mathematical illustration (Kim and Vald)

Function of Activation

The following is the expression for a neuron's mathematical model: (3.2) where the activation function is defined as follows: yi is the output of neuron I, wij is the weight from neuron J to neuron, xj is the output of neuron J, and is the threshold for neuron I. McCulloch and Pitts (1949) define the transfer function, despite the fact that this is a straightforward model that depicts the neuron as a binary processing unit. The logistic sigmoid function, which is represented by the following equation, is the most often used transfer function that neural network models may employ. Where i is the index on the inputs to the neuron, xi is the input to the neuron, wi is the weighting factor attached to that input, and w0 is the bias to the neuron.

RESULTS AND DISCUSSIONS

Model Building with ARIMAj Process for Exchange Rate

The following Steps involved in ARIMA modelling

- Identification
- Estimation
- Diagnostic checking

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- Forecast

Table 4.1: Descriptive Statistic for Exchange Rate

Name of statistics	Imports	After One Differencing
Minimum value	447.7	-15430
1st.Q	1098	-494.3
Median	1694	69.04
S.D	48.71956	2.194506
Mean	4132	-16.84
3rd.Q	7036	492.9
Maximum value	22790	15970

Table 4.11 provides descriptive statistics of Imports of Pakistan used for examining performance of three different models such as ARIMA ANN and hybrid model. The Minimum value of Imports is 447.7 and Maximum value 22790. The monthly datasets from 2003 to 2017 were used for model development.. The data showed that the mean working series is 56.53 with standard deviation 48.71956 taking 685 observations under consideration.

Methods of Checking Stationary

Methods of Checking Stationary
Graphical method (Time series Plot)
ACF and PACF
Box and Pierce Q statistic
Ljung Box Statistic
Augmented Dickey Fuller test

Graphical method

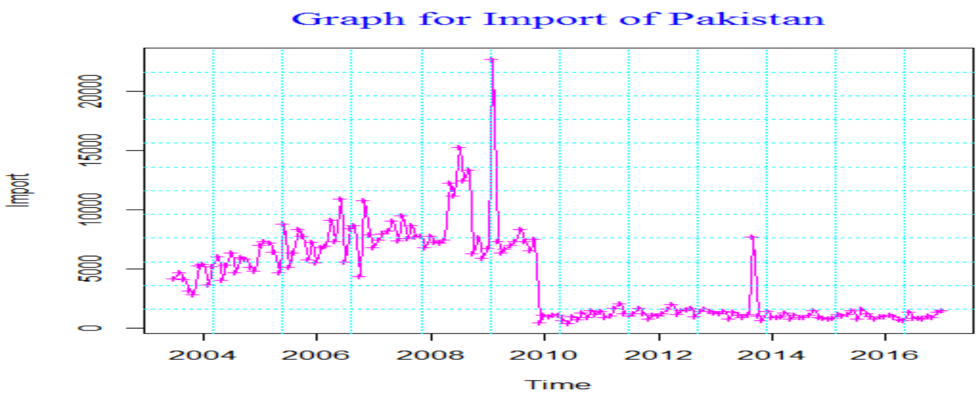

Figure 4.1 depicts the time series plots of different years of imports are not stationary.so we need differencing.

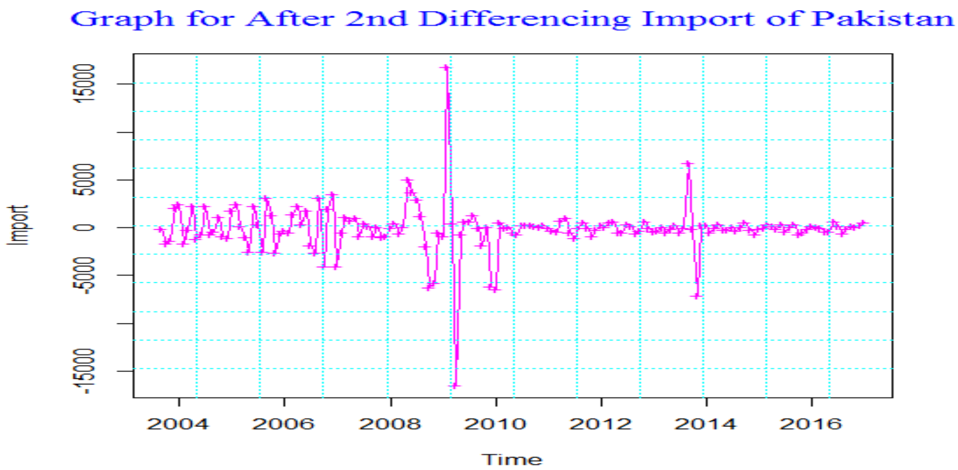

Figure Error! No text of specified style in document.**.2 Imports time series after differencing**.

Mathematical methods

Box and Pierce Q statistic

- $H_0; \rho_k = 0$ (process is stationary)
- $H_1; \rho_k \neq 0$ (process is not stationary and difference is needed)

Table 4.2 P value of Box and Pierce Q test for imports

χ^2 = 98.212	df = 1	p-value = 2.2e-16

2.2e-16<0.05 P- values less than 0.05 so do not accept H_0 and the process is not stationary After two differencing

Table Error! No text of specified style in document.**.3 P value e of Box and Pierce Q test for imports after differencing**

χ^2 = 0.80792	df = 1	p-value = 0.3687

0.2027>0.05 P- values greater than 0.05 so accept H_0 and the process is stationary after one differencing. Box and Pierce Q test shows that imports of Pakistan is stationary after one differencing

The process after one differencing is stationary then next step is to identify different models and check which model is best. Since our ACF and PACF revealed that neither AR nor MA term required in the data, Different models such as ARIMA (1,2,0), (0,2,1), (1,2,1), (1,1,3),(2,2,3) were tested and model is selected on the base of AIC, ME,RMSE,MAE,MPE, MAPE, MASE, and the diagnostic checking is applied to check that best model

Table Error! No text of specified style in document.**.4 ARIM Model selection criteria for Imports**

Models	AIC	ME	RMSE	MAE	MASE
(1,2,0)	3162.69	1.030	3142.29	1611.39	-14.7860
(0,2,1)	2980.62	-42.908	2448.56	1174.68	-16.3121
(1,2,1)	2974.47	-61.716	2013.84	1071.27	-26.4648

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(1,1,3)	2922.64	-16.125	1986.26	1068.62	-23.1011
(2,2,3)	2920.45	-142.0987	1985.302	1067.547	-36.6098

The **(2,2,3)** model has the **lowest AIC (2920.45)**, indicating it has the best trade-off between goodness of fit and model simplicity. The (2,2,3) model has the **largest negative ME**, indicating it might **under predict** on average — but this isn't necessarily bad if other metrics are strong. Measures the square root of the average squared differences between predicted and actual values. Measures the average magnitude of errors in a set of forecasts, without considering their direction. MASE < 1 implies the model outperforms a naïve forecast. Here, negative values are a bit unusual and suggest possible misinterpretation or rescaling—possibly due to how the errors are calculated. Still, we can use them comparative (2, 2, and 3) has the lowest (most negative) MASE, suggesting

Table Error! No text of specified style in document.**.5 ANN Model selection for Imports**

AAN model	Training				Validation			
	R^2	RMSE	MAE	MASE	RMSE	MAE	MASE	R^2
5-6-1	0.960373	0.106883	0.0827317	-0.290897	0.017868	0.0111169	-0.030054	0.99771
4-6-1	0.928471	0.145130	0.1123810	-0.435176	0.021766	0.0164331	-0.047501	0.99710
4-4-1	0.861128	0.192921	0.1496490	-0.630431	0.072436	0.0523565	-0.185443	0.96197
6-7-1	0.979947	0.077938	0.0603535	-0.200746	0.005930	0.0035935	-0.008453	0.99972
5-6-1	0.964117	0.101845	0.0823377	-0.251431	0.016926	0.0116355	-0.028082	0.99797
6-4-1	0.980052	0.075938	0.0546999	-0.145797	0.005284	0.0031735	-0.006794	0.99978
6-7-1	0.979659	0.077720	0.0631151	-0.183784	0.000498	0.0002581	-0.000684	0.99999
5-8-1	0.979842	0.076231	0.0555698	-0.157816	0.004941	0.0029158	-0.004734	0.99980

From table 4.5 we run the different models and select the model that has the minimum values if we observe different models in table 4.19 we see that the model (6-4-1) has the minimum values as compare to other models. And in this model the value of R^2 is highest which shows the strong correlation so we conclude that (6-4-1) has the best fitted model.

SUMMARY AND CONLUSIONS

Over the last few spans the time series analysis and forecasting is a dynamic research area. In many decision processes the accuracy of forecasting time series is very necessary and hence the research for improving the effectiveness of forecasting models has never stopped. More recently, artificial neural network has become very popular in forecasting with their nonlinear modelling skill on the other hand arima model has become very common in linear pattern. Although both ARIMA and ANNs have the flexibility in modeling a variety of problems, none of them is the universal best model that can be used

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indiscriminately in every forecasting situation. In this thesis, combining approach of time series forecasting proposed and ARIMA and ANN techniques were used jointly to get the best prediction results. The hybrid techniques are used to get the unique strength of linear and nonlinear modelling .Various combining methods have been proposed in the literature. However the hybrid arima and ann model is used to select the best model. Three different data sets such as foreign exchange rate, Pakistan imports data and the data of exports of Pakistan have been used in the thesis. The hypothetical and actual results showed that the combination of model gives the best forecasting results than using the single model. Because single model cannot handle the linear and nonlinear situation at the same time. But the combination of model showed the minimum values of RMSE, MAE, and MASE as compare to the ARIMA and ANN techniques.

Recommendations

Replace To use ANN and ARIMA models to create models with a more concise form like to develop predictive models Ensure consistent terminology (e.g., "predictive accuracy" or "forecasting performance stick to one term throughout the document). If this is going into a thesis or proposal, you might briefly explain why MAPE, AAE, and RMSE are appropriate metrics for model comparison. You could consider expanding to mention time frame or data period (e.g., "using monthly data from 2015 to 2024" — if applicable).

If exchange rate prediction has an application in economics or policy, mention the practical relevance too.

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