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A Review on Forecasting Exchange Rate and Volatile Using SPSS Analysis

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Abstract. Forecasting various exchange rates is crucial since a significant amount of activity occurs in the currency exchange market. Future investment depends on accurate forecasting of foreign currency rates, or at the very least properly identifying the trend. The statistical distribution of exchange rates and their linear unpredictability has been extensively studied in the literature on international finance. In the literature on international finance, the statistical distribution of exchange rates and their linear unpredictability has received considerable study. In this paper, the Indian Rupee (INR) exchange rate is taken and analyzed against ten different currencies.
Keywords: Forecasting Exchange, artificial neural networks (ANNs), empirical mode decomposition (EMD), SPSS,

1. Introduction

The futures price [1]. Over the past few decades, the fire market has grown at a never-before-seen rate. Exchange rates are essential for controlling the dynamics of the exchange market [2]. Despite the market's well-known volatility and unpredictability, many organizations (such as banks, agencies, and others) are capable of forecasting exchange rates using a variety of methods [3]. Economists and investors always tend to predict future exchange rates so that they can derive monetary values using predictions. For decades, FET has been a widely and consistently researched topic in the financial industry. Several computational methods are used for forecasting [4]. Feed forward neural networks have been used by several academics to forecast future values of time series by using information from the past. A typical strategy is to use the time-space patterns of economic indicators like interest rates to connect changes in a time series to other economic events. Others think that the information needed to forecast future behavior can be found in currency exchange rates [5].

2. Forecasting Currency Exchange Rate and Volatile

In recent decades, there has been a rapid pace in the development of foreign exchange markets due to increasing cross-border capital. So unsurprisingly, the fire market is the largest and most liquid of the current financial markets. There are many economic indicators for this market, but the most important are exchange rates [6]. Several studies using daily prices support the conclusion that option prices provide more accurate forecasts than historical information. Furthermore, these studies involving low-frequency data have found that all relevant information for volatility prediction is contained in option prices [7]. The benefit leads to financial rewards and makes strategic financial planning easier. Numerous categories may be used to classify these tactics [8]. To accurately predict exchange rates, academic researchers begin to study the behavior of exchange rates from a theoretical perspective. Many studies have been devoted to developing various exchange rate determination models that link exchange rate measures to macroeconomic variables [9]. A given system's behavior may be predicted using two different methods. The first and most effective strategy relies on a precise understanding of the rules governing a particular phenomenon [10]. It is proposed that additional feasible adaptive models be investigated, as well as the incorporation of extra latent financial time series features as model input, to improve forecast performance, particularly for long-term forecasting [11]. The most difficult applications of forecasting, however, involve the prediction of financial time series. Utilizing a variety of statistical and computational techniques as well as information acquired from a recent survey, many anticipated models have been developed [12]. Nonlinear and non-stationary time-varying data can be transformed into stationary signals using empirical mode decomposition (EMD), a potent analytical approach [13]. In many applications, time series analysis is crucial to understanding the features of noisy data that can be found in time series [14]. The three-layer BPNN, one of these neural network models, is frequently employed for fire rate prediction due to its approximatively linear functions and capacity for self-learning. However, there are many drawbacks to back-propagation neural networks [15]. For instance, a back-propagation neural network algorithm's convergence speed is frequently slower since the learning rate is constant, lengthening the network's learning period. To lessen these downsides, various rapid training algorithms, including adaptive learning algorithms, real-time learning algorithms, and other fast learning algorithms, have been constructed [16]. For time series forecasting, various cutting-edge computer techniques have recently produced superior outcomes. The success of artificial neural networks (ANNs) is largely due to their capacity for self-learning, self-prediction, and non-linear correlation detection without prior knowledge of the subject matter [17]. The ability of ANN to learn from data is one of its strongest points. It is a great tool for nonlinear issues since it is unaffected by noise and random

data [18]. International traders for export and import decisions, central banks for interval forecasts of exchange rate volatility within a target zone, and options traders who need volatility forecasts to price options all place a premium on currency exchange rate minimums [19].Portfolio diversification across international borders or the use of internal models by risk managers, such as value-at-risk programmers [20]. Exchange rates between trading partners have a direct impact on trade relations and the cost of exporting and importing goods. Although the exchange rate is classified as having a daily turnover, during trading hours exchange rates are continually changing. [21]. The quantity of training data needed to create each time series forecasting model is the only factor that distinguishes the neural network models for a given currency [22].

3. Experimental Analysis

One of the most often employed KPIs for gauging forecast accuracy is MAPE. Individual absolute error totals divided by demand are known as MAPE. It represents the average of the % mistakes. A useful KPI for gauging forecast accuracy is mean absolute error (MAE). It is, as its name implies, the mean of the absolute error. The important performance metric known as Root Mean Squared Error (RMSE) is peculiar. But incredibly helpful one, as we will discuss. It is described as the mean square error's square root. In reality, mean squared error (MSE), which is closely connected to RMSE, is the foundation of many algorithms, particularly those used for machine learning. RMSE does not handle each error equally to MAE. It emphasises the most significant errors more. That is, a significant error is all that is required to produce a very low RMSE. We used the exchange rates of 10 major foreign currencies for the Indian Rupee in this analysis.

TABLE 1. Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.415	0.705	10

Table 1 shows Cronbach's Alpha Reliability result of Indian rupee exchange rate for ten countries.

TABLE 2. Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
USD	25	5.223	77.521	82.744	1.994E3	7.97477E1	1.632831	2.666	.500	-.700
GBP	25	10.866	87.248	98.114	2.363E3	9.45113E1	2.431421	5.912	-1.108	1.904
EUR	25	5.232	78.348	83.580	2.027E3	8.10878E1	1.293552	1.673	.095	-.334
AUD	25	4.395	51.586	55.981	1.356E3	5.42306E1	1.260513	1.589	-.608	-.447
NZD	25	4.713	45.874	50.587	1.219E3	4.87714E1	1.400780	1.962	-.807	-.323
CZK	25	.2015	3.1808	3.3823	82.3917	3.295668E0	.0490795	.002	-.263	-.158
HUF	25	.02914	.18761	.21675	5.03982	.2015928	.00710852	.000	.228	-.010
PLN	25	1.768	16.459	18.227	430.027	1.72011E1	.488153	.238	.459	-.267
RUB	25	.2764	1.2001	1.4765	33.1402	1.325608E0	.0638295	.004	.128	.392
CHF	25	6.435	77.640	84.075	2.046E3	8.18342E1	1.507684	2.273	-1.366	1.858

USD-US Doller, GBP-Great Britten pound, EUR-Euro, AUD-Australian Doller, NZD-New Zealand Doller, CZK-Czech Koruna, HUF-Hungarian Forint, PLN-Polish Zloty, RUB-Russian Rouble, CHF- Swiss Franc. Above table 2 shows the Descriptive Statistical Analysis of Indian Rupee exchange rate with USD-US Doller, GBP-Great Britten pound, EUR-Euro, AUD-Australian Doller, NZD-New Zealand Doller, CZK-Czech Koruna, HUF-Hungarian Forint, PLN-Polish Zloty, RUB-Russian Rouble, CHF- Swiss Franc. In the above table Range, Minimum, Maximum, Sum, Mean, Std. Deviation, Variance, Skewness, Kurtosis value are given

TABLE 3. Statistics

		USD	GBP	EUR	AUD	NZD	CZK	HUF	PLN	RUB	CHF
Median		7.96050E1	9.48990E1	8.11500E1	5.42930E1	4.90970E1	3.294300E0	.2022400	1.71760E1	1.324600E0	8.21630E1
Mode		77.521[a]	87.248[a]	78.348[a]	51.586[a]	45.874[a]	3.1808[a]	.20256	16.459[a]	1.2001[a]	77.640[a]
Range		5.223	10.866	5.232	4.395	4.713	.2015	.02914	1.768	.2764	6.435
Percentiles	**25**	7.82885E1	9.30475E1	7.99760E1	5.32830E1	4.78530E1	3.260950E0	.1963200	1.68770E1	1.290400E0	8.09285E1
	50	7.96050E1	9.48990E1	8.11500E1	5.42930E1	4.90970E1	3.294300E0	.2022400	1.71760E1	1.324600E0	8.21630E1
	75	8.08160E1	9.61055E1	8.18835E1	5.53010E1	4.99570E1	3.333500E0	.2059300	1.74745E1	1.373800E0	8.27130E1

a. Multiple modes exist. The smallest value is shown. USD-US Doller, GBP-Great Britten pound, EUR-Euro, AUD-Australian Doller, NZD-New Zealand Doller, CZK-Czech Koruna, HUF-Hungarian Forint, PLN-Polish Zloty, RUB-Russian Rouble, CHF- Swiss Franc. Above table 3 shows the statistics analysis of Indian Rupee exchange rate

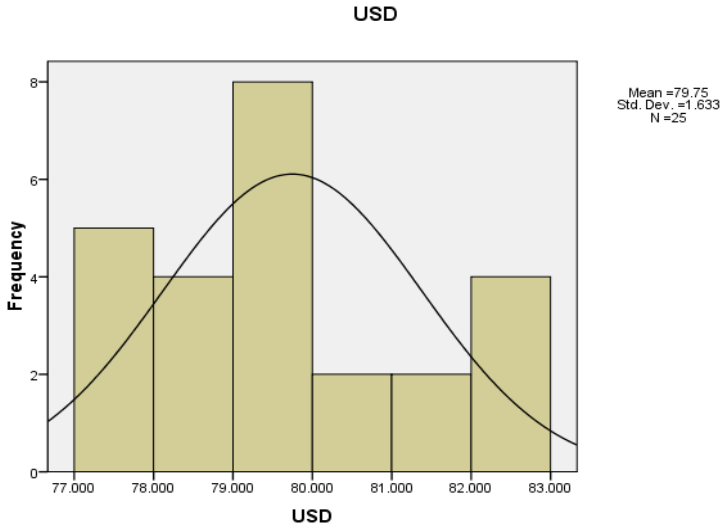

FIGURE 1. Frequency INR/USD Exchange Rate

Figure 1 shows the histogram plot for frequency of INR/USD Exchange Rate. Here shows the normal curve with almost all value under the curve

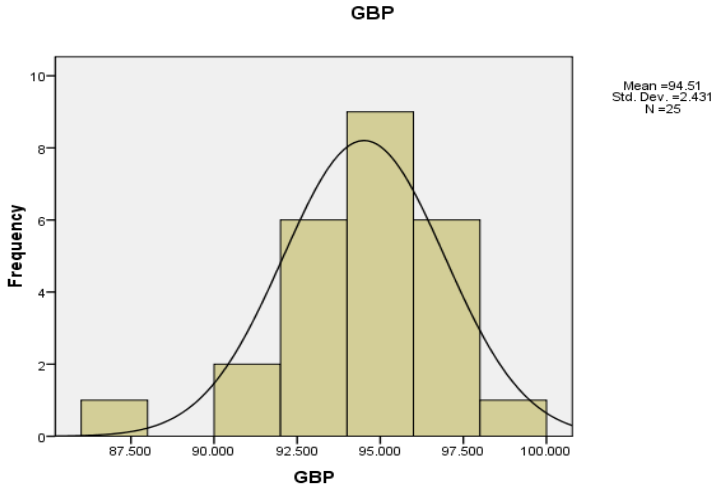

FIGURE 2. Frequency INR/GBP Exchange Rate

Figure 2 shows the histogram plot for frequency of INR/GBP Exchange Rate. Here shows the normal curve with almost all value under the curve with mean value above curve.

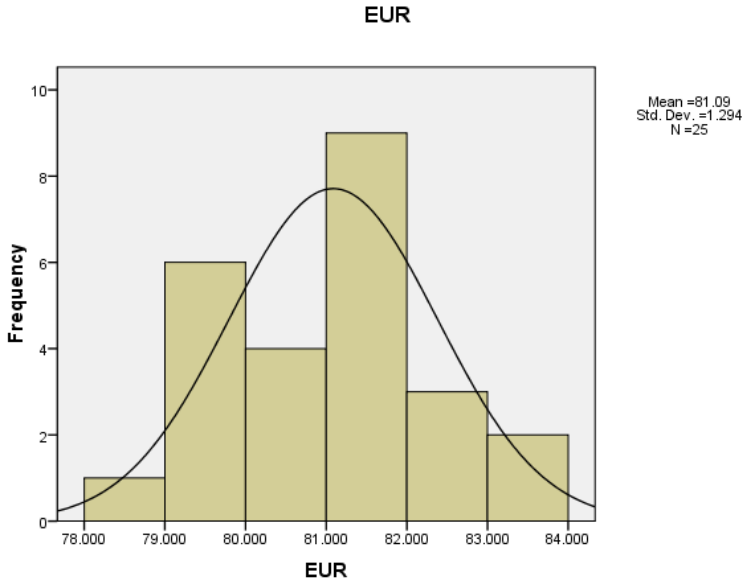

FIGURE 3. Frequency INR/EUR Exchange Rate

Figure 3 shows the histogram plot for frequency of INR/EUR Exchange Rate. Here shows the normal curve with almost all value under the curve.

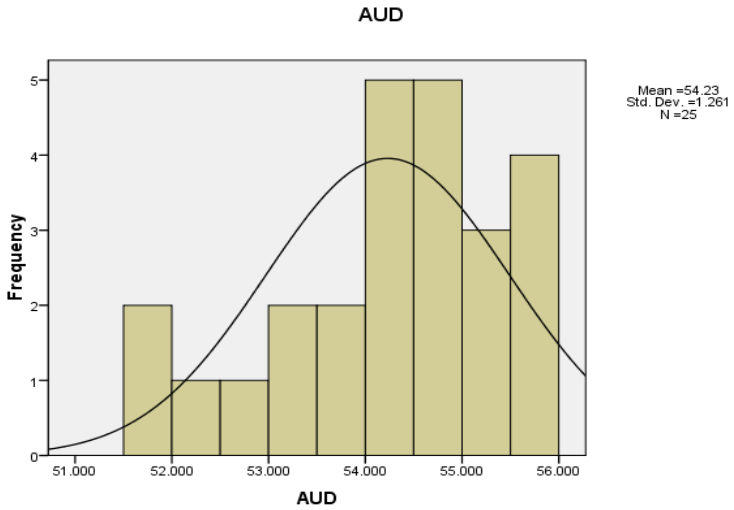

FIGURE 4. Frequency INR/AUD Exchange Rate

Figure 4 shows the histogram plot for frequency of INR/AUD Exchange Rate. Here shows the normal curve with slightly right skewed with almost all value under the curve.

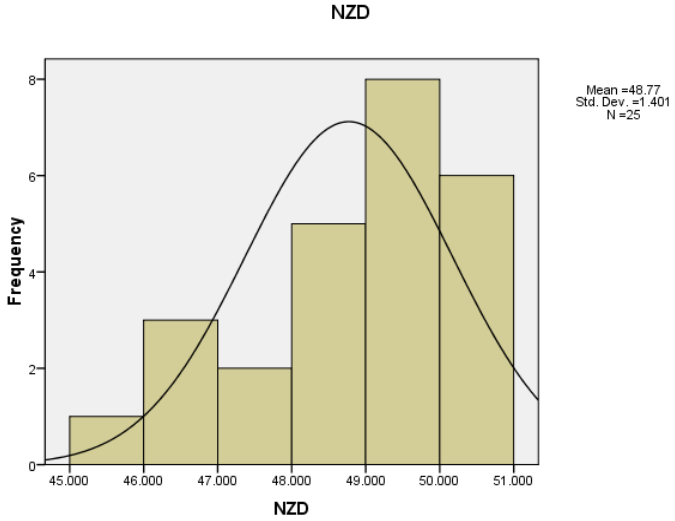

FIGURE 5. Frequency INR/NZD Exchange Rate

Figure 5 shows the histogram plot for frequency of INR/NZD Exchange Rate. Here shows the normal curve with slightly right skewed almost all value under the curve.

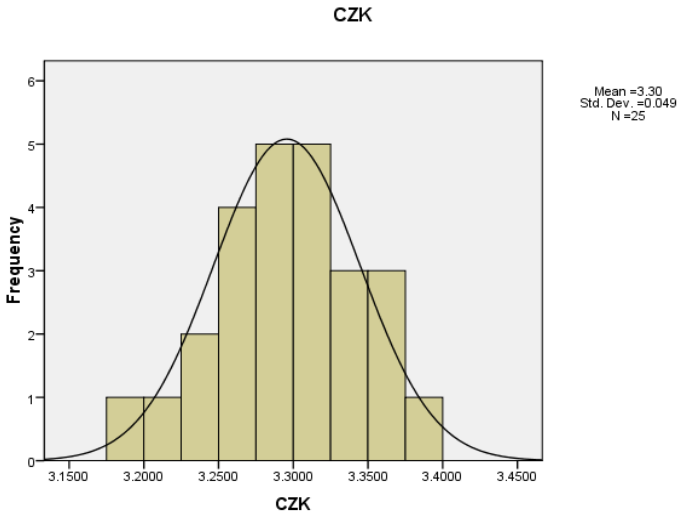

FIGURE 6. Frequency INR/CZK Exchange Rate

Figure 6 shows the histogram plot for frequency of INR/CZK Exchange Rate. Here shows the normal curve can be also called bell curve.

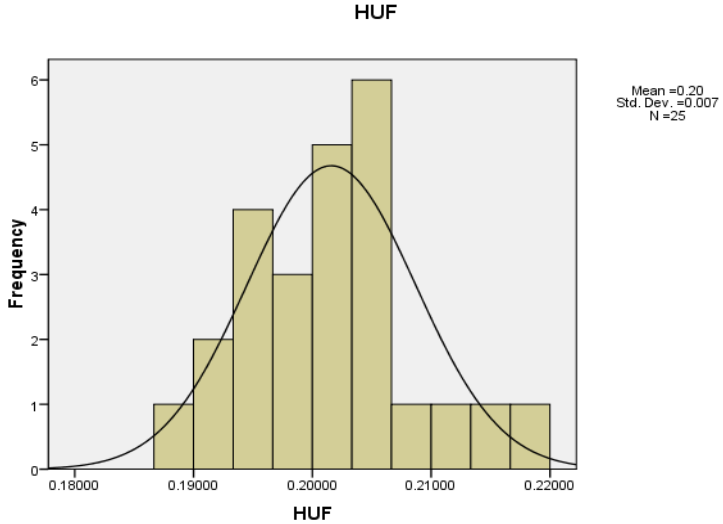

FIGURE 7. Frequency INR/HUF Exchange Rate

Figure 7 shows the histogram plot for frequency of INR/HUF Exchange Rate. Here shows the normal curve with slightly left skewed with almost all value under the curve.

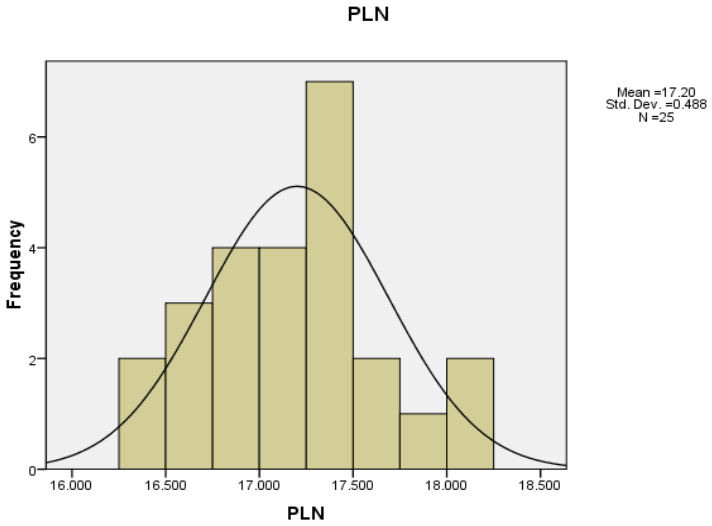

FIGURE 8. Frequency INR/PLN Exchange Rate

Figure 8 shows the histogram plot for frequency of INR/PLN Exchange Rate. Here shows the normal curve with slightly left skewed with almost all value under the curve.

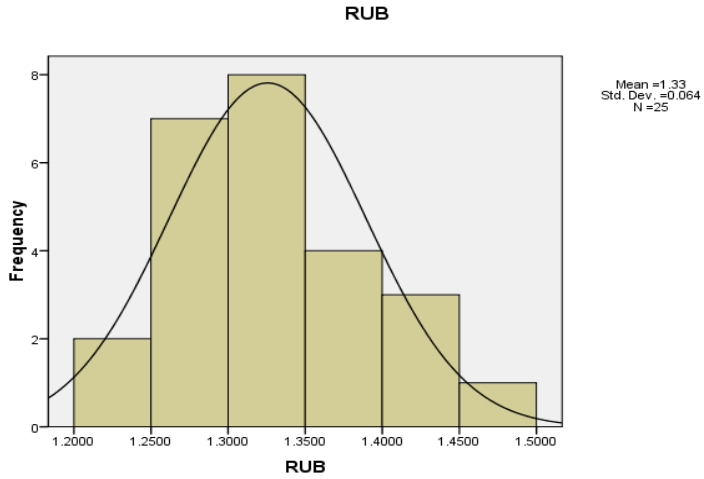

FIGURE 9. Frequency INR/RUB Exchange Rate

Figure 9 shows the histogram plot for frequency of INR/RUB Exchange Rate. Here shows the slightly left skewed curve with significant value under the curve.

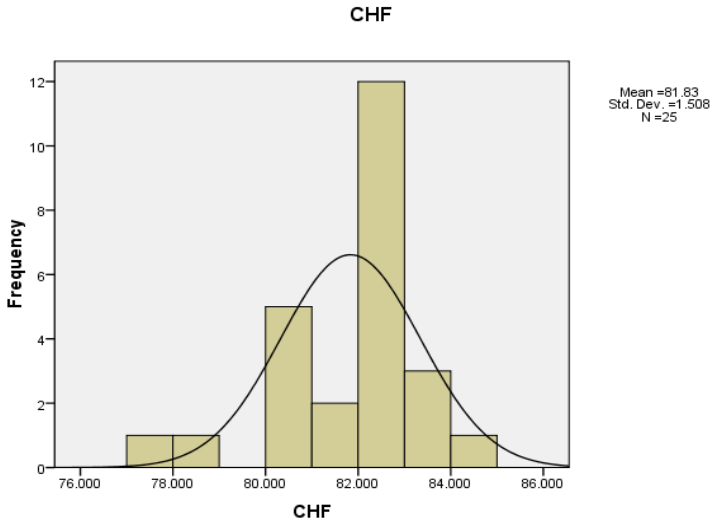

FIGURE 10. Frequency INR/CHF Exchange Rate

Figure 10 shows the histogram plot for frequency of INR/CHF Exchange Rate. Here shows the left skewed curve with some value above the curve

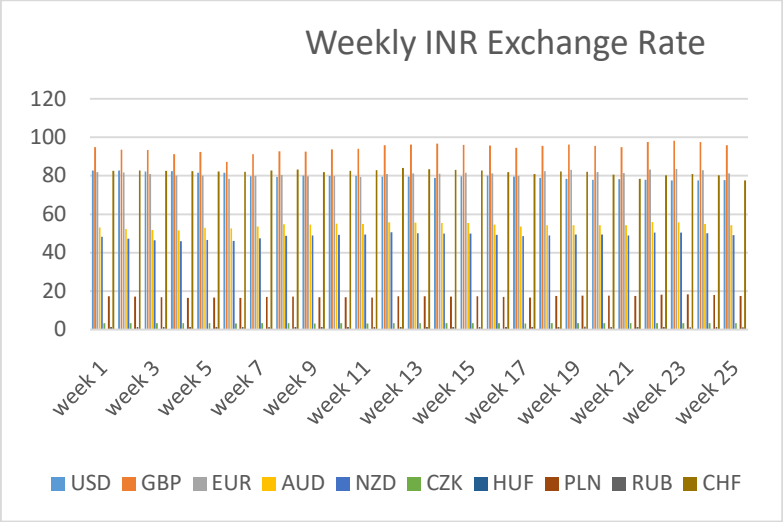

FIGURE 11. INR exchange rate

Figure 11 shows the weekly INR exchange for 25 weeks on Monday for with USD-US Doller, GBP-Great Britten pound, EUR-Euro, AUD-Australian Doller, NZD-New Zealand Doller, CZK-Czech Koruna, HUF-Hungarian Forint, PLN-Polish Zloty, RUB-Russian Rouble, CHF- Swiss Franc.

TABLE 4. Correlation

	USD	GBP	EUR	AUD	NZD	CZK	HUF	PLN	RUB	CHF
USD	1	-.640**	-.495*	-.745**	-.774**	-.355	-.790**	-.710**	.217	.544**
GBP	-.640**	1	.820**	.666**	.839**	.793**	.798**	.792**	-.292	-.264
EUR	-.495*	.820**	1	.363	.550**	.972**	.817**	.918**	-.047	-.305
AUD	-.745**	.666**	.363	1	.942**	.321	.663**	.572**	-.301	-.043
NZD	-.774**	.839**	.550**	.942**	1	.509**	.766**	.700**	-.294	-.147
CZK	-.355	.793**	.972**	.321	.509**	1	.762**	.857**	-.054	-.150
HUF	-.790**	.798**	.817**	.663**	.766**	.762**	1	.940**	-.214	-.430*
PLN	-.710**	.792**	.918**	.572**	.700**	.857**	.940**	1	-.164	-.415*
RUB	.217	-.292	-.047	-.301	-.294	-.054	-.214	-.164	1	.191
CHF	.544**	-.264	-.305	-.043	-.147	-.150	-.430*	-.415*	.191	1

Table 4 indicates correlation between with USD-US Doller, GBP-Great Britten pound, EUR-Euro, AUD-Australian Doller, NZD-New Zealand Doller, CZK-Czech Koruna, HUF-Hungarian Forint, PLN-Polish Zloty, RUB-Russian Rouble, CHF-Swiss Franc. For example USD is having the greatest correlation with CHF and lowest with HUF.

4. Conclusion

For decades, the forecast exchange rate has been a widely and consistently researched topic in the financial industry. Several basic methods have been presented for the FET, including traditional techniques and some nonlinear models. However, it is noted that individual prediction methods still have limited potential as each classifier has inconsistent results across multiple datasets. Exchange rates and their rates of change over time are more volatile than inflation rates and comparable price levels. National governments have identified the influence of this volatility on national monetary policy as something that merits examination in the context of international commerce, especially for nations where economic growth is heavily dependent on export growth. When compared to inferred volatilities, historical forecasts are more accurate when high frequency returns are used rather than long memory specifications. For shorter forecast horizons, forecasts provide more information regarding implied volatility. The majority of research that have utilized machine learning to predict exchange rates have traditionally measured prediction performance using MAPE or MSE. Under such systems, financial transactions are typically not taken into account.

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