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Research paper

Deep Learning and Statistical Approaches in Financial Modeling of Foreign Assets and Liabilities of Nepals Banking System

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Abstract:
This study investigates the detailed mathematical exploration followed by its computational performance of time series and deep learning models: ARIMA, RNN, and TCN applied to foreign assets and liabilities of banking system of Nepal consisting monetary authorities and various depository corporations. We analyze trends, seasonal patterns, trajectories and their descriptive statistics to capture underlying behaviors, identifying the optimal ARIMA order that most effectively captures linear trend. Empirical study shows that the RNN handles non-linear patterns which is determined by performance metrices on the training and testing split. TCN being computationally extensive model is not able to capture robust relation of the data due to lack of long-range dependencies and large time windowed dataset for training. Based on our results, the RNN could be used as the most suitable time series forecasting model for the foreign assets and liabilities of Nepal as it enhances the accuracy, minimizes error, and improves effectiveness in contributing to decision-making in banking system.

Keywords: assets and liabilities, deep learning models, descriptive statistics, performance metrices, seasonal patterns
Classification: JEL Classifications: C22, C45, E44, E60

1 Introduction

To understand the performance of Nepals foreign assets and liabilities in the baking system is mandatory for better financial planning and formulation of banking policies. Time series analysis plays a pivotal role in this context by facilitating concerned regulators to track trends in the prices, yields, and interest rates over time for various types of bonds [7, 18]. Concise forecasting of these economic indicators particularly in current volatile economic situation is crucial, where even a small deviation in predictions of the securities can have substantial impacts on economic stability [12].

The Auto Regressive Integrated Moving Average (ARIMA) model has been the

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most used in time series forecasting. It locates linear relationships from historical data to predict the future values, keeping autocorrelation and moving averages in consideration to minimize forecast errors [7]. However, while ARIMA is effective for simpler data, it lacks the ability to deal with complex data patterns, such as non-linear trends and volatility that is present in financial markets [31]. Likely, the models performance highly relies upon on the appropriate selection of lag orders, commonly measured using tools like the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), along with stationarity tests like the Augmented Dickey-Fuller (ADF) test [9], and the criteria to select the model such as the Akaike Information Criterion (AIC) [1]. To address the persistent limitations of ARIMA, Recurrent Neural Networks (RNNs) have been employed for their ability to capture sequential dependencies and complexities in the model and non-linear relationships amongst the parameters [16]. Unlike ARIMA, RNNs utilizes feedback loops that allow the network to remain hidden across designated time steps, that enhances the accuracy for prediction. However, RNNs also face the vanishing gradient problem, that affects its ability to learn long-term dependencies amongst the parameters [4]. As a result, RNNs may not be capable for capturing the complications of financial time series when extended sequences with long timed window datasets are involved.

Temporal Convolutional Networks (TCN) has been a powerful alternative to traditional recurrent architectures like RNNs and LSTMs for the functions involving sequence modeling. Unlike recurrent models, TCNs use causal convolutions and dilated convolutions to capture long-range temporal dependencies that does not require the need for sequential processing which in turn enables faster training and better parallelization [2]. The causal nature of TCNs ensures that there is no information leakage from future to past, which is better suited for time series forecasting. TCNs also maintain a constant receptive field growth that allows the model to effectively capture both the short-term and long-term dependencies in the data that is somehow lacked by LSTM. Studies have demonstrated that TCNs outperform RNN-based models in tasks that has financial time series prediction due to their stable gradients and superior ability to model temporal structures [2,5].

In this study, we apply ARIMA, RNN, and TCN models using data from Nepals foreign assets and liabilities of the banking system that consists of golds, Special Drawing Rights (SDR), International Monetary Fund (IMF) Reserve Tranche Position with their convertible and interconvertible foreign exchanges. We derive the mathematical foundations of these models along with their respective test procedures and performance metrices like Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) [10]. By applying theoretical analysis to practicality, our comprehensive study not only evaluates the accuracy of the model but also explores the computational and deep learning efficiencies and real-world test scenarios of each forecasting method [21,27].

2 LITERATURE

Understanding the way of the external assets and liabilities of banking system is essential for a sustainable financial planning in order to identify the ownership patterns of monetary authorities and depository corporations. Time series analysis helps the policymakers track changes in prices, yields, interest rates, assets and liabilities. Traditional models like ARIMA have been widely used for such purposes, advanced deep learning models such as RNNs and TCNs offer an improvised accuracy by capturing complex patterns in financial data. In this section, we examine their application in net assets forecasting providing key research findings.

The ARIMA model was first introduced by George Box and Gwilym Jenkins in the early 1970s, in their book Time Series Analysis: Forecasting and Control [7]. Its statistical foundation was further developed by researchers like Peter Brockwell and Richard Davis in 1991 textbook Time Series: Theory and Methods [8] presented the mathematical foundations and formulations of ARIMA models in deeper detail and addressed the estimation and inference procedures necessary to apply ARIMA effectively. Brockwell's work refined the mathematical tools for model selection and hypothesis testing, like the use of AIC for comparison and validation and validation of models. Researchers like Hyndman and Athanasopoulos [18] extended the methodology for ARIMA specializing on computational process with algorithms for model fitting and forecasting. ARIMAs strength lies in its ability to model stationary time series data which combines autoregression, moving averages, and differencing.

Mohammad et al. [22] applied the ARIMA model to forecast banking stock market data, demonstrating its effectiveness in capturing trends and making short-term predictions in financial time series. Similarly, Uddin et al. [28] conducted a time series analysis using the ARIMA model to forecast the Gross Domestic Product (GDP) of Bangladesh, serving as a foundational reference for modeling economic indicators through statistical forecasting methods. Shogole et al. [26] review and analyze existing methods, particularly GARCH and ARIMA models, for modeling and forecasting bank stock prices, highlighting their applications and limitations in financial time series forecasting. Li et al.[20] incorporated economic indicators and market sentiment into machine learning models to enhance the prediction of U.S. Treasury bond yields.

RNNs was introduced by Nobel laureate physicist John Hopfield in the 1980s, based on the idea of recurrent series in mathematics and physics. Hopfield's work on associative memory models in neural networks laid the foundation for the architecture of RNN [17]. Understanding the behavior of networks with feedback loops influenced concurrent developments in computational models for sequential data. Later RNN with backpropagation through time (BPTT) algorithm, was developed by David Rumelhart, Ronald Williams, and Geoffrey Hinton in 1980s [25]. Jeffrey Elman further extended the RNN architecture for time series and natural language processing. Elmans 1990 work [11] focused on the development of simple recurrent networks, which included context units to capture temporal dependencies in sequences that allowed RNNs to handle time series data effectively. Ian Goodfellow, Yoshua Bengio, and Aaron Courville provided theoretical foundations of deep learning and RNN models in their 2016 textbook Deep Learning, concentrating on optimizing neural network mathematically [15]. Fischer and Krauss [13] utilized Long Short-Term Memory (LSTM), a variant of RNN, to forecast stock returns, highlighting its ability to handle long-term dependencies. RNN models have been employed to forecast liquidity demand in banks, aiding in optimizing capital allocation [3]. Boustani et al. [6] review existing techniques for cross-selling consumer loans and explore how deep learning networks can enhance predictive accuracy in this domain. Khandani et al. [19] developed machine learning-based credit scoring models using financial transaction histories, demonstrating that RNNs outperform logistic regression models in predicting borrower defaults.

In the 2010s, Temporal Convolutional Networks (TCNs) started gaining attention as a strong alternative to RNNs for sequence modeling tasks. Bai et al [2] properly shaped the TCN architecture, showing how causal and dilated convolutions, along with residual connections, help in capturing long-term dependencies without facing the vanishing gradient issue. Unlike RNNs, TCNs can process the entire sequence in parallel, that makes its training capacity to be efficient and faster. Oord et al. [24] already explored the use of dilated convolutions for temporal data through their work on WaveNet. Franceschi et al. [14] extended the use of TCNs for tasks like time series classification and forecasting. Recently, many have focused on mixing TCNs with other models like attention mechanisms and Multivariate Adaptive Variable Splines (MARS) to improve both interpretability and performance, especially in fields like finance and agriculture.

Yu et al. [30] integrates the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) technique with various machine learning models, such as LSTM, Temporal Convolutional Network (TCN), Transformer, and Autoformer, to forecast China's interbank bond transaction interest rates over extended periods. Yao et al. [29] developed a hybrid CNN-LSTM model to assess bond default risk, leveraging the sequential processing capabilities of LSTM to identify financial distress patterns in banking assets. Moolchandani [23] applied Markov Chain Monte Carlo (MCMC) techniques to enhance credit risk assessment models, demonstrating improved predictive accuracy and robustness in evaluating borrower default probabilities.

3 METHODOLOGY

In this study, we use ARIMA, RNN and TCN for modelling the temporal data. The data we utilized is sourced from Nepal Rastra Bank, the central bank of Nepals database. This study includes a modelling approach for the Net Foreign Assets for Monetary Authorities and the same for Other Depository Corporations of the banking system that consists of golds, Special Drawing Rights (SDR), International Monetary Fund (IMF) Reserve Tranche Position with their convertible and inter-convertible foreign exchanges along with their Total Net Foreign Assets.

Our data ranges from 1966 to 2024 that holds data of above-mentioned indicators. Net Foreign Assets of Monetary Authorities primarily referring to the central bank is derived by summing four key elements: Gold reserves, Special Drawing Rights (SDRs), IMF Reserve Tranche Position, and Foreign Exchange Reserves. The Foreign Exchange category is further divided into Convertible and Inconvertible currencies, which together form the total foreign exchange reserves. All these components (Gold + SDRs + IMF Position + Foreign Exchange) are added to get the overall total. From this total, Foreign Liabilities represent the country's external debts and are subtracted to determine the final value of Net Foreign Assets. This structure is commonly used by central banks to report a nations international financial position. These values specifically pertain to the monetary authorities, that manages the countrys official reserve assets and external obligations.

The Net Foreign Assets of Other Depository Corporations (such as commercial banks and financial institutions other than the central bank) are first calculated by summing two components: Convertible and Inconvertible foreign currencies. These together make up the Foreign Exchange Total. From this total, the Foreign Liabilities that represent the external debts of these institutions are subtracted. The resulting value is the of Other Depository Corporations. This classification helps in distinguishing between the foreign assets held by the central bank (monetary authorities) and those held by other financial institutions, giving a more comprehensive picture of a countrys external financial position.

We illustrate the data and provide descriptive statistics for each sub-heading. The data analysis and modelling are conducted using the open-source programming language Python version 3.10

Table 1: Summary Statistics of Financial Indicators

Financial Indicators	Mean	Median	Standard Deviation	Max	Min
Monetary Authorities	252454.2	32103.9	446415.1	1918829.0	363.2
Other Depository Corporations	11414.643	2590.200	19447.731	72924.714	4.400
Total Net Foreign Assets	263868.9	37085.50	464857.6	1989279.0	367.60

Source: Authors calculation

Over six decades from 1966 through 2024, these three indicators showcase very different pictures of Nepals financial landscape. The mean of Monetary Authorities is 252454 with standard deviation of 446415 which shows that enormous spike and drop. Other Depository Corporations lies on a much smaller scale. The mean is 11414 and the standard deviation is 19447 which is larger than the mean. This indicates that there is uncontrollable ups and downs in the Other Depository Corporations throughout the time frame. The Total Net Foreign Assets resembles the Monetary Authorities with mean 263868 and standard deviation of 464857. In all the indicators the standard deviation is greater than mean which signifies the influence of extraneous factors playing a major role.

Evaluation Metrics

Three scientifically proven metrics, MAE, MSE, RMSE are used to evaluate the performance of our models. We need to pre-process the data before building and training the model. For RNN log transformation of the data is done to stabilize the variance and reduce skewness. For TCN, Min-Max scaler is implemented to transform the data into a desired range i.e. (0 to 1). The window size of 3 is taken into consideration for all the economic indicators.

We forecast each of the assets using the models described. We project future values over the n time-periods (in years), where n is determined by the total length of the available dataset. Specifically, we set n to be one-fourth of the total data length. This approach ensures that we retain enough data for robust model training while still providing a meaningful forecast horizon for evaluation.

Table 2: Hyperparameters for RNN and TCN Models

Hyperparameters	RNN	TCN
Architecture	32-32-32	32-32-32
Epoch	100	100
Learning rate	0.001	0.001
Kernel Size	NA	2
Dilation	NA	1
Activation Function	Rectified Linear Unit (ReLU)	Rectified Linear Unit (ReLU)
Optimizer	Adam	Adam
Loss	Mean squared error	Mean squared error

Source: Authors calculation

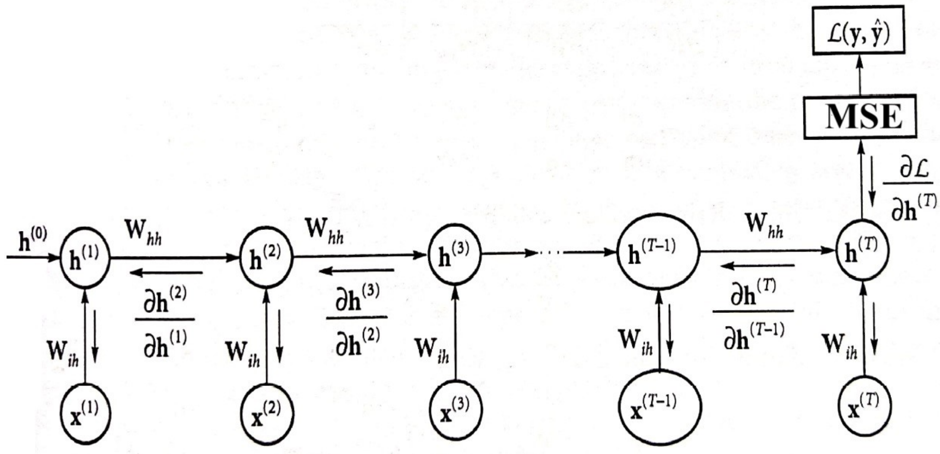

Figure 1: Architecture of RNN and its Training Using Back Propagation Through Time (BPTT)
Source: Author

Training RNN Using Backpropagation Through Time (BPTT)

The training of our RNN involves adjusting its parameters $\mathbf{W}_{hh}$, $\mathbf{W}_{ih}$ and $\mathbf{b}_h$ to minimize the loss function in which we choose mean squared error and to measure the average squared difference between the predicted values and the actual values and we choose mean absolute error to evaluate the accuracy of a models predictions. The mean squared error is computed as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\big(y_i - \widehat{y}_i\big)^2 \tag{1}$$

For our training done using Backpropagation Through Time (BPTT) which is an extension of standard backpropagation for sequential models. Its loss function is:

$$L = \sum_{t=1}^{T} L\big(y_t, \widehat{y}_t\big) \tag{2}$$

The gradients of the loss function with respect to the parameters is computed using chain rule. We have declared $T = 32$ neurons for each layer and the network is 3 layers deep. The gradient of L for hidden weights W_{hh} is

$$\frac{\partial L}{\partial W_{hh}} = \frac{\partial L}{\partial h(T)} \cdot \frac{\partial h(T)}{\partial W_{hh}} \tag{3}$$

The gradient for hidden weight with respect to the recurrent weight matrix W_{hh} requires backpropagation through time:

$$\frac{\partial L}{\partial W_{hh}} = \sum_{k=1}^{T} \frac{\partial L}{\partial h(T)} \cdot \frac{\partial h(T)}{\partial h(k)} \cdot \frac{\partial h(k)}{\partial W_{hh}} \tag{4}$$

Since, $\frac{\partial h(k)}{\partial h(T)}$ is a chain rule, the gradient (3.3) can be written as:

$$\frac{\partial L}{\partial W_{hh}} = \sum_{t=1}^{T} \left(\frac{\partial h(T)}{\partial L} \prod_{k=t}^{T-1} \frac{\partial h(k)}{\partial h(k+1)} \frac{\partial W_{hh}}{\partial h(t)} \right) \tag{5}$$

The gradient with respect to W_{ih} is,

$$\frac{\partial W_{ih}}{\partial L} = \frac{\partial h(T)}{\partial L} \cdot \frac{\partial W_{ih}}{\partial h(T)} \tag{6}$$

This process helps our RNN model learn the complex temporal dependencies in sequential data, making it effective for tasks like time series forecasting and natural language processing.

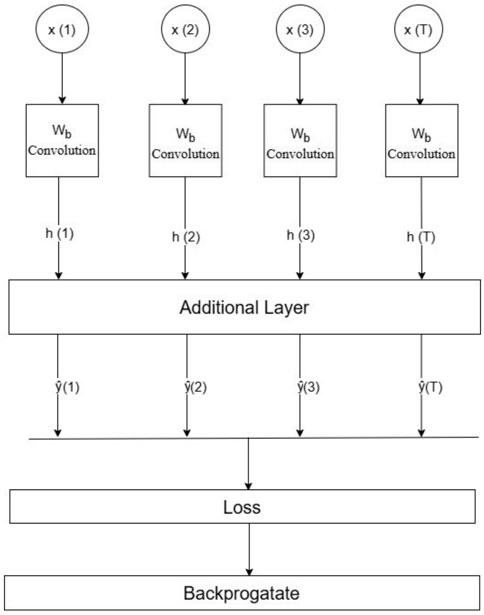

Figure 2: Architecture of TCN and its Training Using Standard Back Propagation
Source: Author

Training TCN Using Standard Backpropagation

Training an TCN involves minimizing a loss function using standard backpropagation. TCNs are feed-forward models with temporal (convolutional) structure and often dilations so that errors propagate back through the layers in a single backward pass rather than unrolling a recurrence over time. The total loss for a sequence of length T is:

$$L = \sum_{t=1}^{T} L\left(y_t, \widehat{y_t}\right) \tag{7}$$

where L is the loss function. A TCN layer applies a 1D causal convolution. For a kernel $W \in \mathbb{R}^k$ and dilation factor d, the output at time t is:

$$h_t = f\left(\sum_{i=0}^{k-1} W_i\, x_{t-i\cdot d} + b\right) \tag{8}$$

TCNs are feed-forward, the gradients are computed by applying the chain rule over the layers as in standard convolutional neural networks for a weight W_i at a given position i in the convolutional filter.

The gradient of the loss with respect to the output of the TCN is then backpropagated through any additional layers computed as

$$\frac{\partial L}{\partial \widehat{y_t}} \tag{9}$$

Consider the pre-activation at time t is

$$z_t = \sum_{i=0}^{k-1} W_i\, x_{t-i\cdot d} + b \tag{10}$$

Then the gradient with respect to pre activation is

$$\delta_t = \frac{\partial L}{\partial z_t} = \frac{\partial L}{\partial h_t} \cdot f'\left(z_t\right) \tag{11}$$

The gradient of the loss with respect to a specific weight W_i in the kernel is obtained by summing over all time steps

$$\frac{\partial L}{\partial W_i} = \sum_{t \in T_i} \delta_t \cdot x_{t-i\cdot d} \tag{12}$$

T_i is the set of all time indices for which the weight W_i is used in the convolution. Similarly, the gradient for the bias term b is

$$\frac{\partial L}{\partial b} = \sum_{t=1}^{T'} \delta_t \tag{13}$$

4 COMPUTATIONAL RESULTS

ARIMA Model

We conducted ADF test to check stationary of the data whose results are given below in Table 3.

For the monetary authorities, the ADF test yielded a statistic of 5.249. Under the

Table 3: ADF Statistics and p-value for Each Sub-heading

Financial Indicators	ADF Statistics	p-value
Monetary Authorities	5.249	1.000
Other Depository Corporations	0.809	0.992
Total Net Foreign Assets	4.869	1.000

Source: Authors Calculation

null hypothesis of a unit root, the entire distribution of the ADF statistic lies to the left of zero, even the 10 % critical value is 2.601. Because our observed value falls completely to the right of this null distribution, the cumulative probability of obtaining a value as large as 5.249 or larger under non stationarity is effectively unity. Consequently, the test returns a p value of 1.00, indicating unequivocal failure to reject the presence of a unit root in the foreign assets and liabilities series.

For net foreign assets, the ADF test produced a statistic of 4.869. Since, under the null hypothesis of a unit root, the distribution of the ADF statistic is entirely to the left of zero with even the 10% critical value at 2.601 our test statistic lies far to the right of this range. This means the probability of obtaining such a large value under the assumption of non-stationarity is essentially 1.00. As a result, the test strongly fails to reject the null hypothesis, confirming the presence of a unit root in the foreign assets and liabilities series.

Since the indicators with has a p-value greater than 0.05. It signifies that the data does not follow stationary.

ARIMA Model Identification, Results, Test and Equation for all Financial Indicators

Table 4: ARIMA Model Performance for Financial Indicators

Indicators	**Models**	**AIC**	**Training Time**
Monetary Authorities	ARIMA (3,2,3)	1438.875	3.592 seconds
Other Depository Corporations	ARIMA (0,1,1)	1206.672	0.440 seconds
Total Net Foreign Assets	ARIMA (3,2,3)	1435.176	5.752 seconds

Source: Authors calculation

In this study, we employed the computationally efficient Auto-ARIMA method to identify the best ARIMA model for our data. It evaluates the models using statistical criteria, including AIC, BIC and HQIC. Here, we select the minimum AIC criterion for model selection. Among all the implemented ARIMA models for forecasting each indicator, we have selected the best one, as shown in the table above. This model was chosen based on its lowest AIC and shortest training time.

Table 5: Performance Measures Over Years

Indicators	Variables	Coefficients	Standard Error	Z	$P > \lvert z \rvert$	0.025	0.975
Monetary Authorities	Intercept	7841.83	8427.3	0.931	0.352	-8675.37	2.44e+04
	AR (L1)	-1.6482	0.154	-10.706	0.000	-1.950	-1.347
	AR (L2)	-1.6640	0.245	-6.794	0.000	-2.144	-1.184
	AR (L3)	-0.9471	0.129	-7.324	0.000	-1.201	-0.694
	MA (L1)	0.7602	0.228	3.336	0.001	0.314	1.207
	MA (L2)	-0.4340	0.371	-1.171	0.241	-1.160	0.209
	MA (L3)	-0.6167	0.128	-4.804	0.000	-0.868	-0.365
	σ^2	3.394e+09	0.053	6.44e+10	0.000	3.39e+09	3.39e+09
Other Depository Corporations	Intercept	1133.0893	1110.065	1.021	0.307	-1042.59	3308.776
	MA (L1)	-0.2897	0.084	-3.465	0.001	-0.454	-0.126
	σ^2	5.753e+07	0.062	9.3e+08	0.000	5.75e+07	5.75e+07
Total Net Foreign Asset	AR (L1)	-1.6399	0.144	-11.406	0.000	-1.922	-1.358
	AR (L2)	-1.6494	0.190	-8.673	0.000	-2.022	-1.277
	AR (L3)	-0.9681	0.114	-8.522	0.000	-1.191	-0.745
	MA (L1)	0.9543	0.208	4.598	0.000	0.574	1.361
	MA (L2)	-0.3543	-0.255	-1.390	0.165	-0.845	0.145
	MA (L3)	-0.6152	0.169	-3.644	0.000	-0.946	-0.284
	σ^2	3.955e+09	1.29e-10	3.06e+19	0.000	3.95e+09	3.95e+09

Where e denotes exponential notation.
Source: Authors calculation.

The table shows that ARIMA models were fitted to each indicator with estimated intercepts, autoregressive and moving average coefficients, their standard errors, z statistics, p values, 95% confidence intervals, and the residual variance. With the aid of the above table the final equation for each of the indicators are created in the following table.

Table 6: Estimated ARIMA Equations for Financial Indicators

Indicators	Equation
Monetary Authorities	$Y_t = 7841.8339 - 1.6482Y_{t-1} - 1.6640Y_{t-2} - 0.9471Y_{t-3} + \varepsilon_t + 0.7602\varepsilon_{t-1} - 0.4340\varepsilon_{t-2} - 0.6167\varepsilon_{t-3},$ $(\sigma^2 \approx 3.394 \times 10^9)$
Other Depository Corporations	$Y_t = 1133.0893 + \varepsilon_t - 0.2897\varepsilon_{t-1}, \quad (\sigma^2 \approx 5.753 \times 10^7)$
Total Net Foreign Assets	$Y_t = -1.6399Y_{t-1} - 1.6494Y_{t-2} - 0.9681Y_{t-3} + \varepsilon_t + 0.9543\varepsilon_{t-1} - 0.3543\varepsilon_{t-2} - 0.6152\varepsilon_{t-3},$ $(\sigma^2 \approx 3.955 \times 10^9)$

Source: Authors calculation

This ARIMA $(3, 0, 3)$ model shows that Monetary Authorities values revert toward about 7841.8 but are pulled down strongly by their own recent history: the one year and two year AR coefficients are both around 1.65, and the three year AR is 0.95, all negative and sizable. On the MA side, the previous years shock still adds to this year +0.76, while shocks from two and three years ago dampen current values 0.43 and 0.62. Overall, the strong negative AR feedback enforces mean reversion, though substantial white noise volatility remains $\sigma^2 \approx 3.4 \times 10^9$.

This MA (1) model depicts that each year the Other Depository Corporations fluctuates around a long run level of about 1133.1. In any given year, the value moves up or down with a fresh random shock (ϵ_t), but it also remembers last years shock to a small degree i.e.; about 0.29 of that earlier surprise carries over and slightly offsets the current years value. In practice, this means unexpected ups or downs tend to die out quickly only about 29% of a past shock tweaks todays number but theres still some short lived smoothing from one year to the next. The remaining fluctuations are pure white noise volatility, with a variance of roughly 5.75×10^7.

This model shows that the changes in Total Net Foreign Asset each year are driven almost entirely by past values and shocks, without a fixed baseline. If last years or the year before values were above zero, todays value is pulled down strongly by about 1.64 and 1.65, and theres still a downward pull from three years ago 0.97. On the shock side, the surprise from last year mostly carries forward +0.95, but surprises from two and three years ago slightly dampen todays figure 0.35 and 0.62. In other words, past highs tend to reverse sharply, old shocks fade unevenly, and the remaining movements are random noise with a variance around 3.96×10^9.

Table 7: Statistical Test Results for ARIMA Models

Indicators	ARIMA (p,d,q)	Number of Observations	Log Likelihood	AIC	BIC	HQIC
Monetary Authorities	(3,2,3)	59	-711.438	1438.875	1455.219	1445.227
Other Depository Corporations	(0,1,1)	59	-600.336	1206.672	1212.853	1209.080
Total Net Foreign Assets	(3,2,3)	59	-710.588	1435.176	1449.477	1440.734

Source: Authors calculation

The table reports which ARIMA specification best captures each indicators dynamics and how well each model balances fit against complexity. For each of the indicators we observe the orders of (p, d, q), the log likelihood, and three penalized measures AIC, BIC and HQIC. Among competing models, the one with the lowest AIC is preferred because it achieves the best trade off between explaining the and keeping the number of parameters small. Similarly, BIC and HQIC give a bigger penalty for extra parameters, so the lowest BIC or HQIC score points to the simplest model that still fits the data well.

Table 8: ARIMA Model Performance for Net Assets (In Million Rupees)

Performance Metrices	Monetary Authorities	Other Depository Corporations	Total Net Foreign Assets
MAE Train	8183.62	1414.03	10150.79
MSE Train	2.493×10^{8}	5.992×10^{6}	2.851×10^{8}
RMSE Train	15789.51	2447.85	16884.36
MAE Test	455237.78	43148.32	499622.10
MSE Test	2.718×10^{11}	2.291×10^{9}	3.081×10^{11}
RMSE Test	521373.28	47862.24	555084.34

The ARIMA models results for Monetary Authorities, Other Depository Corporations, and Total Net Foreign Assets indicate a strong in-sample fit alongside opportunities to strengthen out-of-sample performance. On the training set the model achieves low errors, demonstrating that it effectively captures the core temporal structure of the historical series. Test-set errors are larger, which suggests that there is scope to improve generalization through the inclusion of exogenous predictors.

Forecast for ARIMA

In this we forecast the future values for each economic indicators with upper and lower confidence level and provide a graphical representation of the Total Net Foreign Assets of Monetary Authorities. *(See appendix for forecast of rest of the financial indicators.)*

Table 9: ARIMA Forecast of Total Net Foreign Assets of Monetary Authorities (Million Rupees)

Year	Forecast	CI Lower	CI Upper
2025	1,610,368	1,487,113	1,733,623
2026	1,702,289	1,498,727	1,905,850
2027	2,259,229	2,035,689	2,482,770
2028	2,158,630	1,892,339	2,424,921
2029	1,913,507	1,543,005	2,284,008
2030	2,539,708	2,129,978	2,949,437
2031	2,611,995	2,158,225	3,065,765
2032	2,295,425	1,745,574	2,845,276
2033	2,686,585	2,065,219	3,307,951
2034	3,094,778	2,430,290	3,759,265
2035	2,684,199	1,924,467	3,443,931
2036	2,903,043	2,053,006	3,753,079
2037	3,423,668	2,517,308	4,330,028
2038	3,203,938	2,215,091	4,192,785

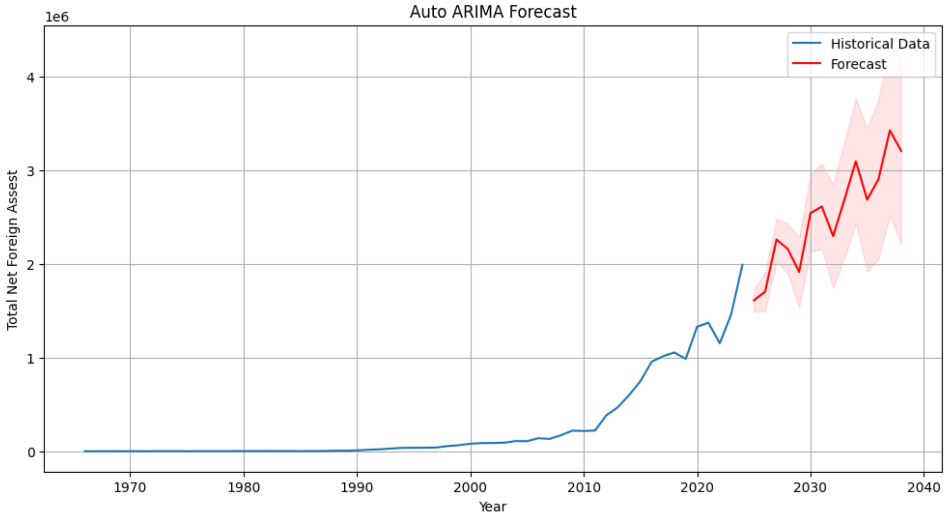

Figure 3: ARIMA Forecast of Total Net Foreign Assets (In Million Rupees)
Source: Author

The forecast plot shows that after a period of slow accumulation from the 1960s through the early 2000s, Nepals net foreign assets have accelerated sharply into the 2020s and are projected by our ARIMA $(3, 2, 3)$ model to continue rising into the 2030s. The red forecast line, which echoes the strong persistence and shockdamping behavior captured by the AR and MA terms, climbs from roughly 1.6 million in 2024 to peaks above 3 million by the early 2030s. The widening pink bands around that line represent 95% prediction intervals, growing from ± 0.5 million in the near term to over ± 1 million by 2035, underscoring increasing uncertainty: while the overall trend remains upward likely driven by sustained trade surpluses, reserve accumulation, and foreigninvestment inflows external shocks such as commodityprice swings or exchangerate volatility could still meaningfully shift the actual trajectory.

Forecast for RNN and TCN models

The process of building the RNN and TCN models is carried out using a training set of 80% and a testing set of 20% for the data included. To make this experiment as fair as possible we have implemented the same number of hidden layers, activation function, learning rate, optimizer and epoch for both the models. The performance of the model is measured by MAE, MSE, RMSE.

The RNN models results reveal a strong ability to generalize and perform accurately on unseen data. While the training errors are relatively higher, the model demonstrates markedly lower error values on the test set. This pattern suggests that the RNN effectively captures the essential temporal dynamics without overfit-

Table 10: RNN Model Performance for Net Assets (In Million Rupees)

Performance Measures	Monetary Authorities	Other Depository Corporations	Total Net Foreign Assets
MAE Train	123,976.77	4,461.31	65,551.92
MSE Train	6.535×10^{10}	8.326×10^{7}	1.867×10^{10}
RMSE Train	255,645.85	9,124.63	136,620.25
MAE Test	1,125.48	813.61	419.59
MSE Test	1.721×10^{6}	737,614.26	241,145.40
RMSE Test	1,311.89	858.84	491.07

Source: Authors calculation

ting, resulting in robust predictive accuracy for out-of-sample data. These findings underscore the RNNs capacity to model complex non-linear dependencies.

Table 11: TCN Model Performance for Net Assets (In Million Rupees)

Performance Metrics	Monetary Authorities	Other Depository Corporations	Total Net Foreign Assets
MAE Train	58,898.30	1,909.22	40,369.04
MSE Train	1.109×10^{10}	2.063×10^{7}	3.900×10^{9}
RMSE Train	105,300.93	4,542.36	62,451.20
MAE Test	34,467.06	164.90	24,409.41
MSE Test	1.188×10^{9}	28,885.19	5.960×10^{8}
RMSE Test	34,468.21	169.95	24,413.14

Source: Authors calculation

The models results signify moderate performance in capturing temporal patterns in the data. The training errors suggest that the model fits the historical series reasonably well. On the test set, the errors remain relatively low showing that the TCN is able to generalize to unseen data without substantial overfitting. These results highlight the models capability to learn temporal dependencies, though its predictive accuracy is somewhat lower than that of the RNN.

Forecast for RNN and TCN models

In this we forecast the future values for each economic indicators and provide a graphical representation of the Total Net Foreign Assets. *(See appendix for forecast of rest of the indicators)*

Table 12: RNN and TCN Model Forecast of Total Net Foreign Assets (In Million Rupees)

Year	RNN Forecast Amount	TCN Forecast Amount
2025	1,633,532.38	1,463,723.88
2026	1,553,789.75	1,418,776.13
2027	1,560,243.00	2,312,384.75
2028	1,509,054.00	1,976,989.38
2029	1,463,403.88	1,276,176.25
2030	1,430,864.00	2,287,524.25
2031	1,398,419.38	2,676,418.50
2032	1,367,661.00	1,334,960.50
2033	1,340,001.12	2,014,973.25
2034	1,314,481.75	3,395,205.75
2035	1,290,814.00	1,592,118.38
2036	1,268,969.50	1,542,869.63
2037	1,248,770.62	3,897,404.25
2038	1,230,058.75	2,094,566.00

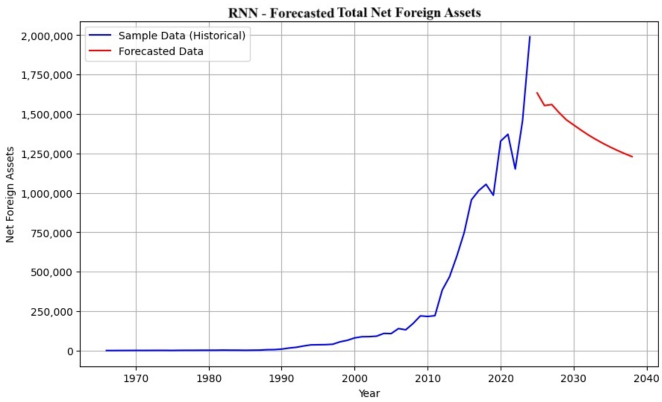

Figure 4: RNN Forecast of Total Net Foreign Assets (In Million Rupees)

The RNN model projects that Nepals net foreign assets having climbed to about 2 million in 2024 will gradually drift downward over the next decade, falling to roughly 1.2 million by 2032. This represents a mild annualized decline of about 3 % per year, suggesting that, in the absence of fresh inflows, routine outflows (such as debt service, import payments, or repatriated profits) may begin to outpace new asset accumulation. Economically, this cautious trajectory implies a reversion toward balance: past surpluses give way to slim or negative net additions, reflecting steady policy frameworks but also limited externalsector dynamism.

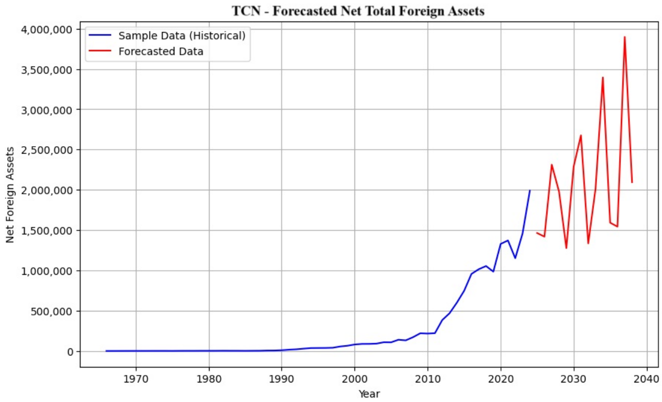

Figure 5: TCN Forecast of Total Net Foreign Assets (In Million Rupees)

By contrast, the Temporal Convolutional Network delivers a highly oscillatory outlook: net foreign assets swing between roughly 1.5 million and 3.9 million from 2025 through 2040. Although the mid cycle trend edges upward implying a modest overall growth rate of around 12% per annum the large peaks and troughs capture the models emphasis on recent shocks and momentum effects. Such pronounced volatility could reflect episodic capitalflow surges (e.g., major FDI projects or commodity windfalls) followed by corrective phases (debt repayments, valuation adjustments). In practice, while the TCNs pattern highlights the potential for strong temporary gains, it also warns of equally sharp reversals, underscoring the economys vulnerability to external events and the challenge of relying solely on pastdata driven forecasts.

From the model performance tables of both deep learning models used in this study, we observe that RNN performs significantly better than TCN across all metrics for the total net foreign assets. This holds true for both the training and testing data.

5 DISCUSSIONS

While comparing the performance of ARIMA, RNN and TCN in this study, we fitted three of the models on Total Net Foreign Assets data because it is the summation of all the economic indicators used in this study along with individual indicators of Monetary Authorities and Other Depository Corporations. This ensures the inclusion of every foreign asset and liability of banking system of Nepal.

In the above table we have performed comparative analysis for the RNN, TCN, and ARIMA. The models were evaluated using both training and test datasets. The RNN model demonstrated competitive test performance, with a MAE of 419.59

Table 13: RNN vs TCN vs ARIMA Model Performance for Total Net Foreign Assets (In Million Rupees)

Model	MAE Train	MSE Train	RMSE Train	MAE Test	MSE Test	RMSE Test
RNN	65,551.92	1.867×10^{10}	136,620.25	419.59	2.411×10^{5}	491.07
TCN	40,369.03	3.900×10^{9}	62,451.20	24,409.41	5.960×10^{8}	24,413.14
ARIMA	10,150.79	2.851×10^{8}	16,884.35	499,622.10	3.081×10^{11}	555,084.39

Source: Authors calculation

and a corresponding RMSE of 491.07. Notably, the RNNs, outperformed both the ARIMA model and the TCN model. Although the ARIMA model showed a comparable training MAE of 499622.10, its relatively higher RMSE of 555084.39 and substantially inferior test performance suggest that its predictive capability on unseen data is limited. Similarly, the TCN models elevated training errors (MAE of 24409.41and RMSE of 24413.14) indicate that it may be overfitting or suggest that the data may not have long-term dependencies due to lack of inherent complexity and large time windowed dataset for training. Consequently, these findings highlight the RNN models superior generalization ability, making it the most effective option among the three models for forecasting in foreign assets and liabilities in the banking system of Nepal.

6 CONCLUSIONS

The analysis of the foreign assets and liabilities has provided valuable insights into their predicted trajectories. In the total net foreign assets, we observed an upward growth with seasonality from the ARIMA and TCN model while RNN shows a sharp downward curve. For net foreign assets of the monetary authorities, the ARIMA model predicts an upgoing pattern with seasonal growth, whereas the RNN shows an exponential growth on the net assets. The TCN projects a steady seasonal growth trend throughout the forecast period. Importantly, model characteristics and data constraints shaped these outcomes. The TCN a computationally intensive architecture was unable to recover robust relationships from the available series, likely because the data do not contain sufficiently long-range dependencies and the sample available for training did not support the large time-window requirements inherent to TCNs. This explains the TCNs relatively conservative, seasonal forecasts compared with the more volatile RNN outputs.

For net foreign assets of the other depository corporations, the ARIMA model shows a steady linear growth trend into the future. In contrast, the RNN model indicates a steep decline with some minute growth towards the end of the predicted years.

The TCN model suggests a steady seasonality trying to be stationary. This offers valuable insights into the future forecast of foreign assets and liabilities, aiding in informed decision-making for economic policies, financial planning, and market stability for policy makers in Nepal.

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7 Appendix

Source: Authors Calculation

ARIMA forecast of Net Foreign Assets for Monetary Authorities (In Million Rupees)

Year	Forecast Amount	CI Lower	CI Upper
2025	1,556,403	1,442,224	1,670,582
2026	1,668,206	1,497,456	1,838,956
2027	2,195,863	2,012,321	2,379,406
2028	2,090,433	1,872,651	2,308,216
2029	1,895,187	1,597,384	2,192,991
2030	2,515,415	2,195,815	2,835,014
2031	2,548,453	2,195,229	2,901,678
2032	2,285,281	1,859,178	2,711,383
2033	2,722,904	2,252,328	3,193,480
2034	3,062,327	2,563,496	3,561,159
2035	2,685,873	2,111,919	3,259,826
2036	2,996,863	2,365,415	3,628,310
2037	3,466,850	2,800,231	4,133,468
2038	3,216,731	2,486,284	3,947,177

ARIMA Forecast of Net Foreign Assets for Other Depository Corporations (In Million Rupees)

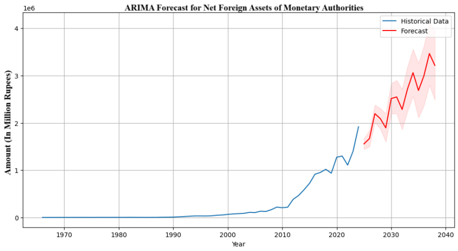
Year	Forecast Amount	CI Lower	CI Upper
2025	67,459.92	52,594.13	82,325.71
2026	68,593.01	50,358.60	86,827.42
2027	69,726.10	48,654.89	90,797.30
2028	70,859.19	47,290.19	94,428.19
2029	71,992.28	46,165.94	97,818.61
2030	73,125.37	45,223.72	101,027.01
2031	74,258.46	44,425.53	104,091.39
2032	75,391.55	43,744.97	107,038.12
2033	76,524.64	43,162.87	109,886.40
2034	77,657.72	42,664.73	112,650.72
2035	78,790.81	42,239.32	115,342.31
2036	79,923.90	41,877.70	117,970.11
2037	81,056.99	41,572.62	120,541.36
2038	82,190.08	41,318.12	123,062.05

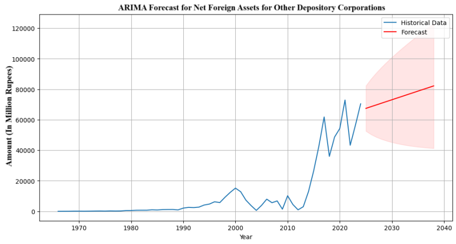
RNN Forecast of Net Foreign Assets for Other Depository Corporations (In Million Rupees)

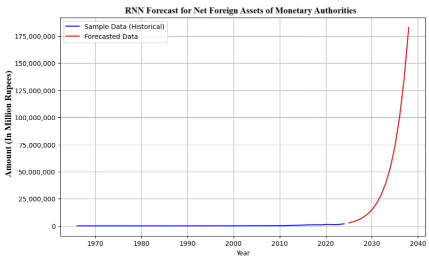
Year	Monetary Authorities	Other Depository Corporations
2025	2,774,831.5	53,191.29
2026	3,886,959.0	43,503.24
2027	5,412,785.5	34,558.21
2028	70,859.19	25,470.52
2029	71,992.28	17,240.68
2030	73,125.37	9,733.64
2031	74,258.46	3,822.84
2032	75,391.55	655.62
2033	76,524.64	3,539.74
2034	77,657.72	8,267.65
2035	78,790.81	5,019.62
2036	79,923.90	4,801.11
2037	81,056.99	1,355.33
2038	82,190.08	7,975.78

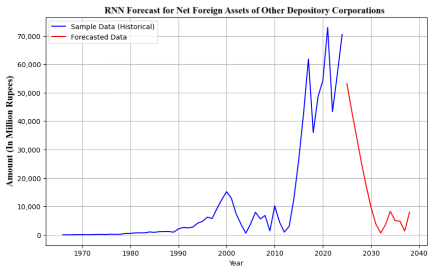
TCN Forecast of Net Foreign Assets for Other Depository Corporations (In Million Rupees)

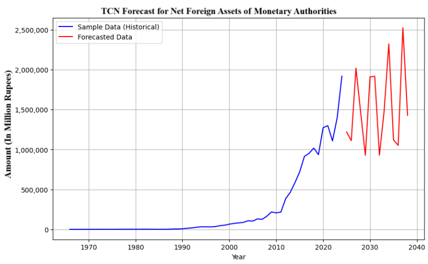
Year	Monetary Authorities	Other Depository Corporations
2025	1,219,332.00	44,144.17
2026	1,111,391.00	52,443.45
2027	2,019,290.00	59,595.49
2028	1,464,220.00	45,087.31
2029	927,281.00	49,062.11
2030	1,909,645.00	53,537.07
2031	1,917,156.00	45,261.57
2032	927,726.00	47,183.21
2033	1,481,494.00	50,176.91
2034	2,323,294.00	45,838.15
2035	1,120,481.00	46,351.02
2036	1,052,315.00	48,156.46
2037	2,524,499.00	45,905.27
2038	1,428,215.00	45,958.54

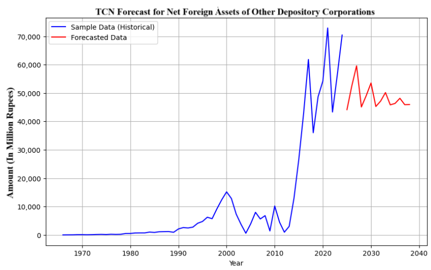




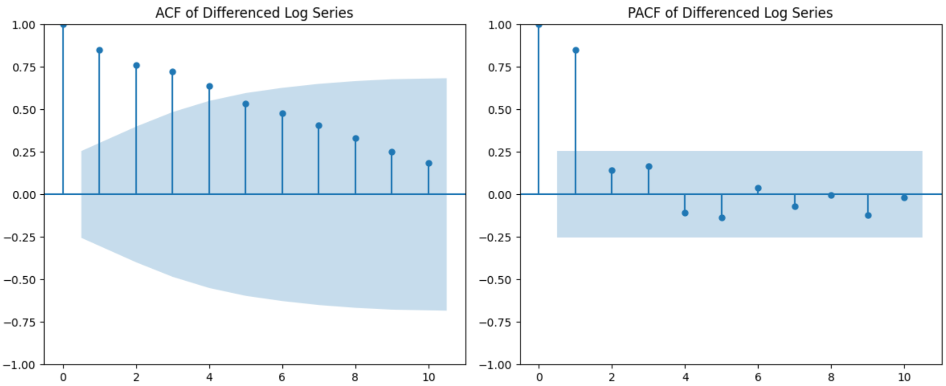




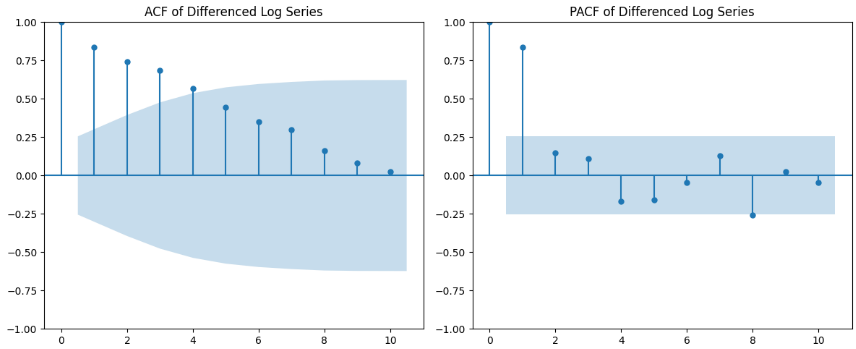




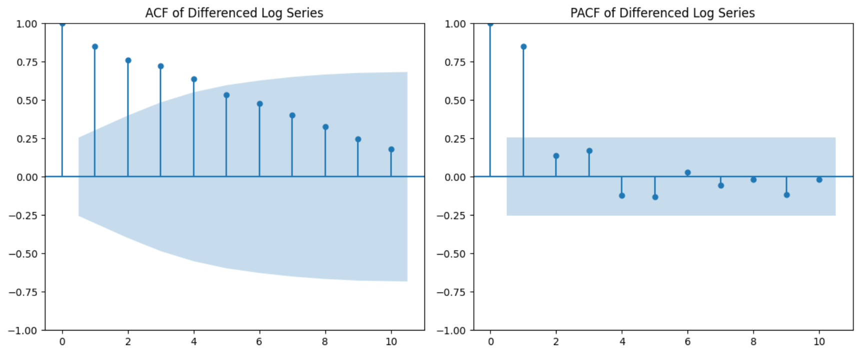
ACF and PACF Tests of Net Foreign Assets for Monetary Authorities



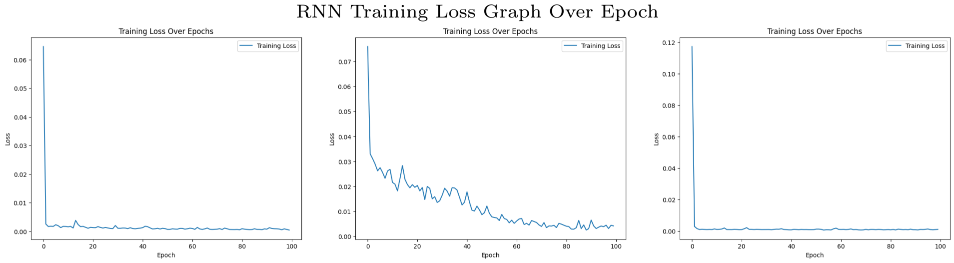
ACF and PACF Tests of Net Foreign Assets for Other Depository Corporations



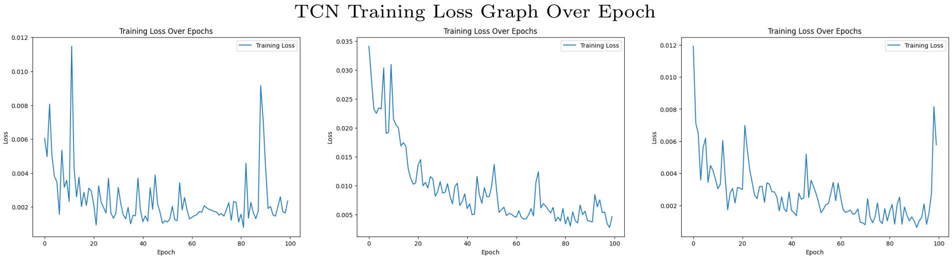
ACF and PACF Tests of Total Net Foreign Assets



RNN Training Loss Graph Over Epoch



TCN Training Loss Graph Over Epoch



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