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Modelling and Forecasting the United States Dollar – Chinese Yuan Exchange Rate | Nonlinear Autoregressive Neural Network vs Seasonal Autoregressive Integrated Moving Average

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Abstract

No time series modelling strategy performs consistently better than others in all situations. Different methods yield differing efficacies for different scenarios. This study compared the nonlinear autoregressive neural network (NARNN) and seasonal autoregressive integrated moving average (SARIMA) methods in modelling the United States Dollar – Chinese Yuan monthly average exchange rates over the period from January 2020 to November 2025. The NARNN outperformed the SARIMA and predicted consistent increases in exchange rates from December 2025 to March 2026. Regulators, speculators, policy makers and investors can make appropriate strategic decisions in anticipation of the statistically inferred fluctuations in the near future.

Keywords: Nonlinear Autoregressive Neural Network (NARNN); Seasonal Autoregressive Integrated Moving Average (SARIMA); Time Series Modelling And Forecasting.

1. Introduction

Time series modelling and forecasting is an indispensable tool in financial and economic analysis. The global economy is undergoing a period of uncertainty [1] due to geopolitical events, rising government debts and proliferation of cryptocurrencies. The need arises for reliable forecasts of financial trends in the immediate future, to allow governments, policy makers and investors to prepare robust strategic plans to manoeuvre the uncertain global financial environment. Valuable insights can be drawn from time series models and reliable forecasts allow investors, nations and policy makers to make judicious strategic decisions in anticipation of future trends [2,3]. Statistical time series modelling methods include autoregressive moving average (ARIMA) [2], Seasonal ARIMA (SARIMA) [3] and exponential smoothing methods.

Modern studies incorporate statistical models as well as neural network based methods [4,5] for time series modelling, often integrating them into hybrid models. Neural network and other programming based analysis techniques extend the capabilities of researchers in handling large amount of data and performing repetitive analysis operations with high levels of accuracy and reliability [6,7,8]. Recurrent neural networks (RNN) were the winning method in the 2020 M4 Forecasting Competition [9, 10]. The model was a combination of an exponential smoothing model and a long short term memory network. Adesina and Obokoh [11] developed a hybrid framework integrating SARIMA modelling with a long short term memory (LSTM) neural network. After fitting a SARIMA model to the time series, the study then used an LSTM to model the residuals. The hybrid framework outperformed strictly SARIMA, strictly LSTM and strictly RNN models in modelling and forecasting the South African Rand (ZAR) – USD exchange rate. Hyndman and Athanasopoulos [12] followed a similar hybridisation approach to time series modelling where a dynamic regression model was fitted

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to time series data, and then an ARIMA scheme was used to model the residuals. Yi [13] used an autoregressive moving average (ARIMA) model combined with a k-nearest neighbour approach to model and forecast the United States Dollar (USD) – Chinese Yuan (CNY) exchange rate from 2023 to 2024. The study correctly predicted a slight increase in the exchange rate for that period.

Xiao [14] modelled and forecasted the USD – CNY exchange rate for the year 2024 using an ARIMA model. The study went on to explore the factors influencing the exchange rate fluctuations. Modern studies have developed techniques go deeper into deducing underlying influences that affect time series and other dynamic phenomena [15, 16]. Spiliotis [17] compared the performance of machine learning and statistical time series modelling techniques for a wide range of scenarios. It was concluded that no particular method or class of methods consistently outperformed other methods in all situations. Instead the choice of best method differed from one situation to another.

In this study the SARIMA and nonlinear autoregressive neural network (NARNN) methods are compared in modelling the USD – CNY exchange rate over the period from January 2020 to November 2025. The more accurate method will be used to model and forecast the USD – CNY exchange rate monthly from December 2025 to April 2026.

Aim

This study aims to model and forecast the USD – CNY exchange rate using the better method between the NARNN and SARIMA.

Objectives

- Model the USD – CNY exchange rate using a NARNN model,
- Model the USD – CNY exchange rate using a SARIMA model,
- Compare the NARNN and SARIMA methods in modelling the USD – CNY exchange rates,
- Use the more accurate method to forecast the USD – CNY exchange rate from December 2025 to March 2026.

2. Methodology

2.1. Data source

The data used in this study was obtained from the International Monetary Fund [18] data portal. USD – CNY exchange rate data from January 2020 to November 2025 was used.

2.2. Software environment

The MATLAB [19] analysis environment was used for neural network modelling and the Minitab [20] analysis environment was used for SARIMA modelling.

2.3. Neural networks

Neural networks are mathematical models of the human brain [15]. They were developed to mimic brain functions such as thinking, knowledge and memory. They are primarily black box models (models that abstract underlying operations) [16] which can be trained to replicate the outcomes of empirical data [4]. A neural network model is trained using sets of input data with corresponding response data. Thereafter the neural network is used to simulate outcomes according to specified input values.

2.4. Time series neural networks

In time series analysis, neural networks are trained to estimate values based on their predecessors. The programmer specifies the number of preceding values (feedback delays) to be considered in making a prediction. A large number of feedback delays improves model fit, however, it also increases the likelihood of overfitting. Thus a balance is to be sought in choose an optimal number of feedback delays. The nonlinear autoregressive neural network is a type of recurrent neural network that uses values from a time series as input for predicting or forecasting other values in the same time series.

2.5. MATLAB source code

The MATLAB source code in **Figure 1** was used to create a nonlinear autoregressive neural network (NARNN) with 20 neurons in the hidden layer and a feedback delay of 12 data points, that is, each new value was determined using the preceding 12 values in the time series. 60 of the 71 monthly average USD – CNY exchange rate values were used to train the NARNN. Thereafter the NARNN was used to predict the last 11 values, that is, from January 2025 to November 2025.

2.6. ARIMA model

The autoregressive integrated moving average (ARIMA) time series model uses past values and errors to predict subsequent values in a time series. Samambgwa and Musora [2] formally stated the model in equation (1).

Z_t is an $ARIMA(p,d,q)$ process if

$Y_t = \nabla^{\mathrm{d}} \mathrm{Z_t}$, the result after differencing the time series d times,

(where ∇ is the differencing operator such that $\nabla Z_t = Z_t - Z_{t-1}$,)

is such that:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q}, \qquad (1)$$

where $\phi_1, \phi_2, \ldots, \phi_p, \theta_1, \theta_2, \ldots, \theta_q$ are constants, and

ϵ_t is a random process with a mean of zero and constant variance.

Time series variables sometimes succumb to seasonal influences, that is, influences that are repeated over a fixed period (season). When an ARIMA model incorporates seasonal influences, it becomes a SARIMA model.

```
%Preparing time series data for training neural network
T = tonndata(data,false,false);
%Setting up Nonlinear Autoregressive Neural Network (NARNN)
trainFcn = 'trainlm';
feedbackDelays = 1:12;
hiddenLayerSize = 20;
net = narnet(feedbackDelays,hiddenLayerSize,'open',trainFcn);
[x,xi,ai,t] = preparets(net,{},{},T);
net.divideParam.trainRatio = 50/60;
net.divideParam.valRatio = 10/60;
net.divideParam.testRatio = 0/100;
%Training NARNN
[net,tr] = train(net,x,t,xi,ai);
%Simulating data for comparison with observed values
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
[xc,xic,aic,tc] = preparets(netc,{},{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(net,tc,yc);
%Simulating and forecasting the next four data points (months)
[x1, xio, aio, t] = preparets(net, {}, {}, T);
[y1,xfo,afo] = net(x1,xio,aio);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(cell(0,11),xic,aic);
y1_1=cell2mat(y1);
y2_1=cell2mat(y2);
plot(1:48,y1_1,'-b');
hold on
plot(49:59,y2_1,'-k');
```

Figure 1 MATLAB source code for training and simulating a nonlinear autoregressive neural network

2.7. SARIMA model

Samambgwa and Musora [3] formally stated the SARIMA model in Equation (2):

$$\lambda_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D Y_t = \mu_q(B)\Theta_Q(B^s)X_t, \tag{2}$$

where:

Y_t is an $ARIMA(p, d, q)$ process,

X_t is a random process with mean zero and constant variance,

s is the length of a season,

$\nabla_s^D X_t = \sum_{j=0}^{D} \ (D\ j\ )Y_{t-js}$, and $\lambda_p(B)$ and $\mu_q(B)$ are polynomials in B of order p and q respectively (Equations (3) and (4)):

$$\mu_q(B) = \left(1 - \mu_1 B - \mu_2 B^2 - \ldots - \mu_q B^q\right), \tag{3}$$

$$\lambda_q(B) = \left(1 - \lambda_1 B - \lambda_2 B^2 - \ldots - \lambda_p B^p\right). \tag{4}$$

3. Analysis

The two time series modelling approaches, that is, NARNN and SARIMA were used separately to model the USD – CNY exchange rate for the first 60 of the 71 data points. That is, the average monthly exchange rates for the months from January 2020 to December 2024. Thereafter, each model was used to forecast the monthly average USD – CNY exchange rates for the months from January 2025 to November 2025. The forecasts were then used to compare the accuracy and select the time series model that better fits the dataset under study.

3.1. NARNN model

The MATLAB source code in **Figure 1** was used to train a NARNN using the first 60 data points (Jan 2020 – Dec 2024). The Levenberg-Marquardt training algorithm stopped after nine epochs, when the minimum gradient criterion had been met. **Table 1** summarises the neural network training statistics.

Table 1 Nonlinear autoregressive neural network training statistics.

Unit	Initial value	Stopped value	Target value
Epoch	0	9	1000
Elapsed time	-	00:00:08	-
Mean square error	0.587	1.65e -19	0
Gradient	1.83	8.1e -10	1e -07
Validation checks	0	4	6

3.2. SARIMA model

The best ARIMA model fitting function in Minitab 22 [20] was used to estimate a best fitting model using Bayesian information criteria. The $SARIMA(3,1,2)(2,1,0)_{12}$ was found to be the best fitting model for the first 60 data values (Jan 2020 – Dec 2024). **Table 2** summarises the final model parameter statistics.

Table 2 Final Estimates of Parameters.

Type	Coef	SE Coef	T-Value	P-Value
AR 1	1.040	0.201	5.19	0.000
AR 2	-1.230	0.161	-7.66	0.000
AR 3	0.342	0.177	1.93	0.061
SAR 12	-0.7833	0.0839	-9.34	0.000
SAR 24	-0.9503	0.0821	-11.58	0.000
MA 1	0.703	0.203	3.47	0.001
MA 2	-0.933	0.226	-4.13	0.000

3.3. Comparison of NARNN and SARIMA forecasts

The NARNN and SARIMA models were used to predict the USD – CNY exchange rate monthly averages for the months from January 2025 to November 2025. The output were then compare with the observed values of the same period. **Table 3** summarises the comparison.

Table 3 Comparison of NARNN and SARIMA exchange rate forecasts from January 2025 to December 2025.

	2025											
USD - CNY	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	MSE
Observed values	7.309	7.279	7.251	7.302	7.209	7.181	7.173	7.175	7.124	7.120	7.112	
NARNN Forecasts	7.304	7.346	7.266	7.163	7.068	7.022	7.027	7.104	7.346	7.387	7.046	
NARNN Error	-0.005	0.067	0.015	-0.139	-0.141	-0.159	-0.146	-0.071	0.222	0.268	-0.065	0.020
SARIMA Forecasts	7.282	7.255	7.291	7.433	7.681	7.589	7.593	7.649	7.890	8.087	8.035	
SARIMA Error	-0.027	-0.024	0.040	0.132	0.472	0.408	0.420	0.474	0.766	0.967	0.924	0.290

The predictions (**Table 3**) resulted in a lower mean square error from the NARNN forecasts. Thus the nonlinear autoregressive neural network (NARNN) was identified as the better fitting model for the dataset. The NARNN was then used to forecast the USD – CNY exchange rate values for the months from December 2025 to March 2026.

3.4. Modelling and Forecasting using the NARNN

The neural network was trained using all the 71 data values, that is, from January 2020 to November 2025. The training algorithm stopped when the number of validation checks had reached the target. The training statistics are summarised in **Table 4**.

Table 4 Nonlinear autoregressive neural network training statistics

Unit	Initial value	Stopped value	Target value
Epoch	0	9	1000
Elapsed time	-	00:00:02	-
Mean square error	1.15	3.41e -11	0
Gradient	3.57	1.26e -05	1e -07
Validation checks	0	6	6

A feedback delay of twelve time steps (month values) was set in the MATLAB simulation program (**Figure 1**). Thus, the model simulated values starting from the thirteenth time step (January 2021).

3.5. Residual analysis

Figure 2 shows the time series plot of observed and simulated values as well as the resulting errors. The errors were all below 0.2, implying that the model could be trusted to make statistically accurate predictions.

The error histogram (Figure 3) was bell shaped with the majority of errors near the mean (zero) indicating that the normality assumption was not violated. The error autocorrelation plot in Figure 4 showed no significant spikes, implying that the NARNN model had incorporated all the statistically significant features in the data.

3.6. Model validation

The linear regression plot (**Figure 5**) of simulated values against observed values had a gradient of approximately one and a coefficient of determination of 0.98 indicating that simulated values were approximately equal to the observed values and the NARNN model was a statistically good fit for the data under study. The model could thus be used to make reliable forecasts.

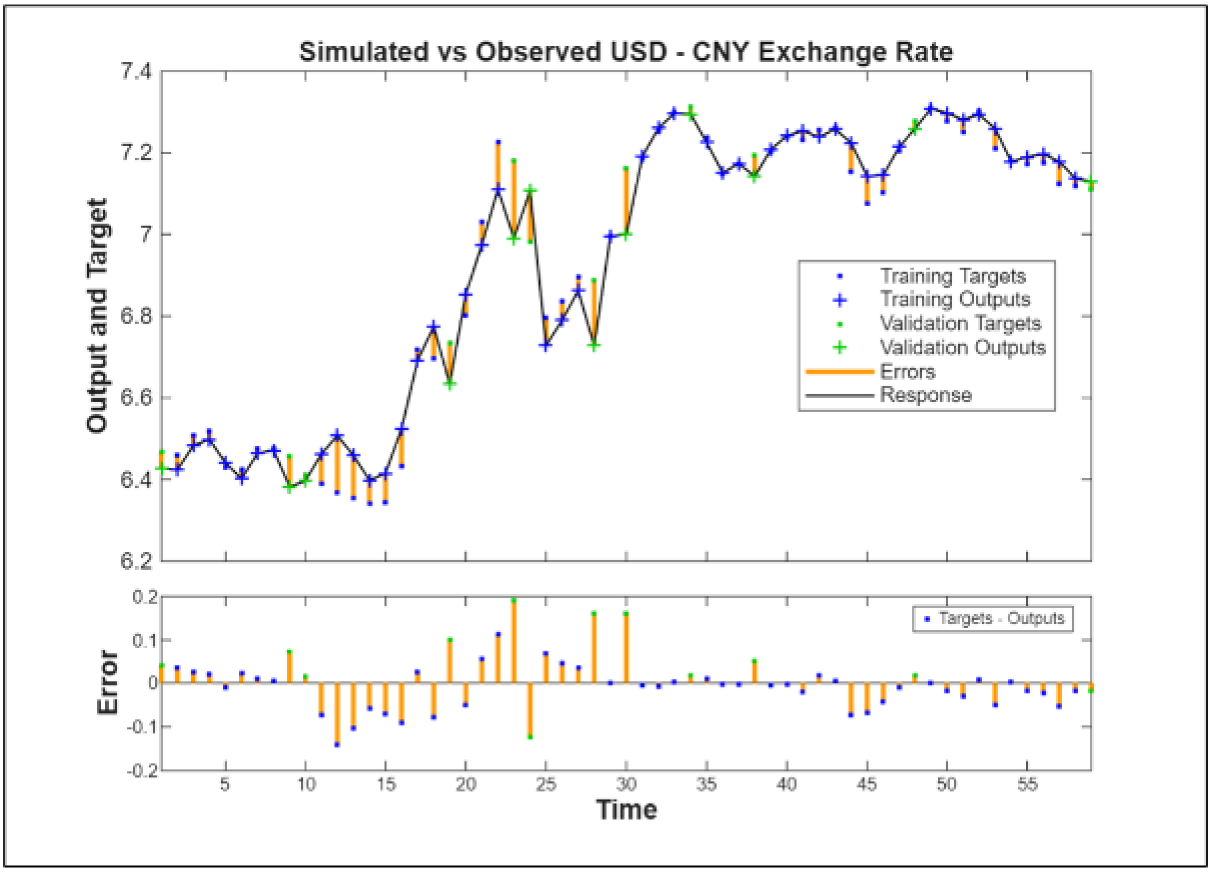

Figure 2 Time series plot of observed and simulated USD – CNY exchange rate values (Jan 2021 – Nov 2025)

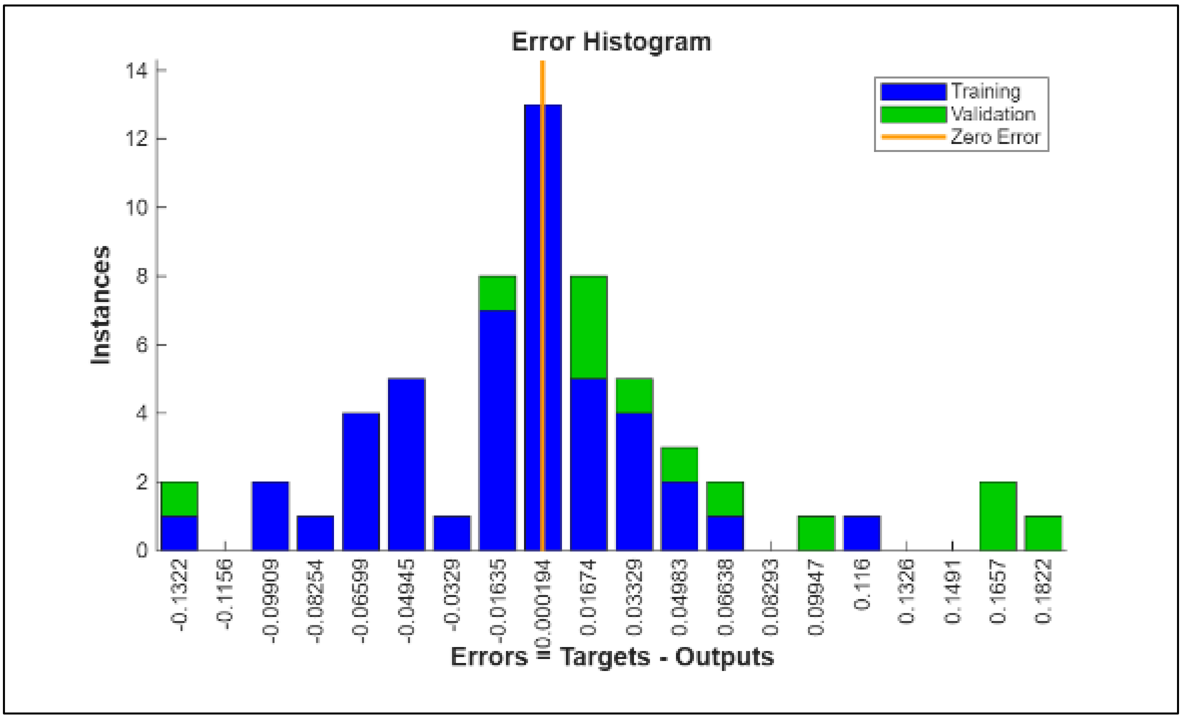

Figure 3 Histogram of errors resulting from the NARNN simulation of USD – CNY exchange rates

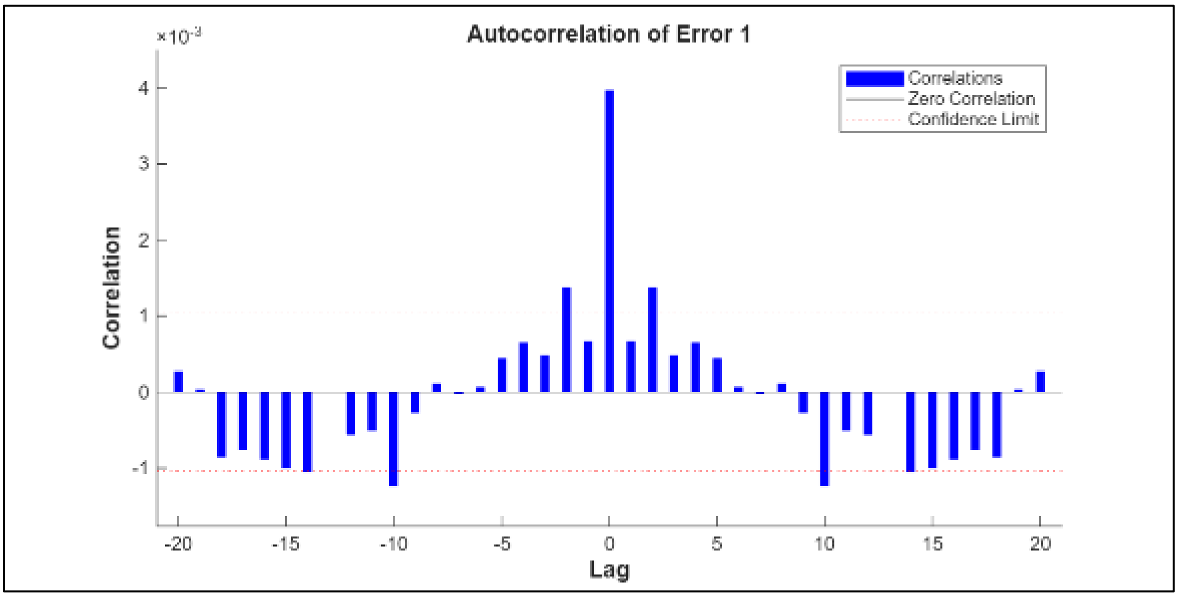

Figure 4 Autocorrelation plot of errors resulting from USD – CNY exchange rate simulation

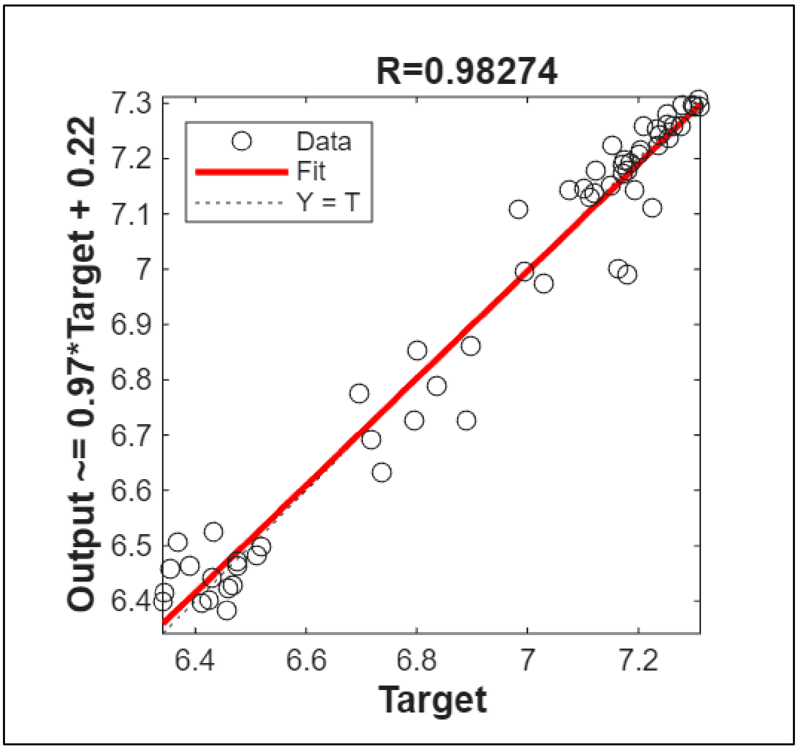

Figure 5 Linear regression plot of simulated values (Output) against observed values (Target)

3.7. Forecasting

The NARNN was used to forecast monthly average USD – CNY exchange rates for the months from December 2025 to March 2026 (**Table 5**). **Figure 6** shows the time series plot of the observed values for the 59 data points from January 2021 to November 2025 as well as the four predictions (forecasts) for December 2025 to March 2026. The USD – CNY exchange rate has been predicted to increase consistently from December 2025 through March 2026.

Table 5 NARNN predictions and forecasts**.**

	Jul-25	Aug-25	Sep-25	Oct-25	Nov-25	Dec-25	Jan-26	Feb-26	Mar-26
Observations	7.173	7.175	7.124	7.120	7.112				
Predictions	6.826	7.174	6.876	6.254	6.599	7.141	7.233	7.264	7.275

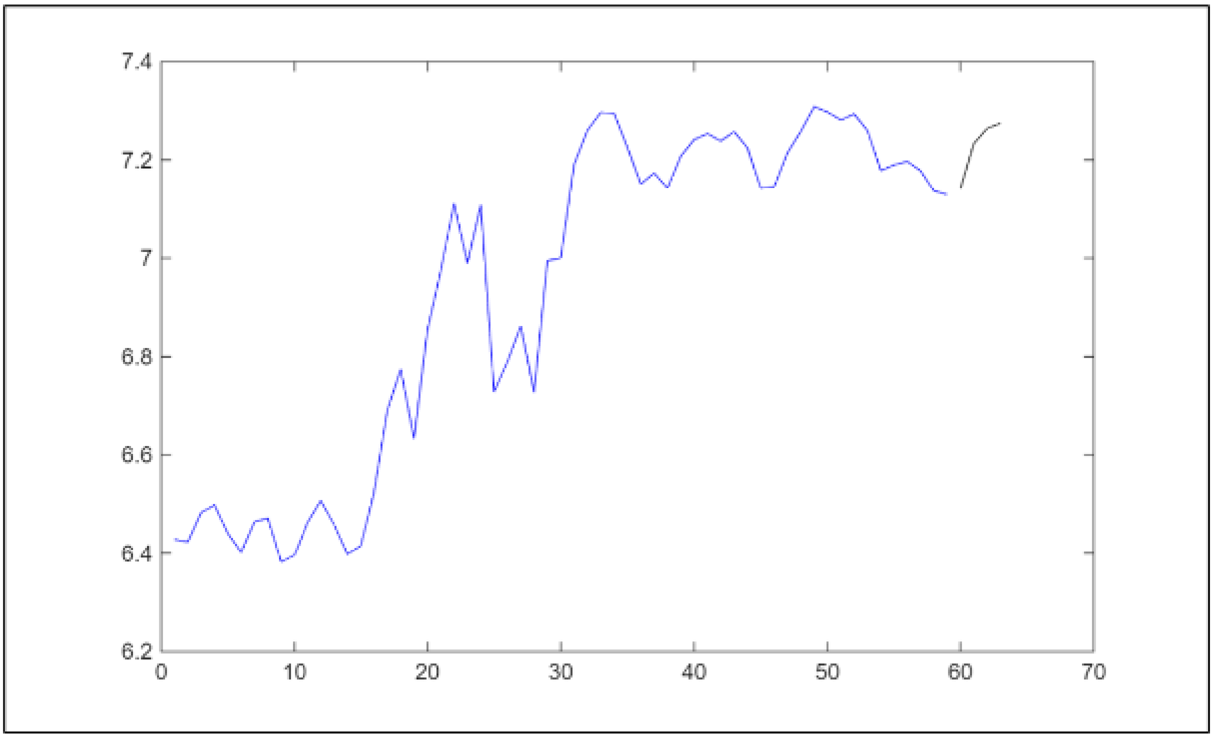

Figure 6 Time series plot of observed USD – CNY exchange rate values and forecasts

4. Discussion

This study compared the efficacy of nonlinear autoregressive neural network (NARNN) and seasonal autoregressive integrated moving average (SARIMA) models in modelling the United States Dollar (USD) – Chinese Yuan (CNY) monthly average exchange rates for the period from January 2020 to December 2024. The NARNN was identified as the more accurate fit when its predictions for January 2025 to November 2025 exhibited a significantly lower mean square error.

It was demonstrated that the NARNN model was a good fit for the data under study and the scheme was used to forecast the USD – CNY exchange rate from December 2025 to March 2026. The results show a consistent increase in the forecasted months. These insights can be used by regulators and speculators to make statistically supported stances in global currency markets.

5. Conclusion

For the USD – CNY monthly average exchange rate in the period from January 2020 to November 2025. The nonlinear autoregressive neural network model outperformed the seasonal autoregressive integrated moving average method. The results predict consistently increasing exchange rates from December 2025 to March 2026. These statistically supported inferences give policy makers and investors the opportunity to make appropriate strategic decisions in anticipation of the near future. Further research can compare different types of time series modelling strategies for modelling other key exchange rates and financial instruments in the global economy.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declared having no competing interests.

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