Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 16, No. 2, 2024

Forecasting China's Consumer Price Index (CPI) Based on Combined ARIMA-LSTM Models

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Abstract: This study aims to construct an efficient consumer price index (CPI) forecasting model to provide policymakers, investors, and businesses with more accurate forecasts of future price levels and inflation trends. in this study, a combined model that integrates autoregressive integrated moving average (ARIMA) with long short-term memory (LSTM) networks is introduced. The model first captures the linear trend of CPI data using the ARIMA model, and then inputs the residuals into the LSTM network to predict the nonlinear part. The model is trained and tested using monthly Chinese CPI data. The findings indicate that the ARIMA-LSTM hybrid model outshines the single ARIMA model regarding prediction accuracy, its predicted values are closely aligned with the actual values, and the model residual series passes the Q-test, which suggests that the model exhibits a strong fitting capability. The article also introduces the evaluation indexes of the model and compares the prediction performance of the single ARIMA model and the ARIMA-LSTM hybrid model. Finally, the article concludes that the ARIMA-LSTM hybrid model has high accuracy and reliability in CPI forecasting, which provides a powerful tool for forecasting future price trends.

Keywords: Time series forecasting, CPI, Deep learning, ARIMA-LSTM.

1. Introduction

The Consumer Price Index (CPI) is among the key performance metrics of changes in consumer price levels. By forecasting the CPI, it can help organizations, such as, central banks and businesses to anticipate future price levels and inflation trends. This is important for adjusting the economy, setting money, and business decision-making and planning. Traditional CPI forecasting methods usually rely on statistical and econometric techniques, which include time series analysis, regression modeling, seasonal adjustment, etc (Gautam & Kanoujiya, 2022). These methods are often based on historical data and predict future CPI changes by identifying patterns and trends in price movements. For example, Di Filippo (2015) used Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) methods to forecast the CPI in the Eurozone and the U.S. Shapovalenko (2021) reviewed the models used by the National Bank of Ukraine (NBU) for predicting short-term CPI trends, researchers assessed the predictive precision of these models and provided suggestions for improving current models, especially in the context of data scarcity and the challenges of prediction in war situations. CPI price indices tend to have certain seasonality and trends, and ARIMA models can capture these linear relationships, providing forecasting power for long-term trends (Riofrio et al., 2023; Álvarez-Díaz & Gupta, 2016). Ahmar et al. (2018) used the predictive modeling tools in R programming language to implement the ARIMA method to forecast CPI data in Indonesia, both of which achieved good forecasting results. Shinkarenko et al. (2021) analyzed the time series data of CPI for Ukraine and constructed the ARIMA*ARIMAS model. Mohamed (2020) compared the performance of the ARIMA model and predictive analytical model with ARIMA errors in forecasting CPI in Somaliland.

Machine learning methods, especially deep learning methods that have emerged in recent years, provide new ideas for CPI forecasting. These methods can handle more complex nonlinear relationships by automatically learning features and patterns from large amounts of data (Maehashi & Shintani, 2020; Du, 2018; Samiami-Namini et al., 2018), and can account for long-term temporal correlations in sequential data, thus demonstrating higher CPI forecasting in terms of accuracy and adaptability (Rohmah et al., 2021; Rohmah et al., 2020; Wang & Fan, 2010; Feihu Qin et al., 2010). such as Recurrent Neural Networks (RNN) or Long Short-Term Memory Networks (LSTM). LSTM model is a deep learning model suitable for processing sequential data, which makes it a powerful tool within the realm of sequential data forecasting through its unique gating mechanism and memory units. For example, S. Zahara et al. (2020) combined LSTM and cloud computing techniques for CPI forecasting, Astrakhantseva et al. (2021) used an LSTM-based model and introduced a "dual attention" mechanism to automatically detect the effect of the time point on the forecasts, Reynaldo Rosado et al. (2021) used an LSTM-based model and introduced a "dual attention" mechanism to automatically detect the effect of the time point on the forecasts. Reynaldo Rosado et al. (2021) used different LSTM model architectures for forecasting CPI with good results. CPI price index is often affected by numerous elements, such as economic activity, market supply and demand, and changes. These factors may produce complex nonlinear relationships, and the LSTM model can better capture and predict these nonlinear trends. Combining the ARIMA and LSTM models, leaving the linear trends to the ARIMA model and the nonlinear trends to the LSTM type, can harness the strengths of both approaches and improve the model prediction accuracy. Sarveswararao and Ravi (2020) proposed a two-stage hybrid model and concluded that the Chaos and Machine Learning hybrid model outperforms the pure machine learning algorithm in terms of Symmetric Mean Absolute Percentage Error, Theil's U statistic, and directional statistics. D Xu et al. (2022) compared and analyzed six models and ARIMA-LSTM used to predict dry weather. The findings indicated that hybrid models outperformed standalone models in terms of predictive precision. Furthermore, the ARIMA-LSTM model achieved the greatest level of forecasting accuracy at 6, 12, and 24-month scales.

Morikawa (2022) aimed to predict in-vehicle carbon dioxide (CO2) concentration by ARIMA and LSTM models and to evaluate the comparative predictive precision of these two approaches. Hadwan et al. (2022) proposed a hybrid prediction method consisting of three models: an initial model grounded in ARIMA; a second model with a backpropagation neural network (BPNN) featuring adjustable gradient and momentum coefficients; and a fusion of ARIMA and BPNN (ARIMA/BPNN) as well as artificial neural network and ARIMA (ARIMA/ ANN) hybridization to obtain the advantages of both linear and non-linear predictive models for predicting CPI index. Du et al. (2014) combined the three methods of ARIMA, gray model, and BPNN. By improving the prediction method, the accuracy of sub-CPI prediction was improved and the method outperformed many frequently employed forecasting techniques regarding their precision and stability.

This literature provides specific methodological and empirical studies on the application of a combination of linear and non-linear models to sequential data forecasting. These studies show that forecasting accuracy can be improved, uncertainty can be reduced, and complex relationships in time series can be better captured by combining multiple models. Although each dataset and application scenario has own specific requirements, these studies provide useful guidance and inspiration for carrying out the practice of combining predictive models.

the remainder of the study is structured in the following manner: In Section 2, this study describes the suggested model in detail. In Section 3 gives the analytical forecasting process of China's CPI, i.e., the linear forecasting of the ARIMA model, the non-linear predictive power of the LSTM model, and the coupled forecasting results. In the 4 sections, a comparative analysis of the hybrid model versus the standalone models is conducted. In the 5 sections, we summarize the findings of the research.

2. Relevant Theoretical Foundations

2.1. Introduction to the ARIMA Model

ARIMA is a frequently employed analytical tool for sequential data examination and forecasting. It models the data by considering the autocorrelation (AR, autoregressive), lagged difference (I, integral), and moving average (MA, moving average) aspects of the series.

The general form of the ARIMA model is ARIMA (p, d, q): p represents the order of the autoregressive term (AR), which denotes the count of time lags for the linear relationship between the historical data and the current values in the model. d signifies the order of the difference (I), which refers to the number of differences that are applied to the original data to smoothen it out. q represents the order of the moving average term (MA), which denotes the number of lags that are accounted for in the model. of the mean of the prediction errors.

The modeling steps for the ARIMA model are as follows:

Determining the model order: the order parameters p, d,and q of the ARIMA model are determined by looking at the time series plot, autocorrelation function (ACF) diagram, and partial autocorrelation function (PACF) diagram.

Data preprocessing: the necessary processing of the raw time series data, such as removing trends (using differencing until the series is smooth), removing seasonal effects, and so on.

Fitting the model: an ARIMA model is applied to processed time series data using a fit function. The parameters of the model can be determined through maximum likelihood estimation or alternative techniques.

Model checking: ensuring that the model has not been left out of the modeling of sequential patterns by analyzing the ACF diagram and PACF diagram of the model residuals and Q-tests, among other methods.

Model diagnosis and improvement: If the model residuals show unreasonable autocorrelation or other problems, model improvement is needed to adjust the order, refit the model, and perform further diagnostics.

Forecasting: The fitted ARIMA model is used to make forecasts at future points in time, and the optimal forecast interval can be selected.

The mathematical expression of the model is as follows:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots \theta_q \epsilon_{t-q} + \epsilon_t$$

Where, Y_t is the observed value of the time series at moment t; c is the constant term; φ is the autoregressive coefficient; ε is the error term (Gaussian white noise); θ is the moving average coefficient. The specific form of these equations will be adjusted according to the order of the particular ARIMA model. The application of the ARIMA model needs to be specifically analyzed and adjusted grounded on the corresponding time series data to ensure correctness and reliability. In addition, there are various improved and extended forms of ARIMA models, such as the Seasonal ARIMA (SARIMA) model, which can better handle time series data with specific properties.

2.2. Introduction to the LSTM Model

The LSTM model has a memory function to better handle long sequence problems (Rui Zhang et al., 2022). In LSTM, the flow of information is controlled by introducing gating mechanisms, including input gates, output gates, and forgetting gates, to control which information needs to be passed and which needs to be forgotten. These gating mechanisms can help LSTM models filter and store important information in the sequence and resist the problem of gradient vanishing. Therefore, LSTM is widely used in language modeling, natural language processing, speech recognition, video processing, etc. LSTM has a wide range of applications in finance, including determining market sentiment, asset management, predicting non-performing loans and fraud, and financial forecasting. LSTM can be used for forecasting financial temporal data such as stock prices and exchange rates. Based on historical data, the model can predict future trends and help investors make better investment decisions.

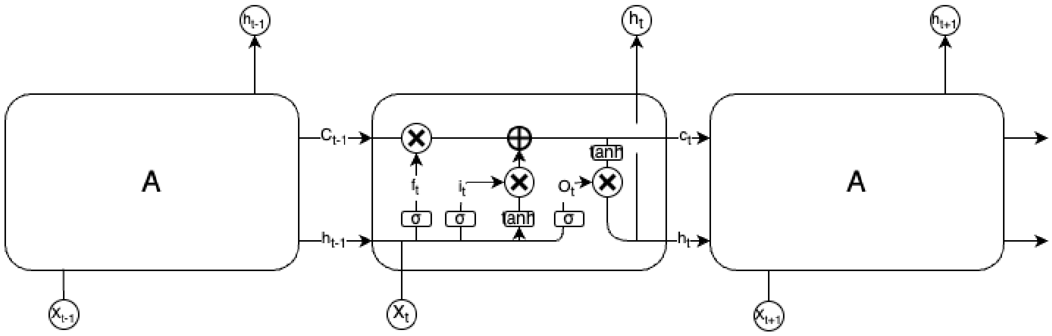

Figure 1. LSTM cell structure

Compared to the traditional RNN, the LSTM model adds a cell state. Let's take the cell structure at the middle moment t of LSTM as an example. In figure 1, the X denotes the input state, the h denotes the hidden layer, and C then denotes the cell update. In the model, the cell state at time $t-1$ will be affected by the hidden layer state at time $t-1$ and the input X at time t, and the resulting output from the cell and hidden states.

There are three main unit structures within the LSTM: the oblivion gate, the update gate, and the output gate. It is called oblivion gate because H_{t-1} and X_t, after the state input, the output activated by the σ function as f_t. If the output value is 0, the C_{t-1}, corresponding information is erased, which is equivalent to complete forgetting. If the output value is (0, 1), it is equivalent to partial retention, and only when the output value is 1, the corresponding information is completely retained. Therefore, this structure is called the forgetting gate structure. The output value i_t activated by the σ function is multiplied by the output value $\widetilde{C_t}$ normalized by the$tanh$ function, the output information is added with the information obtained from the previous forgetting gate, and this process can be regarded as an update process of the C This process can be regarded as an update process of the Therefore it is called an update gate. C_t is normalized by the $tanh$ function and multiplied with the output value O_t to acquire the output value of the next stage.

2.3. ARIMA-LSTM Model

For data in the form of time series, we assume that it consists of a linear part and a nonlinear part, which can be formulated as the following expression:

$$X_t = L_t + N_t + \xi_t$$

Where L_t is the linear part, N_t is the nonlinear part, and ξ_t represents the error term. The ARIMA model performs well in successfully modeling nonlinear relational surfaces in time series data, whereas, the LSTM model is capable of modeling nonlinear components. To achieve the best prediction results, we constructed a hybrid model that combines the benefits of the ARIMA and LSTM models. This hybrid model can be operated within the framework illustrated in Figure 2.

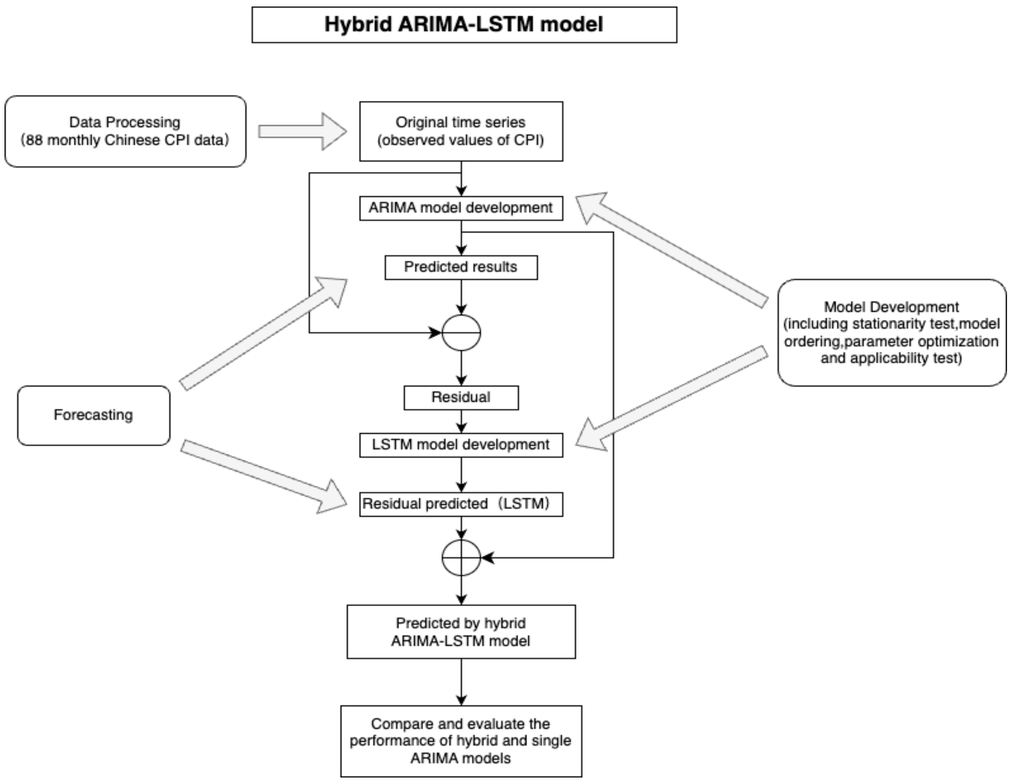

Figure 2. ARIMA-LSTM hybrid model

The hybrid model can be generally categorized into four phases: (1) Data preprocessing. Time series data are generally non-stationary time series, needs to observe its scatter plot or directly conduct the ADF unit root test to observe whether its time series is smooth. If it is not smooth, it needs to be processed by logarithm or difference to transform it into a smooth time series. (2) Linear forecasting of ARIMA model. The ARIMA statistical model is used to extract the linear part of the CPI L_t and return the residual term N_t, which is used as the input term in the next step. (3) The residual term N_t generated by the ARIMA model, that is, the nonlinear part, is fed into the LSTM network for the learning process, and the predicted value of the nonlinear part is generated. (4) The predicted values of the linear part of the ARIMA model and the predicted values of the nonlinear part of the LSTM network are added together to derive the ultimate forecasting outcomes, and the outcomes are evaluated.

2.4. Evaluation Indicators

In this work, four comprehensive evaluation indexes are chosen to evaluate the precision of the forecast of the ARIMA-LSTM model, which are Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Its specific formula is as follows:

(1) Mean Absolute Error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \in [0, +\infty]$$

(2) Mean Square Error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \in [0, +\infty]$$

(3) Root mean square error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \in [0, +\infty]$$

(4) Mean Absolute Percentage Error.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \in [0, +\infty]$$

Where y_i denotes the ith true value, and $\hat{y}_i$ denotes the ith predicted value. The smaller the value of MAE, MSE, RMSE, MAPE, suggesting that the greater the model's precision, the more effective the fit.

3. Empirical Analysis

3.1. Data Sources and Pre-processing

This paper uses monthly data of China CPI from January 2016 to April 2023, with a total of 88 sample values. The source of data is the official website of the National Bureau of Statistics. Figure 3 shows China's CPI data over the past 88 months.

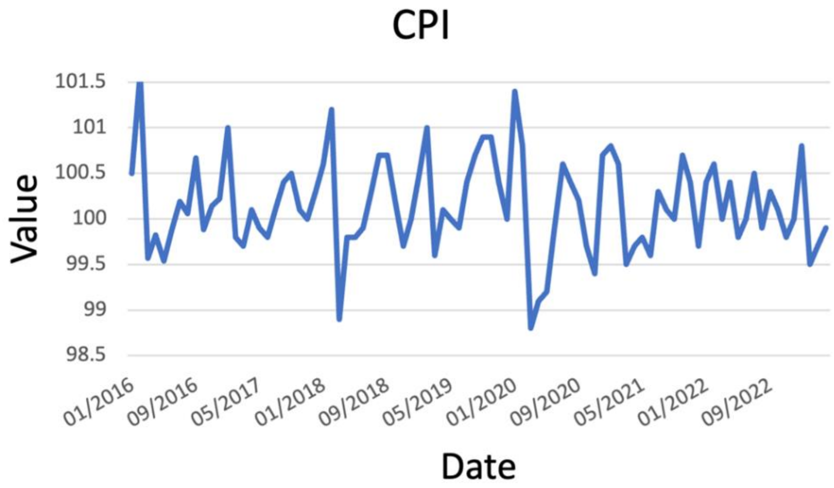

Figure 3. cpi data of China

In order to analyze and forecast the CPI using the ARIMA model, the stability of the time series must be ensured first. However, the selected CPI data may be affected by unexpected events, resulting in data instability. Therefore, before ARIMA analysis and forecasting of CPI, unit root test is needed to guarantee the data's continuity. Unit root denotes the unit root process, if there is a unit root process in the time series it indicates that the series is not smooth, and there could be a spurious regression phenomenon within the context of regression analysis. Common unit root test methods include the augmented Dickey-Fuller (ADF) test, Phillips-Perro (PP) test, Ng-Perron (NP) test, etc. In this study, the ADF test is chosen. When using Stata software to carry out ADF test on the original CPI data, it is found that the T-statistic shows significance at a 1% level of significance, which means that the original CPI series is smooth, and can continue to carry out the subsequent empirical analysis.

3.2. ARIMA Model Fitted with A Linear Component

From the above, it is evident that the original sequence is smooth and does not need to be differenced, so the value of d in the ARIMA model is 0. The next step is to determine the value of p and q by observing the ACF diagram and PACF diagram of the sample data. As shown in Figure 3.

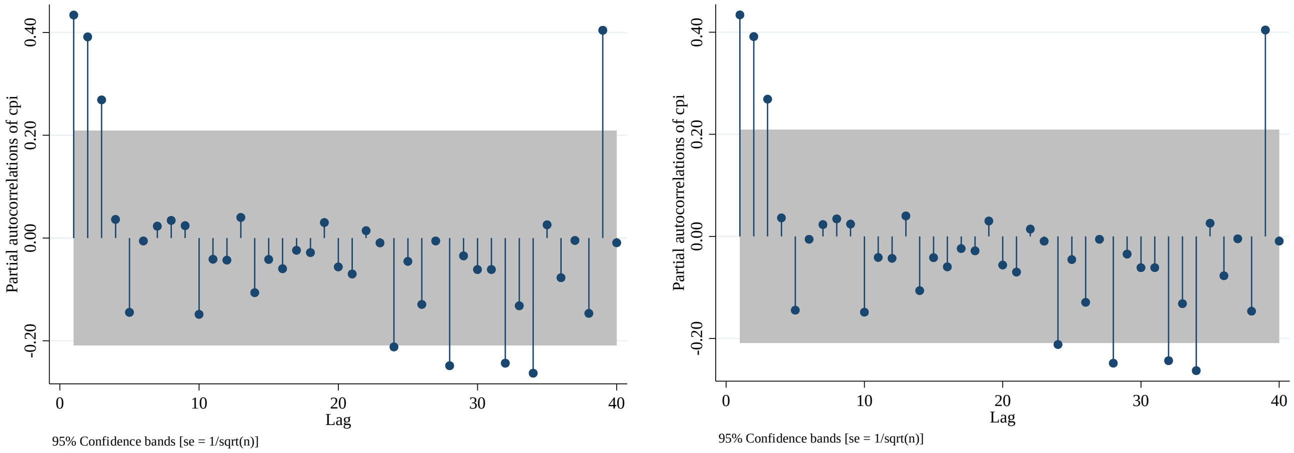

Figure 4. Sample autocorrelation and partial autocorrelation plots

The four models ARIMA (1, 0, 1), ARIMA (1, 0, 2), ARIMA (2, 0, 1) and ARIMA (2, 0, 2) are evaluated. The residual series of the four models were subjected to Q-tests respectively, and the tests were all passed, indicating that the residual series of the four models were white noise and the models were all fully identified. Compare the fit of four models using the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and Khundrin's Law of Iterated Logarithm Criterion (LILC) as evaluation metrics. The more reduced the values of AIC, BIC, and LILC, the more favorable the model fit and the higher the accuracy of the predicted values. By comparing the four models, it was determined that ARIMA (1, 0, 2) was used for sample fitting.

Using stata econometrics software, the parameter values of the model can be calculated as shown in Table 1, with the coefficients of AR (1) being significant at the 1% level and MA (2) being significant at the 5% level. Therefore, the research of this paper can establish the forecasting model of China's CPI index as ARIMA (1, 0, 2), where the coefficients of the model are displayed in Table 1.

Table 1. ARIMA (1, 0, 2) model correlation coefficients

variable	Coefficient	Std. Error	t-Statistic	Prob.
AR (1)	0.7635	.0718773	10.62	0.0000
MA (1)	-0.6549			
MA (2)	-0.3451	0.1726	-2.00	0.046

As shown in figure 4, the model is very close to the actual values in terms of fitted values, which fully reflects the trend of CPI index, thus suggesting that the model exhibits a positive performance in fitting effect. The residual series passes the Q-test and is a white noise series. ARIMA method is an effective tool, but not for nonlinear fluctuations. The blue line represents the residuals between the predicted values of the ARIMA model and the actual values and uses it as test data for the LSTM model.

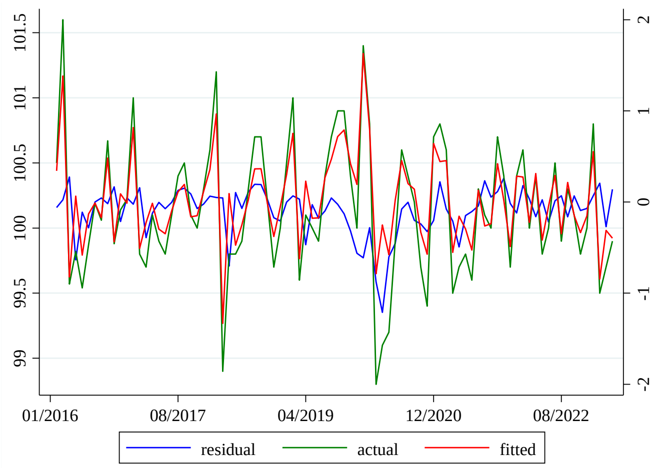

Figure 5. ARIMA (1, 0, 2) model fitted values, true values, and residual series

3.3. LSTM Model Fitting the Nonlinear Component

In order to find the nonlinear relationship of CPI, the LSTM model was developed. In the ARIMA-LSTM hybrid model, the LSTM network is fed exclusively with the residuals obtained from the ARIMA model. We predicted the CPI value of the day from the CPI data of the previous seven months, for example, we predicted the CPI value of August based on the data of January, February, March, April, May, June, and July. The learning rate is configured at 0.009, and the iteration count is set to 250.

The loss function is determined by employing the smooth L1 loss function for computation. The smoothed loss function L1, also known as the absolute value loss function, serves as a frequently utilized function in addressing regression issues. It measures the error of the model by calculating the absolute difference between the forecasted outcome and the target value.

The expression for the smoothing loss function L1 is:

$$\boldsymbol{L(y,\hat{y}) = |y - \hat{y}|}$$

Where y denotes the desired outcome and $\hat{y}$ signifies the model's estimated outcome.

L1 smoothing loss function Compared to other common loss functions (e.g. mean square error), L1 loss has better robustness to outliers and outliers. Since the L1 loss uses absolute differences, outliers have less influence on the L1 loss, making the model better adaptable to noise and outliers;

the L1 loss has a linear gradient at the origin, which means that the response of the L1 loss to parameter tuning remains consistent over different prediction error ranges. This property helps the optimization algorithm to converge better and reduces the risk of overfitting; moreover, the relationship between the form of the L1 loss and the absolute value is intuitively easy to understand. It directly measures the absolute difference between the objective value and the pre-mean, which is more in line with the interpretation of errors in some practical problems.

As depicted in figure 5, the function loss rate of the LSTM network for the residual sequence is relatively low, and the fitted values also highly overlap with the actual values, this suggests that the model possesses a high fitting accuracy.

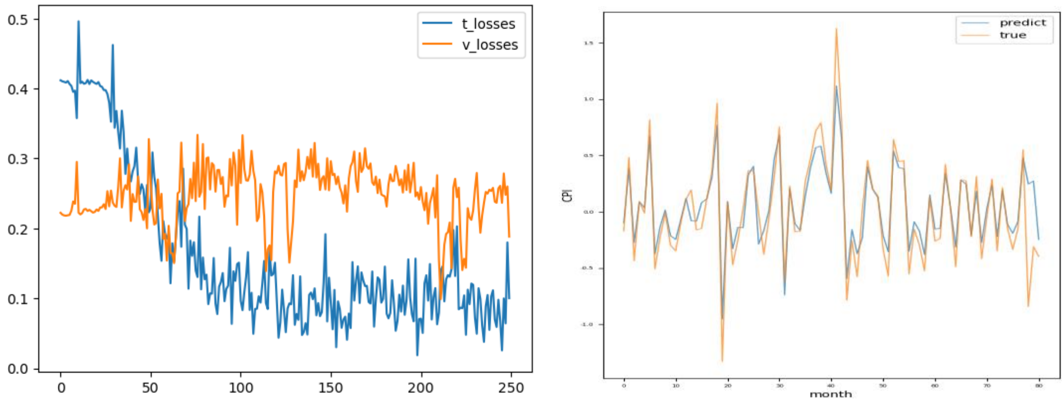

Figure 6. Residual series loss function and fitted values vs. true values

As shown in Table 2, taken together, the LSTM model performs well in fitting the residual series, especially in terms of MAE and RMSE, showing a small prediction error.

Table 2. Comprehensive evaluation metrics for residual sequence fitting in LSTM networks

Comprehensive evaluation index	Value
MAE	0.1257
MSE	0.3780
RMSE	0.1944
MAPE	0.8414

4. Analysis of Results

In addition, when using the ARIMA-LSTM model, the residual sequence fitting values obtained from the LSTM model are added to the linear parts obtained from the ARIMA model and the final prediction result can be obtained. It can be observed through figure 6 that the fitted values of the ARIMA-LSTM model are nearly identical to the actual values and completely reflect the trend of the CPI index, which further confirms the good fitting effect of the model.

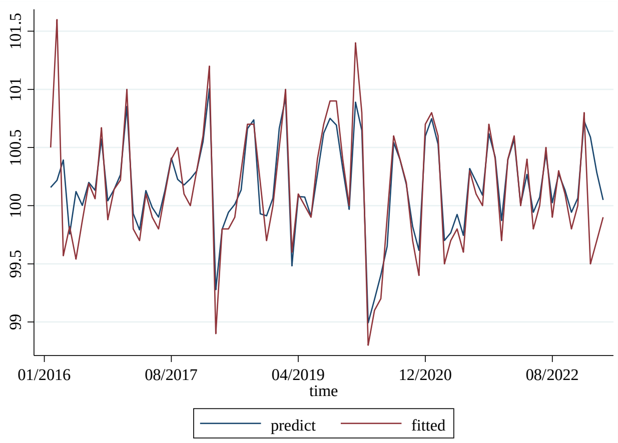

Figure 7. ARIMA-LSTM model predicted and true values

As illustrated in Table 3, comparing the single ARIMA model with the ARIMA-LSTM model forecasting outcomes, by observing the values of the three evaluation indexes, MAE, MSE and MAPE, it can be found that the comprehensive evaluation values of the ARIMA-LSTM model are each less than those of the standalone ARIMA model, and it can be deduced that the ARIMA-LSTM model is superior to the single ARIMA model in CPI prediction. single ARIMA model with better model prediction accuracy. It is further observed that China's CPI index fluctuates more from 2018 to 2020, especially due to the impact of public health emergencies. In conclusion, when compared to the individual ARIMA models, the hybrid model separates the time series into the linear part of the ARIMA model and the nonlinear part of the LSTM model, which has higher forecasting accuracy.

Table 3. ARIMA model and ARIMA-LSTM combined evaluation metrics

	ARIMA	ARIMA-LSTM
MAE	0.3738	0.1536
MSE	0.2320	0.0696
MAPE	0.0037	0.0015

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