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FORECASTING INFLATION RATE USING ARTIFICIAL NEURAL NETWORK: THE CASE OF VIETNAM

Nguyen Tien Nhat*

University of Economics, Hue University, 99 Ho Dac Di St., Hue, Vietnam

* Correspondence to Nguyen Tien Nhat <ntnhat@hce.edu.vn>
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Abstract. This research applies the feedforward artificial neural network (ANN) with a backpropagation algorithm to predict the inflation rate of Vietnam for the year 2022 using a historical dataset from 2000 to 2021. The forecast shows a close similarity to the actual figures, implying that the built-up ANN model is efficient and applicable. The result also points out that money supply is a significant factor in forecasting the inflation rate of Vietnam.

Keywords: artificial neural network, forecasting, inflation, Vietnam

1 Introduction

Inflation is a function of the state of the level of prices which indicates the expansion of the economy. Forecasting inflation in any economy plays a crucial pillar for central bank policymakers since knowing whether inflation will increase or decrease in the future may assist them to modify monetary policy [1], thus both academics and policymakers have given inflation prediction a lot of attention. However, predicting inflation is extremely difficult because of the limited availability of economic data, which is vital for understanding the state of the recent market [2]. The second reason is the possibility of biases in series data measurement in regard to the method used. Therefore, there are several misconceptions about projecting expectations [3]. Numerous studies have attempted to apply a variety of methods to predict inflation. There is strong evidence proving that models built based on the Philips curve typically produced inaccurate predictions [4], so several researchers have developed a variety of different models and variables to enhance inflation forecasts such as [5–6]. They found that the models that incorporate more economic information including the univariate model, decomposition-based approach, Phillips curve motivated time-varying parameter model, VAR and Bayesian VAR models, and dynamic factors model could outperform the random-walk model, with an average of 30% better for the first two quarters in the future. Furthermore, some studies that have employed real-time inflation predictions, such as [5, 8] demonstrate that the predictive performance of this model outperforms forecasts based only on economic derivatives by utilizing a mixed-frequency model for the daily forecasting of euro area inflation in real-time.

A simulation of the biological human brain system is called an artificial neural network (ANN). In their capacity as pattern classifiers and non-linear adaptive filters, neural networks perform two crucial tasks. A non-linear system known as an ANN can interpret data to implement a function (an input/output map). The parameters of the system are altered while it is in operation, which is referred to as the "training phase," after which they are fixed and the system is configured to address the current problem (the testing phase). Because they communicate the crucial information needed to "find" the ideal operating point, the input/output training data are a crucial component of neural network technology. The neural network processing elements (PEs) have non-linear properties that support the system's flexibility in obtaining nearly any required input or output. The neural network is shown an input, and the target response is set at the output (when this is the case the training is known as supervised). The disparity between the acquired answer and the system output yields an error. This erroneous data is fed back into the system, which then adjusts the system parameters routinely (the learning rule). The process is repeated until the performance is satisfactory. The benefits of the neural network include the ability to accomplish tasks that a linear program cannot, as well as an uninterrupted process free of difficulties due to its parallel qualities as an item of the neural network declines. A neural network also determines and does not need to be reprogrammed. Regarding the drawbacks of neural networks, they require training to function, and because their structure differs from that of microprocessors, they take a long time to process data. It may claim that a certain model works well in one market but is inapplicable in another due to significant differences in institutional reality and national settings. In other words, the various criteria chosen would result in varying forecast performance. There is no standard for building the model and a dataset [8]. To address the issues, the study first offers a technique for forecasting inflation using the ANN model. As a result, this might give thorough proof of the efficacy of ANN models in inflation prediction.

For building up a model to predict inflation for the research mentioned above, there are two main challenges. First, it is challenging to identify models that beat simplistic inflation predictions [9]. Second, the models that perform well over extremely short time horizons sometimes struggle over longer time horizons. Similarly, the models that monitor changes in the inflation rate well over the medium-term frequently struggle to determine the appropriate beginning point which leads to significantly underestimating the amount of inflation according to [10]. To anticipate inflation in real time for Brazil, [11] suggests high-dimensional and machine learning models with the use of expert survey estimates as prospective candidate predictors, demonstrating that in data-rich situations, high-dimensional econometric models perform well in the real-time forecasting of inflation. In the field of inflation forecasting, there is a disagreement about the model producing the most accurate output, because a model may be successfully applied to a certain market but not in another due to the great differences in institutional reality and the domestic environment of an economy. In other words, the forecast performance would vary depending on the chosen parameters, therefore there is no standardized model construction and dataset pattern according to [8]. This study initially provides the method for employing the Artificial Neural Network (ANN) model to estimate inflation to alleviate these issues, offering thorough proof that ANN models are a useful tool for anticipating inflation.

Vietnam has been considered to be one of the fastest-growing developing economies in the world with an average growth of Gross Domestic Product (GDP) at about 6% annually. Resolution No. 01/NQ-CP formally announced in 2018 has set the goal of fostering the Vietnamese economy's sustainable growth, in which one of the main allusions is to proactive inflation management in reaction to changes in the local and foreign markets. Through the context of inflation targeting policy, the State Bank of Vietnam (SBV) being in charge of achieving and upholding domestic price stability has always attempted to anticipate the future direction of inflation by using a significant amount of expert judgmental information coming from a number of models such as classical time series models, dynamic stochastic general equilibrium models. However, there is still serious doubt about how accurate these methods employed by the SBV to predict inflation in Vietnam are. This paper uses the ANN model to predict inflation, and then compares the actual and forecast figures for the year 2022 to provide some evidence to support the reliability of the suggested model. The research result demonstrates the widespread applicability of a feed-forward Artificial Neural Network (ANN) model as a powerful measurement for inflation forecasting. Besides, it also highlights that the money supply can be seen as a primary element which significantly influences Vietnam's inflation. The SBV should therefore focus more on adjusting the money supply to a targeted inflation rate. The rest of this study is organized as follows: the ANN model methodology and construction with the description of a dataset are presented in Section 2, Section 3 summarizes the findings, and Section 4 provides the conclusion.

2 Methodology and Data

This section provides a theoretical framework of ANN model and a process of model construction for the research. There are three main reasons why the ANN model is chosen in this paper. First, the ANN approach is more accurate and efficient than other traditional approaches such as multivariate Vector Auto-Regression (VAR) and Aggregate Supply-Aggregate Demand (AS-AD) according to [13, 15]. Second, there are no constraints on input variables, in contrast to the Moving-Average model (MA) which just becomes effective if the data would be in a stationary pattern. Finally, the ANN model does not enforce any fixed relationships in the input variables because of having the ability of hidden association exploration in the data. Therefore, the ANN model is considered to be highly adaptable in applying to financial time series that have considerable volatility such as inflation rate, and stock prices [14].

2.1 Artificial neural network (ANN)

A non-linear relationship exploration and a learning process, that may assist encourage predictions for complex variables, are the primary causes for great growth in the popularity of ANN models. The most popular type of neural network which is employed in this study is the multilayer feed-forward neural network with backpropagation. The model has several neurons placed in layers in an orderly manner, with the input layer connects to the output layer by the hidden layers. For more details, the output (y_t) link to the inputs (y_{t-1}; y_{t-2}; ...; yt_{-p}) as follows:

$$y_t = \propto_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij}\, y_{t-1}\right) + \varepsilon_t \tag{1}$$

where α_j ($j = 0, 1, 2, \ldots, q$) and β_{ij} ($i = 0, 1, 2, \ldots, p$; $j = 1, 2, \ldots, q$) are the connection weights in which p is the number of input nodes and q is the number of hidden nodes. This one-output-node network can afford to estimate an arbitrary function with a condition that the number of hidden nodes q is set up to be sufficient.

The hidden layer is usually in the form of a logistic function as follows:

$$g(x) = \frac{1}{1 + \exp(-x)} \tag{2}$$

Basically, the ANN expresses a nonlinear function connecting the past observations (y_{t-1}, y_{t-2}, …, y_{t-p}) to the future value y_t as follows:

$$y_t = f\left(y_{t-1}, y_{t-2}, \Lambda, y_{t-p}, w\right) + \varepsilon_t \tag{3}$$

where w is a vector of whole parameters; f is a function formed by the network structure and connection weights, hence ANN can be seen as a nonlinear autoregressive model.

The ANN model is capable to send an input pattern to the output units when a backpropagation network cycles through the way of the intermediate input-to-hidden and hidden-to-output weights. For the training process, training samples are used as the input vector, the output's error is estimated, and then the network's weights are changed to minimize the error.

2.2 The introduction of backpropagation neural network techniques

The foundation of neural network training is backpropagation. It is a technique for adjusting a neural network's weights depending on the error rate recorded in the previous epoch (i.e., iteration). By properly tweaking the weights, you may lower error rates and improve the model's reliability by broadening its applicability. The term "backward propagation of errors" is shortened to "backpropagation" in neural networks. It is a common technique for developing artificial neural networks. Regarding each weight in the network, this technique aids in calculating the gradient of a loss function. The gradient of the loss function for a single weight is calculated by the neural network's backpropagation algorithm using the chain rule. In contrast to a native direct calculation, it efficiently computes one layer at a time. Although it computes the gradient, it does not specify how the gradient should be applied. It broadens the scope of the delta rule's computation. Backpropagation neural networks have the advantages of being quick, easy to program, and requies no tuning parameters other than the input data. It is a tried-and-true strategy that typically works well, and it is flexible because it doesn't call on prior network expertise. Furthermore, the characteristics of the function to be learned don't require any special mention. The flowchart of the backpropagation neural network model used in this research is shown in Figure 1.

3 Research model construction

The process of the ANN model construction includes two stages as follows:

Stage 1: Input variables

The chosen input variables used in this study are the past values of the inflation rate (INF), and the money supply growth rate (M2) (all variables are monthly series), according to [17, 18]. In general, the greater the money supply (M2) is, the higher the inflation would be [17]. The broad money M2 monthly rate and the inflation monthly rate are from the IMF database.

The dataset is divided into three parts as follows: (i) 65% of the sample size is for the training process; (ii) 20% of the sample size is for the validation process and the prevention of training before overfitting; (iii) 15% of the sample size is for the test process.

According to [18], the larger the size of the training set, the more accurate the forecast of ANN model, thus 65% of the sample size is selected in this study because it is the maximum percentage

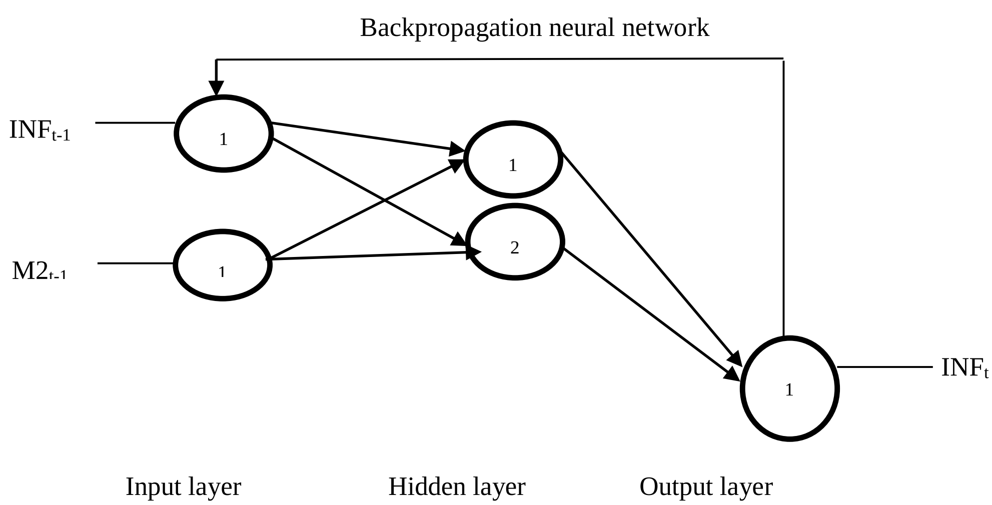

Figure 1. Backpropagation neural network structure used in this research

For the training process. Besides, [19] found that the minimum percentage for the validation process of any model applied to forecast non-linear pattern is 20%.

Stage 2: The number of lags and hidden layer

The previous research argues that the number of lags, which provides crucial information about the complicated autocorrelation structure in the data, is the most crucial problem for time series forecasting ANN models. The number of variables in the input vector used to anticipate future value correlates to the number of lags for each input variable, thus in order to investigate the underlying trend in a time series, lag observation is necessary. Besides, the present inflation rate is permitted to be somewhat influenced by the delayed inflation rates, thus the default number of lags (= 1) is applied.

The ANN model with only one hidden layer is considered to be sufficiently efficient to explore any complex non-linear pattern, according to [22, 16]. The neural network model used in this study has 2 nodes of the hidden layer because the neural network with the same number of hidden nodes as input nodes produce more accurate prediction, according to [21] and [22]. It means the number of hidden nodes is 1 × 2 = 2 nodes. The research model predicts the future value of the inflation growth rate (monthly) based on the previous values of the inflation rate and money supply growth rate (monthly). The form of the model is as follows:

$$y_t = f(y_{t-1}, \dots, y_{t-d}, x_{t-1}, \dots, x_{t-d})$$

where y = target time series of the inflation growth rate (INF); x = exogenous time series of the money supply growth rate (M2); d = the lag number of 1

The feed-forward network is created with 2 inputs and 1 hidden layer with two nodes, and 1 output.

4 Data description

This study uses the dataset of the monthly inflation rate and money supply of Vietnam from 2000 to 2021 as inputs for the training process including training, validation, and test stages to construct the neural network which then performs the forecast of the inflation rate of 2022. The graph below shows the input data of inflation rate and money supply for the period of 2000–2021. The dataset is split into three subsamples: (i) 65% of the dataset is for the training process; (ii) 20% of the dataset is for the validation process and the prevention of training before overfitting; (iii) 15% of the dataset is for the test process. The data used in this research is collected from the IMF database as shown in Figure 2.

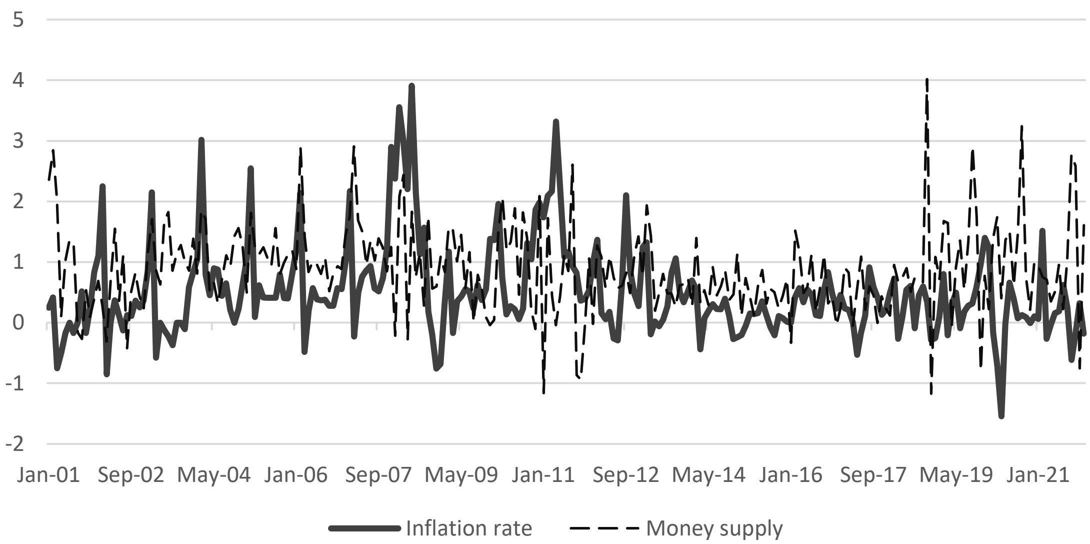

Figure 2. The timeline of a dataset from 2000 to 2021

5 Result and discussion

The validation performance of the training process by applying the Levenberg-Marquardt algorithm is shown in Figure 3. The train (blue line), validation (green line), and test (red line) movements are clearly on the same trend with small gaps. The mean squared error (MSE) of the best validation performance is 0.267 at epoch 2 before the stop of training at epoch 8 that means the training performance has no potential overfitting.

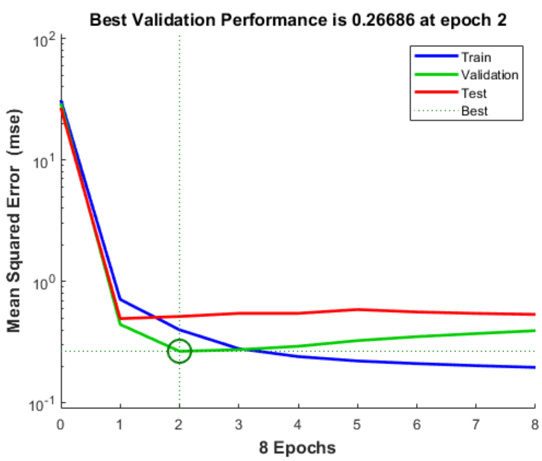

Figure 3. Network training performance

The regression plot reflects the interaction between the predicted values of the inflation rate (outputs) and the actual values (targets) for training, validation, testing, and total data. Theoretically, there should be considerable similarity between the outputs and the targets of a certain neural network as a result of the training perfection, but it hardly happens in practice. Figure 4 presents four plots of the training, validation, and testing samples and all data, respectively. In which, the dashed lines crossing from the left bottom corner to the right top corner are the optimum points where the outputs merge the targets, and the coloured lines are the best fit linear regression points of outputs and targets for a certain neural network. Besides, R-value implies how the outputs connect to the targets, with R = 1 meaning a definite linear connection and 1 > R > 0 meaning no linear connection, according to [23]. The R-value of the training sample is close to 1, implying that the proposed neural network model would be reliable and efficient.

In addition, Figure 5 shows the error-autocorrelation of the neural network, including a cross-check of the network performance. The graph points out that most correlation bars stay approximately within the 95% confidence area with the up-line at 0.05 and the down-line at (-0.05) and zero line in the middle, except for the bars at lags of 0; 1; 4; 5 and 12.

Figure 6 shows the response of the output in a comparison with the target, and the errors during the timeline. In which, the gaps between the outputs and the targets of training, test and validation stages are depicted for each point of time. Moreover, the plot on the bottom is the error of the model illustrating the difference between the output and the target with some points being

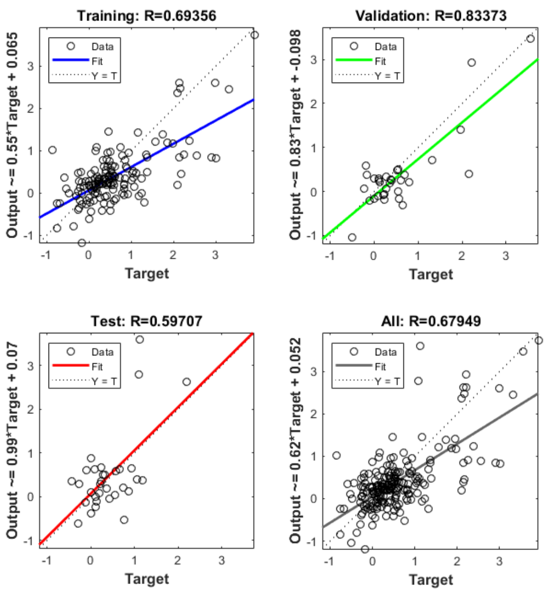

Figure 4. Training regression of our ANN model

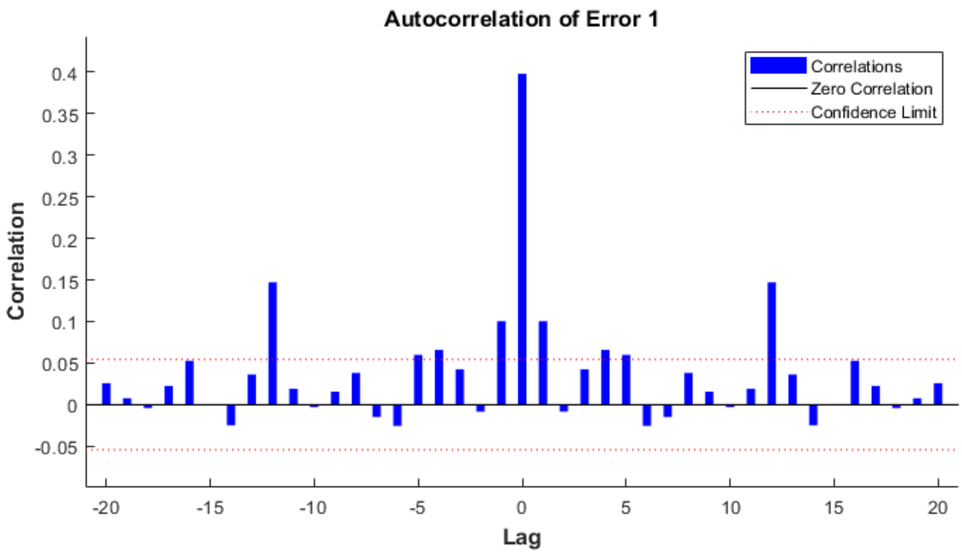

Figure 5. Error autocorrelation of the proposed model

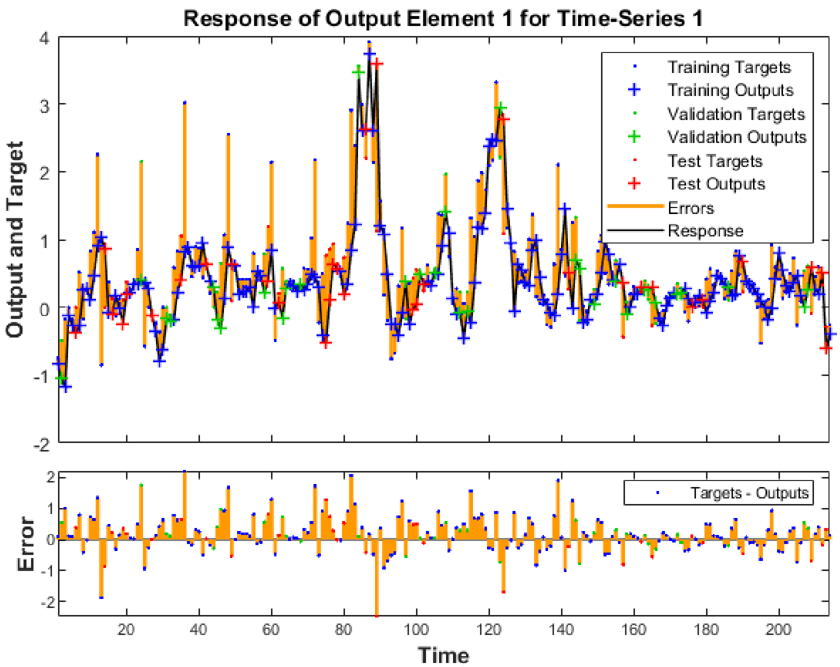

Figure 6. The response of output for time series

bias at 90 and 125 that probably reflect the influences of the global financial crisis of 2008–2009 and the European debt crisisof 2011–2014 on the inflation rate of Vietnam.

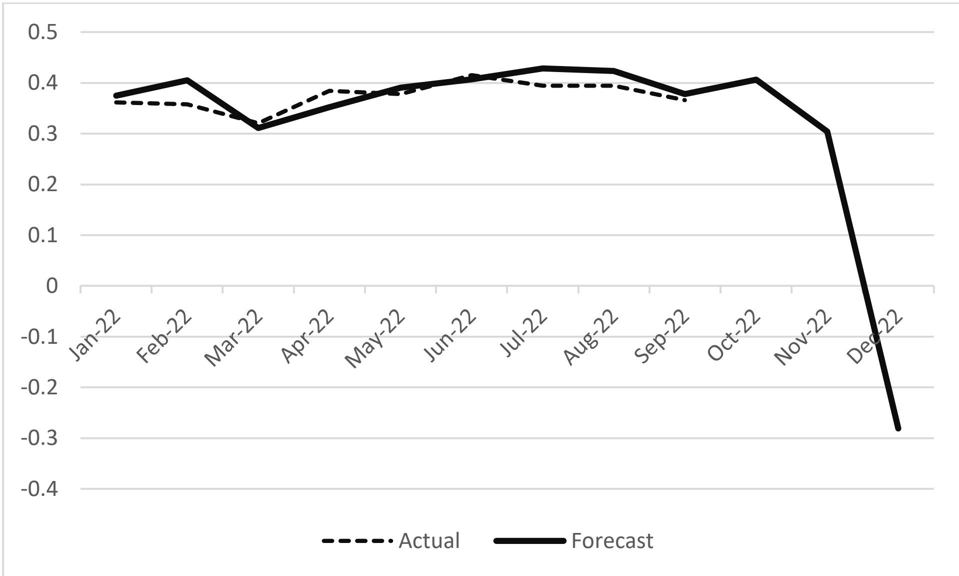

Figure 7. Actual and forecast of Vietnam's inflation rate

Figure 7 depicts the forecast of Vietnam's inflation rate for the year 2022. For more details, the actual inflation rate (the dashed line) and the forecast series (solid line) are tightly close to each other, implying that the build-up neural network model of this research is accurate and efficient in forecasting the inflation rate of Vietnam. Furthermore, the study also provides the forecast of the inflation rate for the rest of 2022 as showing a sharp downward trend of rate from October 2022 to the end of the year.

6 Conclusion

The research applied the feed-forward Artificial Neural Network (ANN) model to predict the inflation rate of Vietnam for the year 2022 based on monthly data from 2001 to 2020. The result demonstrates that the proposed ANN model of this study is likely to be efficient and applicable to perform the prediction of inflation rate. Furthermore, the research finds that the money supply plays a vital role in an empirical model to predict inflation of Vietnam, so the State Bank of Vietnam probably pay more attention to this factor.

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