Engineering Journal issn: 0125-8281

Article

Leveraging Partner Country Factors in Deep Learning for Thailand's Forecasted Inflation Accuracy Enhancement

Techin Arnonwattana[1,a] **and Parames Chutima**[1,2,3,b,*]

1 Regional Centre for Manufacturing Systems Engineering, Chulalongkorn University, Thailand
2 Department of Industrial Engineering, Faculty of Engineering, Chulalongkorn University, Thailand
3 The Academy of Science, The Royal Society of Thailand, Thailand
E-mail: [a]nine.nninee@gmail.com, [b,*]parames.c@chula.ac.th (Corresponding Author)

Abstract. This paper focuses on improving the accuracy of headline inflation forecasts in Thailand. By evaluating the performance of deep learning models, time series forecasting models, and hybrid models in 1-, 3-, 6-, and 12-month advance forecast periods are investigated. In addition, the efficacy of including partner countries' inflation variables in the model is evaluated. There is a comparative analysis of various models, including ANN, RNN, LSTM, VAR, the hybrid model (VAR-ANN), and the BOTMM benchmark model of the Bank of Thailand. This study aimed to identify the most efficient model and demonstrate the impact of including partner countries' inflation on forecast accuracy. The results reveal that the hybrid model (VAR-ANN) consistently outperforms other models over several forecast periods, showing its superiority in capturing inflation trends. Specifically, the hybrid model (VAR-ANN) shows an average RMSE improvement of 50.36% over the BOTMM benchmark model from 2020 to 2022, with performance improvements of 52.94% in 2020, 56.56% in 2021, and 47.25% in 2022. In addition, the inclusion of partner countries' inflation significantly increases the accuracy of the predictions. These results are helpful for policymakers and practitioners working on inflation forecasts and emphasize the practical advantages of the hybrid model for enhancing prediction accuracy for Thailand's economic indicators.

Keywords: Inflation forecasting, neural networks, time series models, hybrid models, partner countries' inflation, forecast accuracy, deep learning, Bank of Thailand, economic indicators.

ENGINEERING JOURNAL Volume 28 Issue 6
Received 31 January 2024
Accepted 31 May 2024
Published 30 June 2024
Online at https://engj.org/
DOI:10.4186/ej.2024.28.6.37

DOI:10.4186/ej.2024.28.6.37

1. Introduction

Forecasting inflation is a crucial component of economic policy. The central bank, the authority on policy, needs to make predictions to make decisions [1]. The successful implementation of policy under the inflation target framework depends on the effectiveness of monetary policy, whether it is an interest rate adjustment or purchasing bonds from the private sector or government. Furthermore, the effects of implementing monetary policy on the economic system are subject to delay. As a result, central banks must be aware of the impending trends in economic variables, and accurate forecasting models are indispensable for monetary policy implementation [2]. In addition to the government sector, bond market investors in the private sector need future inflation predictions to determine the trend of actual returns. Some private enterprises must estimate certain inflation components to predict price changes and avoid risks. Finally, predicted inflation trends have a significant impact on both public and private debt levels as well as interest payments. These are just a few instances of the importance of inflation forecasting [3].

The Bank of Thailand (BOT) has implemented a monetary policy under a flexible inflation-targeting framework since May 2000, emphasizing the importance of maintaining price stability through inflation targeting. This policy is highly connected to managing economic expansion and ensuring the financial system's stability. In 2022, the inflation target range was 1-3 percent for medium-term price stability. Monetary policy under the inflation targeting framework operates by transmitting nominal interest rates to real interest rates, where the real interest rate influences economic activities to recover or slow down. Inflation poses an economic challenge in each country, significantly affecting economic stability. In addition, inflation affects the economic system at both the micro and macro levels. This influence is observed in households, affecting the cost of living while income remains relatively stagnant, as well as in industries facing long-term financial adjustments due to increased production costs, labor wages, and raw material expenses. As a result, this situation leads to a reduction in exports and acts as an impediment to long-term economic expansion. The rise in inflation rates directly affects the pricing of goods. Central banks must align their monetary policies with changing inflation rates, ensuring that inflation remains appropriate for effective monetary policy implementation [4].

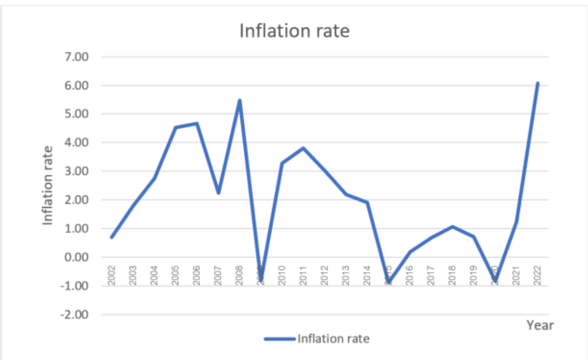

Fig. 1. Inflation rate of Thailand.

Following the recent economic consequences of the COVID-19 pandemic, central banks have been confronted with unprecedented measures in monetary policy. This issue causes Thailand's inflation rate to be highly volatile. In 2022, demand has increased in line with the global economic recovery after many countries prioritized vaccine distribution instead of strict measures to control the outbreak to deal with COVID-19, including government compensation for households. These factors enhance the purchasing ability of the populace. The demand subsequently rebounded rapidly. At the same time, although the manufacturing sector suspended during the first period of the pandemic has gradually returned, it remains inadequate to meet the demand. As a result, the overall product price has increased. Fig. 1 shows that headline inflation has grown considerably outside the target range. Table 1, when collecting and analyzing data on the BOT's quarterly inflation forecast from the Monetary Policy Report, uses the Bank of Thailand's Macroeconomic Model (BOTMM) for forecasting. BOTMM is an econometric model that illustrate the relationships and impacts of various economic variables. It was discovered that the forecast for 2022 had a higher error value than prior years. When the root mean square error (RMSE) is used in the evaluation, the RMSE value is 1.82, while the RMSE values in 2020 and 2021 were 1.02 and 1.22, respectively. In addition, when accounting for the error value from 2020 to 2022, the RMSE value is 1.39, which is considered relatively high compared to the actual value. This is primarily due to the significant inaccuracies in the forecasts, leading to delays in implementing BOT policies. The decision to raise the policy interest rate to address inflation comes with considerable delay. Figure 2

Table 1. Inflation forecast of BOT.

Year	Quater	BOT prediction	Actual Quarter prediction	RMSE
2020	1	0.8	0.42	1.02
	2	-1	-2.67	
	3	-1.7	-0.73	
	4	-0.9	-0.39	
2021	1	1	-0.53	1.22
	2	1.2	2.37	
	3	1.2	0.70	
	4	1	2.42	
2022	1	1.7	4.75	1.82
	2	4.9	6.47	
	3	6.2	7.29	
	4	6.3	5.81	
2020-2022	-	-	-	1.39

Note: BOT prediction from Monetary Policy Report, web address is https://www.bot.or.th/th/our-roles/monetary-policy/mpc-publication/Monetary-Policy-Report/mpr-previous-reports.html.

shows the first interest rate increase in the third quarter. Moreover, just quarterly inflation forecasts may not be enough to predict the trend. Aras [5] has created forecast models 1-, 3-, 6-, and 12 months in advance for an advantage in interpreting and explaining forecast values.

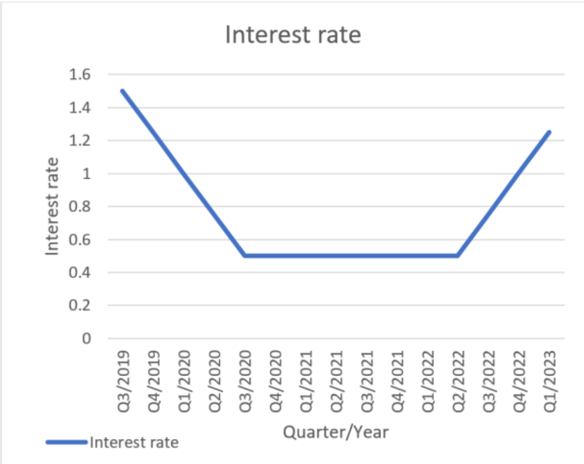

Fig. 2. Interest rate.

Further research has shown that, in addition to the issue of imbalanced demand and domestic supply, which causes Thailand's inflation rate to be highly volatile, rising global inflation as a consequence of the economic impact of the COVID-19 pandemic is also one of the reasons. This dynamic occurs because Thai and global inflation move together due to common shocks. Sitthichaiviset et al. [6] explain that when considering the overall movement of Thailand's inflation rate compared to inflation rates abroad, Fig. 3 shows that global inflation tends to move in the same direction. This phenomenon can be explained for two main reasons. First, countries, whether closed or open economies, share necessary production resources such as oil, agricultural products, and minerals. Therefore, when a shock occurs in the prices of these commodities, it will simultaneously affect the inflation of many countries. However, the size of the impact in each country is different. It depends on the importance of the commodity in the production process, the role of the exchange rate, price control measures by the authorities, and others. Second, trade liberalization has led to increased trading and substitution of goods between each other. It indicates that production in open economies, such as Thailand, is not just for domestic consumption but also for overseas markets. Therefore, Thai and foreign inflation movements often go in the same direction because Thai inflation is influenced by foreign consumption or world demand and numerous demand shocks in other countries. Which from this transmission of global inflation. Researchers are interested in utilizing foreign inflation rates related to Thailand in terms of trade to enhance forecast performance and models that can handle domestic and international shocks. Consequently, the researcher searched for data about Thailand's important trading partners. Table 2 shows that Thailand's important trading partners with the highest trade, export, and import values are 13 countries, including China, the United States, Japan, Malaysia, Vietnam, the United Arab Emirates, Indonesia, Singapore, Australia, India, South Korea, the Philippines, and Germany, including the two republics of Taiwan and Hong Kong. The researcher found historical inflation data for all 11 countries and one republic, except Australia, the United Arab Emirates, and Hong Kong.

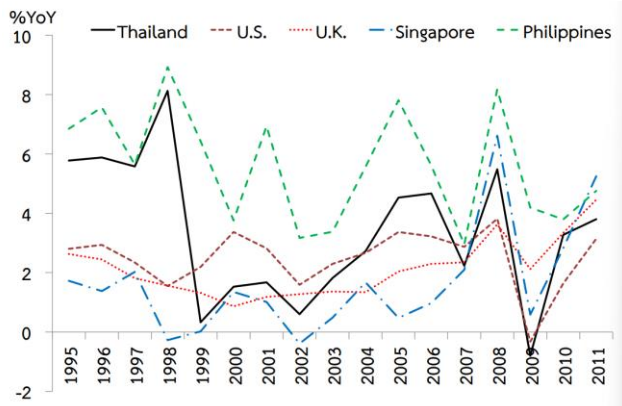

Fig. 3. Thai inflation rate and foreign inflation rate. (Source: Ministry of Commerce and Bloomberg) [6].

Table 2. Thailand's trading partners in 2022.

No.	Country/Republic	Trade value (Million baht)
1	China	3,686,110
2	The United States	2,282,625
3	Japan	2,069,032
4	Malaysia	949,306
5	Vietnam	738,965
6	The United Arab Emirates	731,007
7	Indonesia	698,300
8	Singapore	644,383
9	Australia	641,206
10	India	615,637
11	Taiwan	579,191
12	South Korea	576,622
13	Hong Kong	444,464
14	The Philippines	390,616
15	Germany	378,769
	Total	15,426,232

Note: Data from Ministry of Commerce, web address is https://tradereport.moc.go.th/TradeThai.aspx.

In the past, inflation forecasts employed time series models such as vector autoregressive (VAR), autoregressive integrated moving average (ARIMA), and error correction models (ECM) [1]. They are a model capable of capturing patterns and trends in historical inflation data. However, there are some drawbacks. It cannot capture the complicated non-linear correlations between inflation data and other economic variables. Currently, deep learning models are being actively developed for a wide range of applications, including forecasting. These models, such as neural networks, are characterized by their complex hierarchical structure comprising multiple hidden layers to be precise. This arrangement enables the neural network to acquire knowledge and make informed choices. The main benefit of this approach is its ability to capture intricate non-linear correlations between variables [7]. For example, Long Short-Term Memory (LSTM) is one type of modern Recurrent Neural Network (RNN) that recognizes patterns over time; other architectures, such as Gated Recurrent Unit (GRU), offer similar capabilities with a simpler structure. This feature makes it excellent for applications such as language processing, speech recognition, and prediction that need models to learn from and make decisions based on sequential or time-series data. In principle, it is suitable for forecasting headline inflation [8].

Based on the above, the researcher intends to build a headline inflation forecasting model using various types of neural network models, including artificial neural networks (ANN) and recurrent neural networks (RNN). RNNs are divided into traditional recurrent neural networks (RNN) and long short-term memory (LSTM) networks. Additionally, a hybrid model combines a time series model, which is a VAR model that can capture linear relationship data patterns, with a neural network model that can capture complex nonlinear relationship data patterns [9]. To optimize the model, the researchers included partner countries' inflation as an independent variable along with other macroeconomic factors. This approach assessed whether incorporating partner countries' inflation improved the model's accuracy compared to a version without this additional variable. Inflation forecasts are also challenging to model since they strongly correlate with other macroeconomic variables. Factor analysis is a well-acknowledged problem-solving method [5]. In terms of prediction horizon, each model forecasts inflation 1-, 3-, 6-, and 12 months in advance to provide a short-term and long-term overview. The performance of each method is evaluated using the Mean Squared Error (MSE) metric. The best method's findings will then be compared to the forecast values from the macroeconomic model of the Bank of Thailand (BOTMM), which serves as a benchmark. This research aims to be helpful to those involved in inflation forecasting and those interested in neural network forecasting models.

The other sections of this study are organized as follows: Section 2 reviews the findings from the literature. Section 3 discusses the methodologies; meanwhile, Section 4 compares the results of the models' forecasting abilities. Section 5 deals with the summary and concluding remarks.

2. Literature Review

Forecasting inflation is crucial for economic policymakers, and recent advancements in deep learning algorithms have opened new avenues for improving the accuracy of inflation predictions. This literature review explores existing research on forecasting Thailand's headline inflation, explicitly focusing on the combination of partner countries' inflation factors using deep learning algorithms.

2.1. Historical Approaches to Inflation Forecasting

Although historical inflation forecasting approaches relied on traditional time series models such as Vector Autoregressive (VAR) and Autoregressive Integrated Moving Average (ARIMA), which are effective to some extent, these models struggled to capture the nonlinear and complicated correlations apparent in inflation data, limiting their ability to provide accurate predictions in the face of complex economic relationships and changing macroeconomic factors.

DINH [10] applied Vector Autoregressive (VAR) to study the impact of inflation on economic growth in both the short and long run. The results from the first VAR model (VAR 1) showed that the GDP and inflation variables have a negative relationship. High inflation due to continued growth in the money supply causes GDP to fall in the long run. These results are consistent with Keynesian economic theory, which suggests a non-linear correlation between inflation and economic growth. On the other hand, the second VAR model (VAR 2) showed that moderate inflation is positively related to economic growth, particularly stable in the medium term, indicating that a relevantly moderate inflation rate, coupled with growth in the money supply, fosters GDP growth. The combination of these two models yields a linear curve representing the relationship between these variables.

Uko [1] assessed the comparative forecasting efficacy of ARIMA (despite being a univariate model), VAR, and ECM models in predicting inflation. In the study conducted by Uko [1], a substantial correlation was observed between the Domestic Consumer Price Index, the US dollar exchange rate, and government expenditures. The findings indicate that ARIMA, while also appropriate for short-term forecasting, serves as a reliable benchmark model, VAR is effective for short-term forecasting, and ECM is appropriate for long-term forecasting.

Buddhari and Chensavasdijai [4] discussed inflation dynamics and its implications for monetary policy. The research elucidated the transmission mechanism of inflation using the BOTMM model. Overall, domestic inflation is impacted by global commodity prices, the exchange rate, wages, the difference between actual and potential production, and the inflation expectations of the private sector. Factors are categorized into short-term and long-term relationships.

Pongsaparn [11] proposed constructing a small semi-structural model at the Bank of Thailand (BOT) and its practical applications. The Bank of Thailand's inflation forecasting employs the BOTMM model, a customized economic model utilizing the econometric approach, specifically the error correction mechanism (ECM), to estimate economic trends between the variables. This model incorporates 25 behavioral equations and 44 identity equations. This study further demonstrates that the model has sufficient comprehensiveness to depict the interconnections and fluctuations among significant macroeconomic variables accurately.

This research will use the BOTMM model as a benchmark model, which will use the prediction results of the BOTMM model from Table 1 to compare its performance with other models.

2.2. Incorporating Partner Countries' Inflation Factors

The interconnectedness of economies suggests that the inflation rates of partner countries may impact Thailand's inflation. Research by Sitthichaiviset et al. [6] presented a report on monetary policy and inflation management. By researching Thailand's qualitative and quantitative inflation dynamics, it was stated that Thai inflation and global inflation move together from common shocks due to the sharing of resources around the world and international trade. According to the research, factors that predict inflation and domestic demand play a significant role in determining the dynamics of Thai inflation.

Ranchhod [12] examined inflation trends in New Zealand's trading partner economies over the past decade. This study found that the increase in inflation in the countries of New Zealand's trade partners is linked to the robust expansion of the global economy and the growing integration of Asia and developing markets into the global economic system. These advancements have led to a higher need for productive resources and a substantial rise in commodity prices. These rises have been seen in elevated consumer prices and export prices in the economies of New Zealand's trade partners.

Yang et al. [13] used vector autoregression analysis to investigate the international transmission of inflation among the G-7 countries. This research discovered that fluctuations in U.S. inflation had an unexpectedly significant impact on inflation in other countries. Likewise, shocks in certain countries statistically and economically substantially impact U.S. inflation.

Kandil and Morsy [14] examined the variables influencing inflation in the oil-rich Gulf Cooperation Council (GCC) using an empirical model that considers domestic and external influences. The findings indicated that inflation in crucial trading partners significantly impacts domestic inflation from foreign sources. Over time, increased inflation among trading partners has caused domestic prices to rise.

Arango-Castillo et al. [15] investigated whether incorporating global inflation into forecasting models may improve the prediction of headline inflation in emerging market economies by using multiplicative seasonal autoregressive integrated moving average models (SARIMA). The results confirm that including global inflation rates in models can improve forecasting accuracy.

Based on the evidence from the literature review, the researcher decided to include the trading partner country's inflation rate as an independent variable in the inflation forecast.

2.3. Deep Learning in Inflation Forecasting

Deep learning models can capture non-linear patterns. This capability differentiates these models from traditional models such as VAR and ARIMA. This efficiency is achieved through a complex and hierarchical architecture. This architecture enables the models to analyze complex relationships within the data. This section explores how deep learning has been used to increase the accuracy of inflation predictions.

Recent studies, such as the work by Szafranek [16], employed a robust modeling technique to examine the accuracy of short-term headline inflation forecasts generated by a combination of bagged single hidden-layer feed-forward artificial neural networks. The research demonstrated that there were further improvements in predicted accuracy when combining linear and non-linear approaches with various underlying model assumptions. The findings indicated that the model's accuracy improves during constantly declining inflation. Furthermore, the model demonstrates superior statistical performance compared to some widely used benchmarks, particularly over longer horizons.

Paranhos [8] used neural network models, namely the long-short-term memory model (LSTM) with grid search hyper-parameter tuning, to predict inflation. This study showed that LSTM is more effective than the standard feed-forward network for predicting inflation. This ability indicates that the recurrent model has an advantage in accurately capturing the long-term pattern of inflation. The US data analysis reveals that the neural network consistently performs better prediction than standard benchmarks, particularly over longer horizons. Moreover, neural networks with macroeconomic data capture the nature of inflation during and after the Great Recession, which may indicate the role of nonlinearities and macroeconomic data.

Barkan et al. [3] introduced the innovative Hierarchical Recurrent Neural Network (HRNN) model, which incorporates data from the Consumer Price Index (CPI) to forecast specific inflation components. The findings of this study assist policymakers and market administrators in creating consistent forecasts and evaluations of feasibility for various sub-components.

Aras [5] demonstrated using several machine learning algorithms to forecast inflation. The emphasis is on providing forecasts that can be easily understood and explained. Machine learning algorithms, which are the foundation of deep learning, provide a variety of methods for analyzing complicated economic data. It contains various forecasting periods to provide a comprehensive view of inflation patterns. The findings of this study suggest that tree-based ensemble models can achieve a competitive edge by providing better accuracy and explainable predictions.

Furthermore, there is research that compares Artificial Neural Networks (ANN) to the Bank of Thailand's regression model. Rurkhamet et al. [17] developed a forecasting model for the value of newly

DOI:10.4186/ej.2024.28.6.37

issued banknotes by constructing an Artificial Neural Network (ANN) model utilizing various input data. The study revealed that models with different input data, although related variables have different forecasting performances.

2.4. Application of Hybrid Models Algorithms

Recent years have witnessed a shift toward leveraging hybrid model algorithms for various forecasts, including economics, before entering the content of the application of the hybrid model. It is critical to understand what a hybrid model means. Hybrid models integrate the strengths of various modeling approaches to increase overall prediction accuracy in forecasting. These models often combine elements from both traditional time series models and advanced machine learning techniques. This integration allows a broader range of patterns and relationships within the data to be captured. The model's performance is enhanced by combining a neural network model, which is excellent in handling non-linear interactions, with a time series model that is efficient in linear relationships. Some research examples apply the use of hybrid models as follows.

Dave et al. [18] employed the hybrid (LSTM-ARIMA) model to forecast Indonesia's future exports. The hybrid model combines the ARIMA and LSTM models, using their respective strengths. LSTM is used to handle the non-linear component of the data, while ARIMA is used for the linear component. The hybrid learning model is compared to individual learning models to determine the most accurate model. The findings demonstrated that the hybrid model provided improved outcomes compared to the individual learning models.

Wen et al. [19] implemented a hybrid model (ARIMA-LSTM) based on the inverse error combination approach to forecast carbon emissions in each region of China, addressing both linear and nonlinear correlations of carbon emission data. This methodology employs the random forest feature ranking algorithm to determine the significance of 14 carbon emission factors in each region. The results indicate that the ARIMA-LSTM model is more accurate than a single model in forecasting China's future trend of CO2 emissions.

Cheevachaipimol et al. [20] investigated the prediction of airport departure delays in the United States using a hybrid model. It combines a feed-forward artificial neural network model with a standard gradient-boosted tree model (XGBoost). The results showed that the hybrid model provided significantly improved prediction accuracy compared to the pure neural network model.

Saravanan and Kumar [9] explored air quality index prediction using a hybrid FA-ANN-ARMA model using factor extraction and regression methodologies. This research provides a hybrid model based on the Internet of Things (IoT) that employs Factor Analysis (FA), Artificial Neural Networks (ANN), and Auto-Regressive Moving Average (ARMA) approaches to handle the issue. The Factor Analysis (FA) model is used to isolate contaminating components. The quantitative analysis of the suggested hybrid model demonstrates an increase in accuracy.

Senneset [21] employed a hybrid model to forecast the correlation value of stock pairings, with an ARIMA component describing the linear trend and an LSTM component accounting for the non-linear trend. It incorporates data from the Oslo Stock Exchange's components into the model. The study's findings showed that the hybrid model outperforms traditional techniques in terms of prediction accuracy. However, the consequences of these results are equivocal since the improvement in predictive accuracy cannot be stated to balance the rise in implementation costs.

Deng et al. [22] applied a hybrid approach to estimate the number of out-of-hospital patients. Outpatient visits are susceptible to complicated and unpredictable variations. The ARIMA and LSTM models were used to determine the linear and nonlinear trends, respectively. The results of the hybrid model outperformed the single model in terms of forecast accuracy and efficiency.

Hajirahimi and Khashei [23] analyzed hybrid models from 150 research and classified them as parallel, series, and parallel-series. The hybrid model study findings showed that the model combination may be employed in various ways and that the hybrid model is highly accurate in time series forecasting.

A review of the literature on hybrid models revealed that most research employs LSTM models to handle nonlinear trends in forecasting time series data due to their high complexity. Without wondering, highly complex models may not always provide accurate predictions. As a result, the researcher plans to evaluate neural network models ranging from basic to complex (ANN, RNN, and LSTM) before selecting a model to include in the hybrid model.

2.5. Gaps in the Current Literature

Although considerable progress has been achieved in forecasting inflation using deep learning algorithms, it has yet to be revealed from the Bank of Thailand that it employs deep learning models to forecast inflation. There is still a significant gap in research that focuses on forecasting Thailand's headline inflation rate by incorporating partner countries' inflation factors. This review attempts to fill these gaps by presenting guidelines for applying deep learning models combined with partner countries' inflation factors to improve headline inflation forecasts in Thailand.

This literature review focuses on the development of inflation forecasting methods. It demonstrates the potential of deep learning algorithms to capture the complexities of economic data. The next section of this research will provide a methodological and customized approach to Thailand's headline inflation forecast. It combines partner countries' inflation factors using deep learning algorithms.

Table 3. Summary of the literature review.

Author(s)	Model Used	Data Used	Relevance to Current Study
DINH [10] (2020)	VAR	GDP, Inflation	The non-linear relationship between inflation and economic growth.
Uko [1] (2012)	ARIMA, VAR, ECM	Domestic Consumer Price Index, USD exchange rate, government expenditures	The forecasting efficacy of different models for various time horizons.
Buddhari and Chensavasdijai [4] (2003)	BOTMM	Global commodity prices, exchange rates, wages, production differentials, private sector inflation expectations	Illuminates the factors influencing inflation of Thailand and their short-term and long-term relationships.
Pongsaparn [11] (2008)	BOTMM	Not specified	Highlights the BOTMM model's comprehensiveness in depicting macroeconomic variable interconnections.
Sitthichaiviset et al. [6] (2012)	Not specified	Thailand's inflation, Global inflation	The interconnectedness of global economies and the impact of global inflation on Thailand's inflation dynamics.
Ranchhod [12] (2008)	Not specified	Inflation in New Zealand's trading partner economies	Emphasizes the impact of inflation in trading partner economies on New Zealand and, by extension, global inflation trends.
Yang et al. [13] (2005)	VAR	Inflation among the G-7 countries.	Reveals U.S. inflation's unexpected and substantial impact on other countries, suggesting a potential influence on Thailand.
Kandil and Morsy [14] (2011)	Empirical Model	Inflation of group of oil countries (GCC)	Emphasizes the impact of inflation in trading partners on domestic inflation.
Arango-Castillo et al. [15] (2023)	SARIMA	Global inflation rates	Provides evidence that incorporating global inflation rates into models can enhance forecasting accuracy, supporting the researcher's decision to include partner countries' inflation.
Szafranek [16] (2019)	ANN	The economic indicators	Improvement in accuracy through combining linear and non-linear approaches in inflation forecasting.
Paranhos [8] (2021)	LSTM	The FRED-MD data base, a compilation of monthly US data, i.e. the CPI and its components	LSTM's effectiveness in predicting inflation patterns, especially over longer horizons, and the advantage of using macroeconomic data.
Barkan et al. [4] (2023)	HRNN	The US CPI-U index	Application of Recurrent Neural Network model.
Aras [5] (2022)	SVM, MLP, RF, GBDT, XGBoost	Economic indicators	Forecasts are available for a variety of time periods to provide an overview and simplicity of interpretation.
Rurkhamet et al. [17] (1998)	ANN	GDP, deposit rates, values of admitted banknotes	Although related variables, the models with different input data have different forecasting performances.

Table 3. Summary of the literature review. (cont.)

Author(s)	Model Used	Data Used	Relevance to Current Study
Dave et al. [18] (2021)	ARIMA-LSTM	Monthly Indonesian exports data	Demonstrates improved forecasting accuracy by combining the strengths of LSTM and ARIMA.
Wen et al. [19] (2023)	ARIMA-LSTM	Carbon emission data	Addresses linear and nonlinear correlations in carbon emission data, offering accuracy.
Cheevachaipimol et al. [20] (2021)	ANN-XGBoost	Flight data	It significantly improved the prediction accuracy of hybrid models compared to pure neural network models.
Saravanan and Kumar [9] (2022)	FA-ANN-ARMA	The particulate data of pollutants	Utilizes FA-ANN-ARMA approaches for improved accuracy.
Senneset [21] (2020)	ARIMA-LSTM	Stock prices	The hybrid model outperforms traditional techniques in predictive accuracy, considering linear and nonlinear trends.
Deng et al. [22] (2020)	ARIMA-LSTM	The outpatient visits to the digestive department and cardiology department	The hybrid model outperforms single models in forecast accuracy and efficiency using ARIMA and LSTM.
Hajirahimi and Khashei [23] (2019)	Various Hybrid Structures	Hybrid models from 150 research	Classifies hybrid model structures.
This study	VAR-ANN	Macroeconomics and Partner Countries' inflation	Leveraging Partner Country Factors in Deep Learning for Thailand's Forecasted Inflation Accuracy Enhancement

3. Research Methodology

The methodology for research will be presented, beginning with data collection until model evaluation. Figure 4 shows the sequence of various steps in performing research. Begin with data collection, data cleaning, and factor analysis. After performing factor analysis, the data will be separated into two formats for use in the model. The first format contains only macroeconomic data (MCE), while the second format includes macroeconomic data and partner countries' inflation (PCI) to show that models that include partner countries' inflation perform better. The models employ each format of data to forecast inflation. In deep learning models, the model with the best results is selected and utilized to build a hybrid model combined with the VAR model. The accuracy of all models (ANN, RNN, LSTM, VAR, and hybrid) in each data format was then compared to determine the best model. The best model is compared to BOTMM to show the improvement in forecasting performance.

3.1. Preprocessing

Data preprocessing refers to steps and techniques applied to raw data before it is used in analysis or modeling. Data preprocessing ensures the data is appropriate, accurate, and ready for analysis. This process is a critical step in data analysis since the input data quality significantly impacts the analysis or modeling outcome. The method is divided into two parts: data collection and data cleansing.

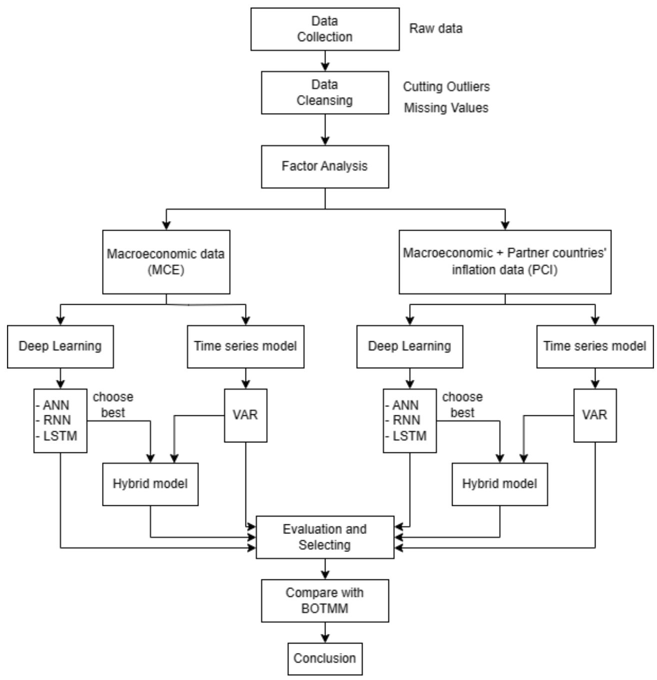

Fig. 4. Methodological diagram.

Table 4. Variables used in the analysis.

Variables	Source
Macroeconomics	
- Inflation rate of Thailand (THA)	TH Investing
- Exchange rate (USD)	BOT
- Reference price of North American crude oil (WIT)	TH Investing
- Reference price of European and Russian crude oil (BRENT)	TH Investing
- Reference price of Middle Eastern crude oil (DUBAI)	TH Investing
- Real Baht Value Index (REER)	BOT
- Baht currency index (NEER)	BOT
- Policy interest rate (IR)	BOT
- Government bond yield (GBV)	BOT
- Unemployment rate (UR)	BOT
- Average Monthly Minimum Wage (RMW)	BOT
- Consumer Confidence Index (CCI)	BOT
- Producer Price Index (PPI)	ETID
- Money supply in the narrow and broad sense (M1M2)	BOT
- Gross Domestic Product (GDP)	NESDC
- Value and quantity of total agricultural exports (AP_EXPORT)	BOT
- Total value of imported goods classified by product group (IMPORT)	BOT
- Total value of export products classified by product group (EXPORT)	BOT
- Total Consumer Price Index (CPI_ALL)	ETID
- Consumer Price Index excluding fresh food and energy (CPI_xE_xFE)	ETID
Partner Countries' inflation	
- South Korea (KOR)	TH Investing
- Taiwan (TWN)	TH Investing
- Singapore (SGP)	TH Investing
- Vietnam (VNM)	TH Investing
- Malaysia (MYS)	TH Investing
- Indonesia (IDN)	TH Investing
- Philippine (PHL)	TH Investing
- China (CHN)	TH Investing
- United States (USA)	TH Investing
- Japan (JPN)	TH Investing
- Germany (DEU)	TH Investing
- India (IND)	TH Investing

Note: BANK OF THAILAND (BOT) web address is https://www.bot.or.th/. Economic and Trade Indices Database (ETID) web address is https://price.moc.go.th/. Office of the National Economic and Social Development Council (NESDC) web address is: https://www.nesdc.go.th/main.php?filename=qgdp_page. TH Investing is https://th.investing.com/equities/thailand.

3.1.1. Data collection

The data for the research on inflation forecast modeling were drawn from a study of numerous components and their relationships with theoretical inflation rates. Including numerous aspects from relevant studies and partner countries' inflation, the researchers are interested in combining the various models. As seen in Table 4, the researcher separated the data into two sets: macroeconomic data and partner countries' inflation.

Information collected from the Bank of Thailand's website, the Trade Economic Index Database, the Office of the National Economic and Social Development Council (NESDC), and th.investing.com are websites that provide information about various economic variables. All data has been collected monthly for the past 21 years, from January 2002 to December 2022, and divided into the training dataset from January 2002 to September 2018. There are 201 data points, accounting for 80%, and the testing dataset from October 2018 until December 2022 has 51 data points, accounting for 20%.

In addition, quarterly inflation estimates from the Bank of Thailand using the BOTMM model are collected from the Inflation Forecast Trend Report and used as a benchmark model to evaluate performance with the model employed in this study.

3.1.2. Data cleansing

The process of finding and resolving faulty, incorrect, or irrelevant data is known as data cleaning. This critical stage of data processing, also known as data scrubbing or cleansing, is essential for improving data consistency and dependability. This process involves entering or editing specific values or, in some cases, deleting them.

3.1.2.1. Cutting outliers

A Boxplot analysis of all the data revealed outliers in 19 of 32 variables, including THA, DUBAI, USD, REER, UR, CCI, PPI, GDP, AP_EXPORT, IMPORT, TWN, VNM, MYS, IDN, PHL, CHN, USA, JPN, and DEU as shown in Fig. 5. Outliers in the data will be removed, as indicated. After the removal of outliers, the data was checked to ensure that no outliers remained. This process helps to reduce the impact of extreme values on the analysis.

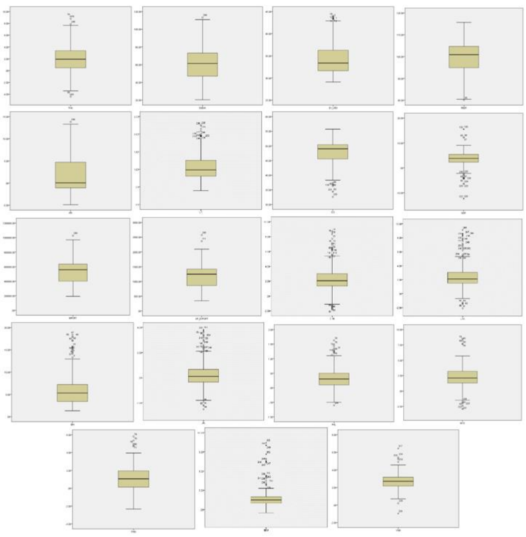

Fig. 5. Boxplot of variables with outliers.

3.1.2.2. Missing value

During data collection, it was discovered that there were missing values due to incomplete data and cutting outliers, leading to the missing values being replaced. Dempster et al. [24] first proposed the expectation-maximization algorithm, which blends a statistical approach with algorithmic execution and has acquired popularity in various missing data issues. Expectation maximization has also been shown to outperform approaches like listwise, pairwise data deletion, and mean substitution since it assumes incomplete situations have data missing at random rather than entirely at random. In addition, Rubin [25] suggests that multiple imputation (MI) is one of the most attractive methods for handling missing data in multivariate analysis. By replacing the missing data with the MI method, the results will come out 3-5 times. The researcher selected to experiment with two methods: expectation maximization (EM) and multiple imputation (MI). The approach with the lowest standard error of estimate and the highest R-square and F values from the model summary and ANOVA will be selected.

3.2. Factor Analysis

Figure 6 shows that the data employed as independent variables in the inflation forecasting model are too correlated to the inflation rate. From the collation test, it was found that the pair-wise correlation coefficient between two regressors is mostly greater than 0.80; multicollinearity is an issue [26]. Factor analysis is one of the methods used to handle multicollinearity. This method is a multivariate statistical method that has several applications. Factor analysis reduces several variables into a smaller set of variables (also known as components). The purpose of using factor analysis was to minimize the number of variables. In other words, factor analysis is a statistical approach that allows for the grouping, combining, or merging of related variables into a single category [27]. In addition, fundamental dimensions are created between the measured variables and the latent constructs, leading to the development of a model and refining the theory. It also supports the construct validity evidence [28]. This study will be separated into factor analyses using macroeconomic data and partner countries' inflation data.

After factor analysis, multicollinearity was measured statistically using the variance inflation factor (VIF) and the tolerance value, which is the reciprocal of the VIF. There is no multicollinearity if the VIF value is less than 1, and it could prove acceptable if it is less than 5. If the VIF is greater than 5, the multicollinearity is considered an issue. On the other hand, tolerance is considered to have multicollinearity if it is less than 0.1. [29]

3.3. Model

3.3.1. Neural network (NN)

A neural network (NN) comprises several interconnected processors known as neurons, each producing a series of real-valued activations. Input neurons are triggered by sensors that perceive the environment, while other neurons are stimulated by weighted connections from previously active neurons. The learning assignment involves determining the optimal weights that cause the neural network to demonstrate the desired behavior. The transformation of the aggregate activation of the network is typically done in a non-linear manner, depending on the challenge and the connectivity of the neurons at each stage. [30]

This study created a neural network model using the Python programming language on a web browser called Google Colab. The model was divided into an artificial neural network (ANN), a recurrent neural network (RNN), and a short-term memory model (LSTM). Grid search was used for hyperparameter tuning, and manual tuning experiments were performed to select a set of hyperparameters appropriate for the model's algorithm's learning process. Table 5 displays the neural network hyperparameters used in this study. The hyperparameter range was determined through Paranhos's literature review [8], and the maximum, minimum, and scope values were experimentally adapted to fit the data of this research. The working process of the neural network in this research is shown in the flowchart in Fig. 7.

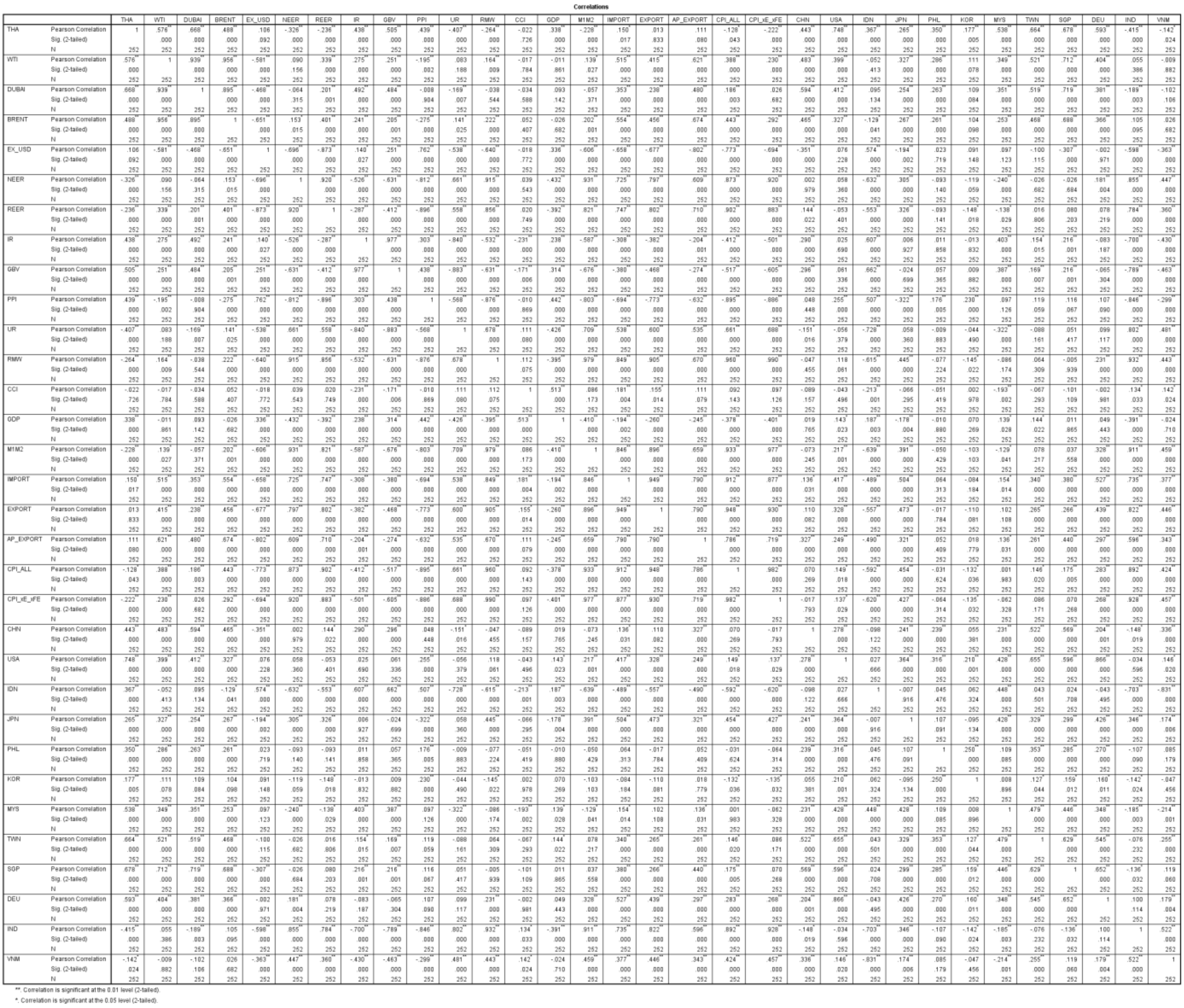

Fig. 6. Correlations.

Table 5. Hyperparameter value range.

Hyperparameters	Hyperparameter value range	Description
layers	[16, 64], [32, 32], [64,16], [16, 32, 64], [32, 32, 32], [64, 32, 16]	Number of hidden layers and number of nodes in each snake layer.
batch_size	32, 64	Sets the amount of data to be calculated in each batch.
epochs	30, 50, 100, 200, 300	The number of cycles to learn and adjust the weights of the model.
learning_rate	0.001, 0.0001	The learning rate of the model.
dropout_rate	0, 0.1, 0.2, 0.3, 0.4	The proportion of random stops during the learning of nodes in each layer.
regularization_strength	0, 0.01, 0.001, 0.0001	Value that normalizes the model by weight reduction.
activation	relu, linear	The activation function is the processor that combines the results to decide what to output.

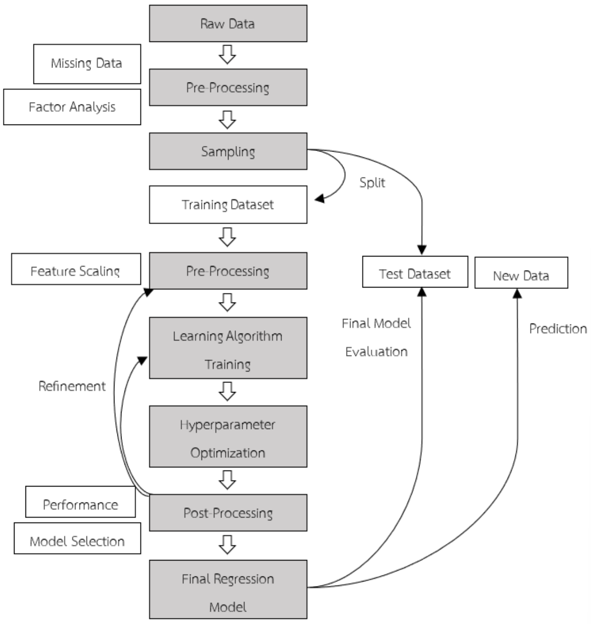

Fig. 7. A Flowchart of the neural network working process.

3.3.1.1. *Artificial neural network (ANN)*

An artificial neural network (ANN) is a processing approach that simulates the human brain's operations. In this research, a Feedforward Neural Network (FFN) architecture was employed. FFNs consist of several nodes and layers, including an input layer, one or more hidden layers, and an output layer. Weights and biases within the network are adjusted during the learning process to optimize the model's performance.

Figure 8 depicts the model's operations by considering input, weight, bias, and output data using the calculation equation shown in Eq. (1) [31].

$$y_k = \left(\varphi \sum_{j=1}^{N} w_{kj} x_j + T_k^{hid}\right) \tag{1}$$

where φ is the activation function, N is the number of input neurons, w_{kj} is the weight, x_j is the input value of the input neuron, and T_k^{hid} is the number of hidden neurons.

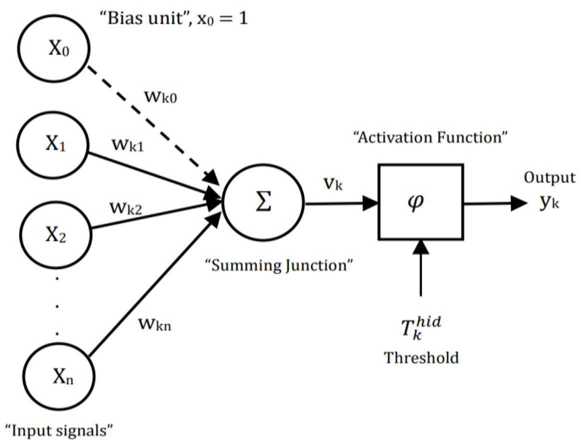

Fig. 8. Mathematical model of ANN. [31]

3.3.1.2. *Recurrent neural network (RNN)*

A recurrent neural network (RNN) is a type of neural network that processes past input sequences and predicts the upcoming sequence. It is appropriate for predicting time series data. RNN employs the principle of managing the model's internal state by using the preceding layer's output data as input data together with new input data in a hidden state, as shown in Fig. 9. This allows the model to recognize and recall the pattern of the preceding data series using Eq. (2) and Eq. (3) [32].

$$S_t = f(U \times X_t + W \times S_{t-1}) \tag{2}$$
$$O_t = g(V \times S_t) \tag{3}$$

where S_t is the network memory at time t, the values U, W, and V are the share weight matrices in each layer, the values X_t and O_t represent the inputs and outputs at time t, and $f(\,)$ and $g(\,)$represent a nonlinear function.

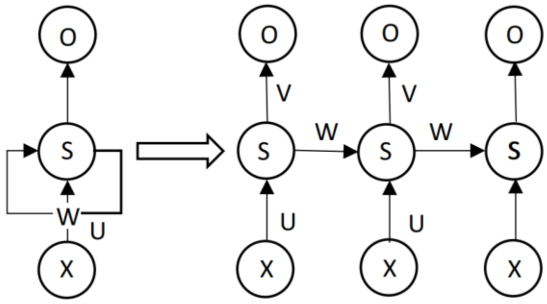

Fig. 9. A simple recurrent neural network structure. [32]

3.3.1.3. *Long short-term memory model (LSTM)*

As shown in Fig. 10, the Long Short-Term Memory Model (LSTM) was built from RNN to overcome the long-term dependence issue by improving the internal structure of the hidden state. It consists of three sets of variable-property element multiplication gates: the input gate, the output gate, and the forget gate. The input Xt at time t is selectively recorded into cell Ct by the input gate, while the forget gate selectively forgets the state of cell Ct-1 at the final instant. Finally, the output gate determines which part of the Ct cells is added to the ht output.

LSTM can be represented as follows with memory cells and gate units, as shown in Eq. (4), Eq. (5), Eq. (6), Eq. (7), and Eq. (8). [32]

$$i_t = \sigma\left(W_i \times \left[h_{t-1,x_t}\right] + b_i\right) \tag{4}$$
$$f_t = \sigma\left(W_f \times \left[h_{t-1,x_t}\right] + b_f\right) \tag{5}$$
$$o_t = \sigma\left(W_o \times \left[h_{t-1,x_t}\right] + b_{fo}\right) \tag{6}$$
$$h_t = \sigma_t \times \tanh(C_t) \tag{7}$$
$$C_t = f_t \times C_{t-1} + i_t\left(\tanh\left(W_c \times \left[h_{t-1,x_t}\right] + b_c\right)\right) \tag{8}$$

where f_t, i_t, o_t, h_t, and C_t signify, the forget gate, input gate, output gate, hidden state vector, and cell state, respectively. The weight matrix is denoted by W . b

denotes the bias matrix, the value of which is dictated by the training outcomes. σ denotes the activation function, h_{t-1} denotes the preceding cell's output, and x_t is the input vector at time t.

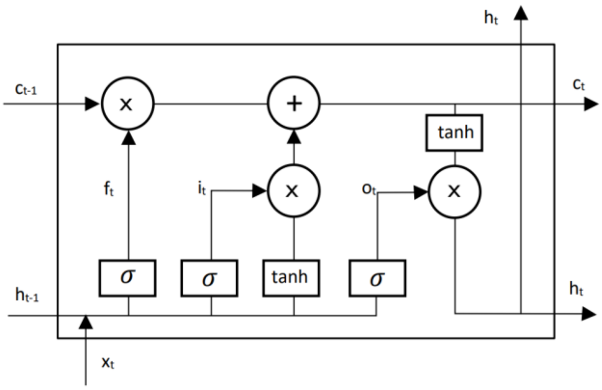

Fig. 10. Inner structure of LSTM. [32]

3.3.2. Vector autoregressive model (VAR)

The Vector Autoregressive Model (VAR) is an econometric time series model used to describe and analyze the joint dynamics of many variables that are related to each other without knowing the pattern of relationships among the variables. However, it will consider the relationship between past data of the variables within the system. Each endogenous variable is influenced by its previous values and the values of other endogenous variables. The present values of exogenous variables make them an excellent tool for capturing complicated linkages in economic time series data. This approach is often used for economic data. The model's equations may be represented as in Eq. (9). [33]

$$Y_t = \mu + \sum_{i=t}^{p} A_i Y_{t-i} + \epsilon_t \tag{9}$$

where Y_t is a vector of size K × 1 of endogenous variables at time t (endogenous variables), μ is a vector of size K × 1 of constants (constants term), p is the number of lag periods, A_i is a matrix of size K × K of coefficients (coefficients), and ϵ is the K × 1 vector of econometric error values.

3.3.3. Hybrid model

A hybrid model is a model that combines two models to improve efficiency and minimize prediction errors by combining each model's strengths and covering its weaknesses. This approach enhances the model's flexibility by fitting different data formats, such as combining a model for forecasting linear time series data with a model for forecasting non-linear time series data. Hajirahimi and Khashei [23] classified hybrid model structures into three categories. The first type is the parallel hybrid structure, which weights the outcomes of each forecast model, such as the average, linear regression, and others. The series hybrid structure is the second type, which employs the forecasted values to develop a model sequentially. Two processes are involved in distinguishing the prediction for linear and non-linear data: First, forecast using a model appropriate for linear data. The error value, or the difference between the actual and predicted values, is then employed as the input of a non-linear data model, which results in the series hybrid structure. The last form, Parallel-Series Hybrid Structure, is a blend of parallel and series structures that maximizes the benefits of each. The model's drawback is that it is more complicated and requires more calculation time.

This study will develop a hybrid model by combining VAR and neural network models with the neural network model that provides the best prediction values being selected. Figure 11 shows that Hybrid1, Hybrid2, and Hybrid3 are parallel hybrid structures, series hybrid structures, and parallel-series hybrid structures, respectively. Hybrid1 is a weighted combination of the results obtained in each forecast model, such as the average, linear regression, and others. Hybrid2 takes the forecast results and builds a model sequentially, separating the forecasted data into linear and non-linear data. There are two steps: First, forecast with a model suitable for linear data, then use the difference between the actual value and the forecast value (residuals) as the input of the model suitable for non-linear data. While Hybrid3 combines parallel structure and series structure to bring out the advantages of both structures, the negative is that it complicates the model and requires more time to compute. In addition, this study performed an experiment by integrating Hybrid3 with the forecasted values from the neural network model to create Hybrid4, which represents a novel idea introduced in this research by applying the concept of parallel hybrid structures [23]. Hybrid modeling evaluates all four structures and chooses the most appropriate structure for each forecast period and input data format. The best-performing hybrid model was then compared to the other models.

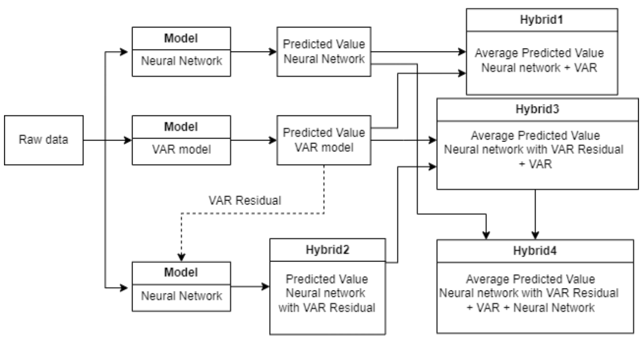

Fig. 11. The structure of Hybrid model.

3.4. Evaluation Metrics

The root mean square error (RMSE) is the primary consideration when evaluating model performance in forecasting to identify the best model fit. A review of related literature by Yan and Su [34] revealed that in many studies, the RMSE value is used as a measure of accuracy based on the size of the error as well as the direction of the forecast value. In contrast, the mean absolute error (MAE) is used as a secondary consideration in cases where the RMSE values are similar. The MAE assumes all errors are equal and less susceptible to outliers since the predicted value's direction is disregarded, including R-square values, to evaluate the appropriateness of the independent variables in the forecasting model. It has a value between 0 and 1. The model used appropriate independent variables if the value is close to 1. According to the literature review, Saravanan and Kumar [9] measured findings using RMSE, MAE, and R-square values, whereas Aras [5] measured results using RMSE and MAE values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{x_i})^2} \tag{10}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \widehat{x_i}| \tag{11}$$

$$R^2 = \frac{\sum_{i=1}^{n} R_i}{\sum_{i=1}^{n} S_i} \tag{12}$$

Eq. (10) and Eq. (11) show the mathematical expressions for the calculations of $RMSE$ and MAE, respectively. Where, n, x_i and $\widehat{x_i}$ are the number of observed data, observed values and predicted values, respectively. The equation of R^2 is denoted as Eq. (12), where R denotes the residuals and S represents the squares. The coefficient of determination is based on the sum of residuals and the sum of squares [9].

4. Results and Analysis

When conducting research according to the methodology mentioned in Section 3, the following results will be obtained: missing value replacement method selection, factor analysis results, Neural Network hyperparameter selection results, VAR model results, and results of model performance evaluation.

4.1. Results of the Missing Value Replacement Method Selection

Table 6. Model Summary and ANOVA of Missing Value.

Expectation-maximization	**F**	**R-square**	**Std. Error of the Estimate**
1	113.035	0.941	0.58347
Imputation Number	**F**	**R-square**	**Std. Error of the Estimate**
1	109.912	0.939	0.59120
2	241.921	0.972	0.40526
3	170.010	0.960	0.48054
4	104.959	0.937	0.60413
5	132.116	0.949	0.54201

Table 6 reveals that when comparing the methods for replacing missing values between EM and MI, it is found that the MI method of Imputation Number 2 produces the greatest F value of 241.921, the highest R-square of 0.972, and the lowest standard error of the estimated value of 0.40526. As a result, the MI method of Imputation Number 2 was chosen for this study to replace missing data values.

4.2. Factor Analysis results

Table 7. KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.842
Bartlett's Test of Sphericity	Approx. Chi-Square	12354.152
	df	190
	Sig.	0.000

Before extracting the factors, it is necessary to conduct tests to evaluate the appropriateness of the data for factor analysis by using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO index has a scale of 0 to 1, where values equal to or more than 0.50 are considered appropriate for factor analysis, while Bartlett's test of sphericity should have a p-value below 0.05 (Willians et al., 2010). According to the results in Table 7, the KMO index test provided a value of 0.842, more significant than 0.50. Additionally, Bartlett's Test of Sphericity has a p-value below 0.05. Therefore, the data were considered appropriate for factor analysis.

Table 8. Total Variance Explained of Macroeconomic data.

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.851	54.253	54.253	10.851	54.253	54.253
2	4.469	22.344	76.597	4.469	22.344	76.597
3	1.641	8.206	84.803	1.641	8.206	84.803
4	1.061	5.303	90.106	1.061	5.303	90.106

Table 8 shows four macroeconomic components with eigenvalues greater than 1. When the component matrix is rotated according to Table 9, it is discovered that the independent variables are divided according to each component by the name of each component and definitions, as shown in Table 10, which will be done in the same way as the partner countries' inflation data, with all three components as shown in Table 11.

Factor analysis results divided the data into macroeconomic and partner countries' inflation data. It was discovered that the components can be extracted as follows: Macroeconomic data includes EA, EH, MG, and CS&GDP, while partner countries' inflation data includes AdEcon, EmEcon, and AsEcon. When data is imported into the model, it is divided into two formats: the model that uses only macroeconomic independent variables (MCE) and the model that uses macroeconomic independent variables, including partner countries' inflation (PCI).

Table 12 shows that the VIF value is less than 5 and the Tolerance value is more significant than 0.1, suggesting no multicollinearity exists. The data could be included in the model.

Table 9. Rotated Component Matrix of Macroeconomic data.

	Component			
	1	2	3	4
CPI_xE_xFE	0.941			
CPI_ALL	0.938			
PPI	-0.935			
REER	0.934			
RMW	0.930			
NEER	0.895			
M1M2	0.885			
EXPORT	0.873			
IMPORT	0.817			
EX_USD	-0.749			
AP_EXPORT	0.689	0.540		
WTI		0.947		
DUBAI		0.936		
BRENT		0.910		
THA		0.725		
IR			-0.905	
GBV			-0.858	
UR			0.826	
CCI				0.868
GDP				0.814

Table 10. Definitions of Macroeconomics Components (MCE).

Variable	Components	Definitions
EX_USD NEER REER PPI RMW M1M2 IMPORT EXPORT AP_EXPORT CPI_ALL CPI_xE_xFE	Economic activity indicators (EA)	This group includes variables related to the inflation rate and the country's economic activity level, such as consumer price indices, minimum wage, exchange rates, money supply, imports and exports, and agricultural exports.
THA WTI DUBAI BRENT	Energy prices and historical inflation (EH)	This group includes variables related to energy prices, such as WTI, DUBAI, and BRENT, as well as historical inflation data.
IR GBV UR	Monetary policy and government spending indicators (MG)	This group includes variables related to monetary policy, such as policy interest rates, government bond yields, and the unemployment rate. It could reflect the impact of these factors on the economy.
CCI GDP	Consumer sentiment and GDP (CS&GDP)	This group includes variables related to consumer sentiment and the economy's overall performance, such as the Consumer Confidence Index and Gross Domestic Product.

DOI:10.4186/ej.2024.28.6.37

Table 11. Definitions of Partner Countries' inflation Components.

Variable	Components	Definitions
CHN USA JPN MYS TWN SGP DEU	Advanced Economies (AdEcon)	A group of countries with highly developed economies, including the United States, Malaysia, Taiwan, Singapore, Germany, China, and Japan.
IDN IND VNM	Emerging Economies (EmEcon)	A group of countries with rapidly growing economies, including Indonesia, India, and Vietnam.
PHL KOR	Associates Economies (AsEcon)	A group of countries with close economic ties to Thailand, including the Philippines and South Korea.

Table 12. Collinearity Statistics of Tolerance and VIF.

Components	Collinearity Statistics	
	Tolerance	VIF
EAI	0.333	3.006
EH	0.455	2.198
MG	0.569	1.757
CSGDP	0.978	1.022
AdEcon	0.521	1.919
EmEcon	0.314	3.184
AsEcon	0.532	1.880

Table 13. Hyperparameter selection of ANN.

Model	Input data	Horizon (months)	Hyperparameters					
			layers	batch_size	epochs	learning_rate	regularization_strength	dropout_rate
ANN	MCE	1	[16,64]	32	30	0.001	0	0.1
		3	[16,32,64]	32	300	0.0001	0	0
		6	[16,64]	32	30	0.001	0	0.1
		12	[16,32,64]	32	30	0.001	0	0.1
	PCI	1	[16,64]	32	200	0.0001	0	0
		3	[16,64]	32	50	0.001	0	0.1
		6	[16,64]	32	300	0.0001	0.001	0
		12	[32,32,32]	32	50	0.001	0.0001	0.3

Table 14. Hyperparameter selection of RNN.

Model	Input data	Horizon (months)	Hyperparameters					
			layers	batch_size	epochs	learning_rate	regularization_strength	dropout_rate
RNN	MCE	1	[32,32,32]	32	30	0.001	0.001	0
		3	[16,32,64]	32	300	0.001	0.0001	0
		6	[16,32,64]	32	30	0.001	0	0.3
		12	[16,64]	32	30	0.001	0.001	0
	PCI	1	[32,32]	32	300	0.0001	0.001	0
		3	[16,64]	32	50	0.001	0.01	0
		6	[32,32]	32	50	0.001	0	0.2
		12	[16,32,64]	32	300	0.0001	0.0001	0

Table 15. Hyperparameter selection of LSTM.

Model	Input data	Horizon (months)	Hyperparameters					
			layers	batch_size	epochs	learning_rate	regularization_strength	dropout_rate
LSTM	MCE	1	[16,64]	32	30	0.001	0.0001	0
		3	[16,32,64]	32	30	0.001	0.1	0
		6	[16,64]	32	30	0.001	0	0.1
		12	[16,32,64]	32	30	0.001	0	0.1
	PCI	1	[32,32]	32	300	0.0001	0	0.2
		3	[16,64]	32	50	0.001	0.01	0
		6	[16,64]	32	50	0.001	0	0
		12	[16,32,64]	32	300	0.0001	0.0001	0

Table 16. Hyperparameter selection of Hybrid model.

Model	Input data	Horizon (months)	Hyperparameters						
			structure	layers	batch_size	epochs	learning_rate	regularization_strength	dropout_rate
Hybrid (VAR-ANN)	MCE	1	Hybrid 3	[16,32,64]	32	30	0.001	0	0
		3	Hybrid 4	[16,64]	32	30	0.001	0	0
		6	Hybrid 4	[16,32,64]	32	30	0.001	0.001	0
		12	Hybrid 2	[16,32,64]	32	30	0.001	0	0
	PCI	1	Hybrid 4	[16,64]	32	50	0.001	0	0.2
		3	Hybrid 2	[32,32]	32	50	0.001	0	0.3
		6	Hybrid 2	[32,32,32]	32	50	0.001	0	0.1
		12	Hybrid 2	[16,64]	32	50	0.001	0.001	0

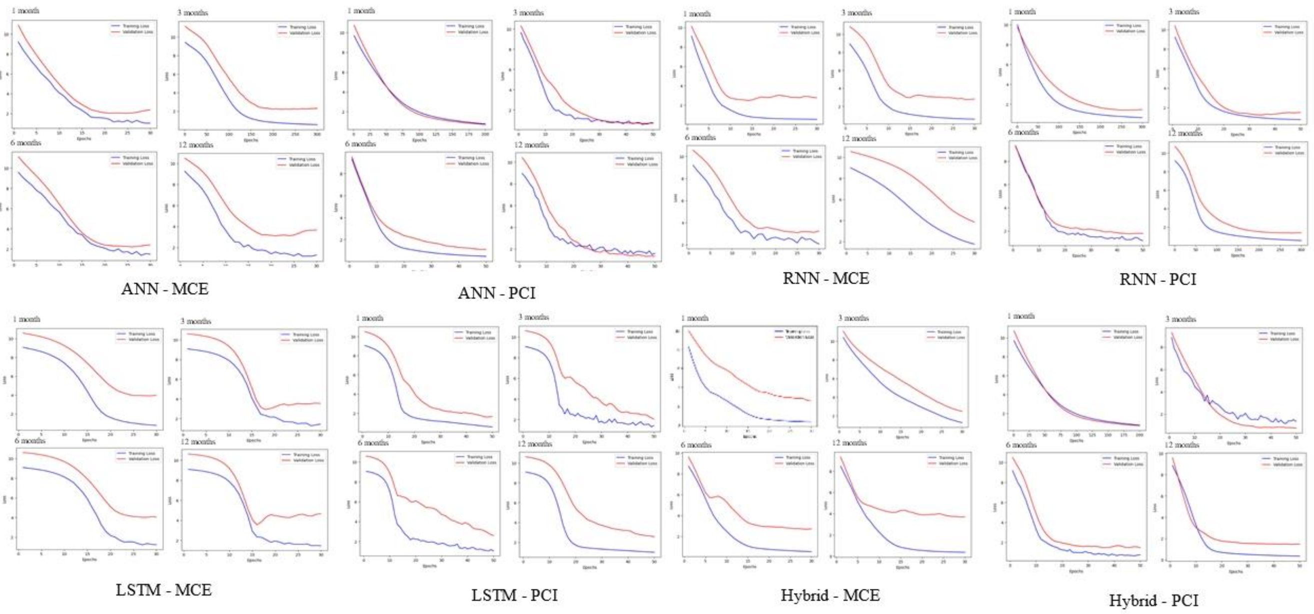

Fig. 12. Learning curve for the neural networks and hybrid models.

4.3. Neural Network Hyperparameter Selection Results

Grid search and manual adjustment tests were carried out as a result of this study to determine the most appropriate hyperparameter values in each model, including the independent variable data employed and the forecast period in advance. It performs three searches simultaneously and selects the hyperparameter value that provides the best prediction. Based on the appropriateness of the data and usage to reduce the use of resources in Grid search's work. The Rectified Linear Unit (ReLU) activation function is used in the hidden layer because ReLU can handle non-linearity and capture complicated patterns in time series data. This ability is critical to forecasting economic variables such as inflation at the time of the output layer. The linear activation function allows the model to predict continuous variables over various values efficiently [35]. The results of optimal hyperparameter values were obtained, as shown in Table 13-16.

Table 16 demonstrates that importing the same input data but different forward forecast periods or the same forward forecast period but different input data. The hybrid structures with the highest efficiency are also different. In addition, the Hybrid4 structure produced by the experiments conducted in this research also demonstrates the highest forecasting efficiency during certain forward forecast periods.

Examining the learning curve is essential in evaluating overfitting by plotting the training loss and validation loss against the number of epochs. This information provides insight into how the model works. A clear sign of an overfitting problem is when the validation loss after the initial decrease starts to increase while the training loss continues to decrease. This sign indicates that, in later epochs, the model is fitting the training data too closely. As a result, the ability to conclude is reduced [36]. Fig. 12 shows the learning curves representing the training and validation loss on the test set at different epochs. A notable observation is the absence of overfitting problems in our neural networks (ANN, RNN, LSTM) and hybrid models. This observation is evident from the stability of the verification loss. This result highlights the robustness of our model for maintaining good generalization performance.

4.4. VAR Model Results

Check the stationary independent variable data using the Augmented Dickey-Fuller test (ADF test), with the results shown in Table 17. EAI, EmEcon, and AsEcon are the three non-stationary variables. To make the data stationary, the researcher employed a technique to determine the difference in data sequence between all three data sets.

Table 17. The Augmented Dickey-Fuller test (ADF test).

Component	**ADF test**
EAI	Non-stationary
EH	Stationary
MG	Stationary
CS&GDP	Stationary
AdEcon	Stationary
EmEcon	Non-stationary
AsEcon	Non-stationary

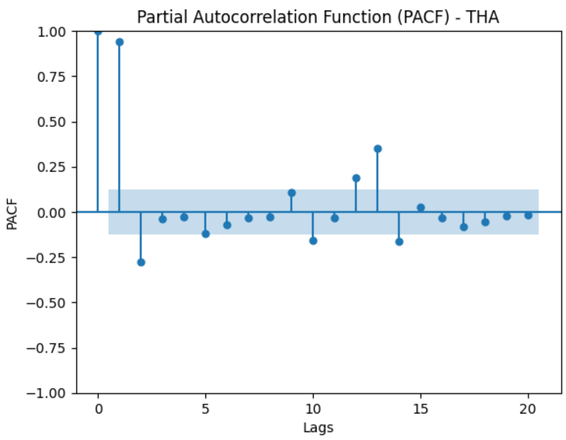

Fig. 13. Partial Autocorrelation Function (PACF).

Plot the Partial Autocorrelation Function (PACF) graph to obtain the maximum lag value (max lag) to use in determining the Summary of Regression Results to produce a forecast equation when the independent variable data is all stationary, as illustrated in Fig. 13. The PACF value was discovered to be outside the confidence ranges at lag 14. In lag 14, the PACF values are significantly related.

Create a Summary of Regression Results with a max lag value of 14, dividing it into MCE and PCI data formats. As demonstrated in Eq. (13) and Eq. (14), we will obtain a prediction equation that employs MCE and PCI, respectively.

$$\mathrm{THA} = 0.75\mathrm{THA}_{(t-1)} - 0.65\mathrm{MG}_{(t-1)} + 1.4\mathrm{EH}_{(t-1)} - 2.03\mathrm{EAI}_{(t-5)} - 2.11\mathrm{EAI}_{(t-8)} - 1.26\mathrm{EH}_{(t-11)} + 0.48\mathrm{THA}_{(t-13)} - 0.61\mathrm{MG}_{(t-14)} + 0.75\mathrm{EH}_{(t-14)} \quad (13)$$

$$\mathrm{THA} = 0.83\mathrm{THA}_{(t-1)} - 0.82\mathrm{MG}_{(t-1)} + 1.27\mathrm{EH}_{(t-1)} - 3.07\mathrm{EAI}_{(t-8)} + 0.39\mathrm{EmEcon}_{(t-11)} + 0.44\mathrm{THA}_{(t-13)} \quad (14)$$

4.5. Performance Evaluation Results

Figure 14 shows the actual inflation values compared to the forecast values in the different models, divided into 1-, 3-, 6-, and 12-month advance forecast periods. Each forecast period is divided into two data formats: MCE and PCI. It is found that all models can effectively capture the trend of inflation in short-term forecasts, but their performance decreases in longer-term forecasts.

Table 18 shows that ANN performed best among the neural network models, followed by RNN and LSTM. The findings demonstrate that highly complex models may not necessarily provide excellent results, depending on the data and hyperparameter settings. Based on the findings, the researcher decided to employ the ANN model to develop a hybrid model that included a VAR model. After comparing the outcomes of all models (ANN, RNN, LSTM, VAR, and hybrid), it was discovered that the hybrid model (VAR-ANN) employing PCI performed the best across all forecast periods. Moreover, the input data models were compared, and it was discovered that the model that used PCI provided better forecasts except for VAR at 1- and 3-month in advance forecast periods.

Table 19 Comparing the efficacy of using data from MCE and PCI in the hybrid model (VAR-ANN) shows that using PCI data improves the efficiency of the hybrid model (VAR-ANN) by 29.05%.

Table 20 The best model in this research is the hybrid model (VAR-ANN), which, when compared to the benchmark model (BOTMM), has a more excellent forecasting performance of 50.36% when comparing quarterly (3-month) forward forecasts in 2020–2022.

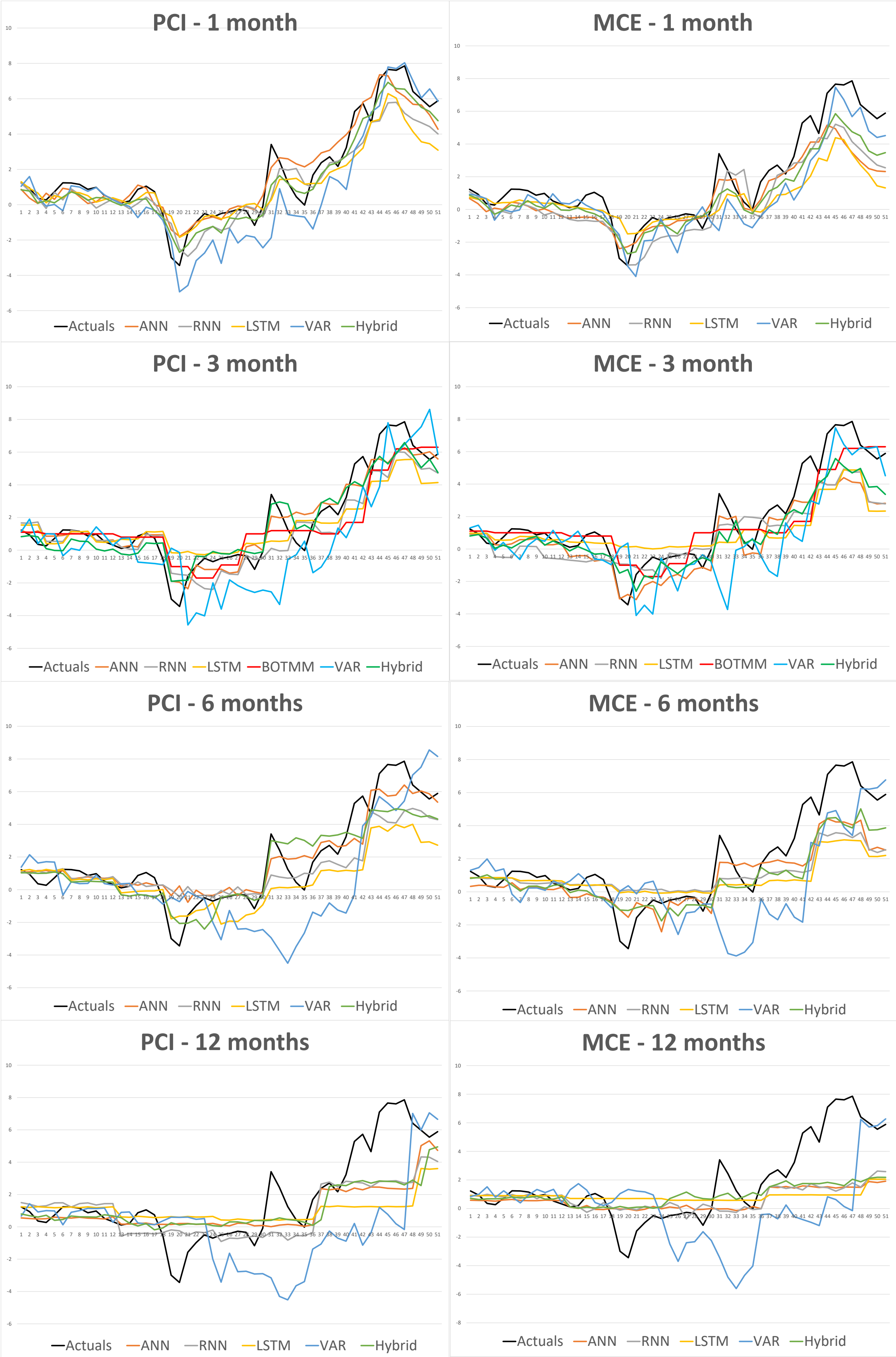

Fig. 14. Comparison between Actual values and forecast values.

Table 18. Performance results for all models.

Model	Input data	RMSE				MAE				R-square			
		h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
ANN	MCE	1.54	1.60	1.67	2.50	1.14	1.21	1.22	1.71	0.69	0.67	0.63	0.18
	PCI	0.84	0.95	1.47	2.02	0.64	0.73	1.14	1.34	0.91	0.88	0.72	0.46
RNN	MCE	1.64	1.68	1.98	2.61	1.34	1.33	1.42	1.83	0.65	0.63	0.49	0.11
	PCI	1.19	1.33	1.52	1.96	0.93	1.02	1.06	1.41	0.81	0.77	0.70	0.49
LSTM	MCE	2.00	1.87	2.18	2.73	1.38	1.38	1.53	1.90	0.48	0.54	0.38	0.02
	PCI	1.29	1.46	1.87	2.51	0.89	1.08	1.30	1.74	0.78	0.72	0.54	0.17
VAR	MCE	1.52	2.13	2.61	3.53	1.17	1.53	1.94	2.52	0.69	0.40	0.09	-0.66
	PCI	1.54	2.19	2.53	3.36	1.12	1.72	1.94	2.46	0.68	0.36	0.14	-0.51
Hybrid (VAR-ANN)	MCE	1.22	1.38	1.61	2.37	0.94	1.06	1.19	1.66	0.80	0.75	0.65	0.26
	PCI	**0.70**	**0.89**	**1.33**	**1.88**	**0.56**	**0.72**	**1.01**	**1.28**	**0.93**	**0.90**	**0.77**	**0.53**

Note: The bolded values denote the best performance.

Table 19. Performance input data results.

Model	Input data	RMSE			
		h=1	h=3	h=6	h=12
Hybrid (VAR-ANN)	MCE	1.22	1.38	1.61	2.37
	PCI	0.70	0.89	1.33	1.88
Performance Improve (%)		42.62	35.68	17.39	20.50
Average Improve (%)					29.05

Table 20. Performance comparison results of the hybrid model with BOTMM.

Model	RMSE			
	2020	2021	2022	2020-2022
BOTMM	1.02	1.22	1.82	1.39
Hybrid (VAR-ANN)	0.48	0.53	0.96	0.69
Performance Improve (%)	52.94	56.56	47.25	50.36

5. Conclusion

This study investigated the application of deep learning combined with PCI factors to forecast headline inflation rates in Thailand. The performance of neural network models, time series forecasting models, and hybrid models was compared. Furthermore, the predicting performance of the independent variables between MCE and PCI was compared. After finding the best model, its performance was compared to the BOTMM model to show that deep-learning models were better at predicting inflation.

Historically, inflation, a significant economic indicator for the entire country, has experienced fluctuations due to several economic crises. In particular, the COVID-19 pandemic over the past year has caused the Bank of Thailand's inflation forecasts to be less accurate, resulting in delays in policy implementation. Hence, it is crucial to develop appropriate and accurate models. As a result, this study aims to identify the most appropriate and accurate model for forecasting headline inflation in Thailand and demonstrate that including the independent variable of PCI can improve the model's forecasting accuracy.

According to the findings of this research study, the hybrid model (VAR-ANN) was able to best capture the direction of inflation in all forecast periods 1-, 3-, 6-, and 12 months in advance. Furthermore, including the independent variable PCI in the model can significantly improve prediction performance. The forecast accuracy increased in every forward forecast period and every model, except for the VAR model in the 1- and 3-month advance forecast periods. Moreover, when comparing the forecast values of the hybrid model (VAR-ANN) that incorporates the independent variable of PCI with the forecast values of the BOTMM model for the period 2020–2023, it is shown that the hybrid model (VAR-ANN) provided a more accurate forecast value of 50.36%.

5.1. Academic Contribution

The academic contribution of this research is to systematically evaluate and compare the performance of various forecasting models, including traditional time series, deep learning, and hybrid models. The strengths and limits of each model are also examined. This study combines current knowledge about inflation forecasting methods from a comprehensive literature review. Furthermore, including PCI factors in the model is a novel direction for this study and can fill existing research gaps. This result improves knowledge of inflation-related economic factors, resulting in more accurate forecasting models.

5.2. Practical Contribution

An effective inflation forecasting model helps monetary policymakers plan monetary policies to effectively cope with economic fluctuations caused by both domestic and international factors. In addition, this research provides a guideline for building forecast models more widely, which benefits people interested in developing forecast models in various fields by demonstrating the application and effectiveness of deep learning models.

To facilitate the use of the developed hybrid model (VAR-ANN) by other cooperates, the VAR and ANN models, along with datasets and implementation instructions, are available on Google Colab (https://colab.research.google.com/drive/1YmQ57FCJ2H499PcwG2tvjmVHcjRQsyPW?usp=sharing and https://colab.research.google.com/drive/1iWlfaWs4hNg9uVKvniUH3r8z7vkqdbZn?usp=sharing). Users need to prepare their data according to the specified format, including historical and optionally partner countries' inflation data.

5.3. Further Research

The following is potential research that is worth further exploration. First, factors other than the value of international imports and exports may be considered in selecting partner countries for inclusion in the model. For example, consider the economic structure, industrial composition, market interdependence, stability of each trading partner's economy, and monetary policies. Further research can explore these factors to refine the criteria for selecting partner countries and increase the accuracy of inflation forecasting models.

Second, experiment with other combinations of models for further research due to the variety of forecasting models currently available. There might be alternative hybrid models with better prediction performance. This approach may improve forecasting methods and find more effective ways to capture inflation fluctuations.

Last, experimenting with more comprehensive hyperparameter settings is advised. Tuning hyperparameters is an essential part of model optimization. A proper setup may result in more excellent prediction performance. This method provides for a greater understanding of model behavior and may lead to the identification of optimal hyperparameter values for future inflation forecasts.

References

[1] A. K. Uko and E. Nkoro, "Inflation forecasts with ARIMA, vector autoregressive and error correction models in Nigeria," *European Journal of Economics, Finance and Administrative Sciences*, vol. 50, pp. 71-87, 2012.

[2] A. Orphanides and V. Wieland, "Economic projections and rules-of-thumb for monetary policy," *Federal Reserve Bank of St. Louis Review*, pp. 307-324, 2008.

[3] O. Barkan, J. Benchimol, I. Caspi, E. Cohen, A. Hammer, and N. Koenigstein, "Forecasting CPI inflation components with hierarchical recurrent neural networks," *International Journal of Forecasting*, vol. 32, no. 3, pp. 1145-1162, 2023.

[4] A. Buddhari and V. Chensavasdijai, "Inflation dynamics and its implications for monetary policy," Bank of Thailand Discussion Paper, 2003.

[5] S. Aras, and P. J. Lisboa, "Explainable inflation forecasts by machine learning models," *Expert Systems with Applications*, vol. 207, p. 117982, 2022.

[6] C. Sitthichaiviset, V. Khemangkorn, and A. Saikaew, "The monetary policy and inflation management report," Bank of Thailand Discussion Paper, 2012.

[7] G. Cybenko, "Approximation by superpositions of a sigmoidal function. Mathematics of control," *Mathematics of Control, Signals and Systems*, vol. 2, no. 4, pp. 303-314, 1989.

[8] L. Paranhos, "Predicting inflation with neural networks," Warwick Economics Research Papers, 2021.

[9] D. Saravanan and K. S. Kumar, "IoT based improved air quality index prediction using hybrid FA-ANN-ARMA model," *Materials Today: Proceedings*, vol. 56, pp. 1809-1819, 2022.

[10] D. V. Dinh, "Impulse response of inflation to economic growth dynamics: VAR model analysis," *The Journal of Asian Finance, Economics and Business*, vol. 7, no. 9, pp. 219-228, 2020.

[11] R. Pongsaparn, "A small semi-structural model for Thailand: Construction and applications," Bank of Thailand, 2008.

[12] S. Ranchhod, "Inflation in New Zealand's trading partner economies," *Reserve Bank of New Zealand: Bulletin*, vol. 71, no. 3, pp. 14-25, 2008.

[13] J. Yang, H. Guo, and Z. Wang, "International transmission of inflation among G-7 countries: A data-determined VAR analysis," *Journal of Banking & Finance*, vol. 30, no. 10, pp. 2681-2700, 2006.

[14] M. Kandil and H. Morsy, "Determinants of Inflation in GCC," *Middle East Development Journal*, vol. 3, no. 2, pp. 141-158, 2011.

[15] L. Arango-Castillo, M. J. Orraca, and G. S. Molina, "The global component of headline and core inflation in emerging market economies and its ability to improve forecasting performance," *Economic Modelling*, vol. 120, pp. 106-121, 2023.

[16] K. Szafranek, "Bagged neural networks for forecasting Polish (low) inflation," *International Journal of Forecasting*, vol. 35, no. 3, pp. 1042-1059, 2019.

[17] B. Rurkhamet, P. Chutima, and M. Reodecha, "Comparative study of artificial neural network and regression analysis for forecasting new issued banknotes," *Science & Technology Asia*, vol. 3, no.2, pp. 21-28, 1998.

[18] E. Dave, A. ALeonardo, M. Jeanice, and N. Hanafiah, "Forecasting Indonesia exports using a hybrid model ARIMA-LSTM," *Procedia Computer Science*, vol. 179, pp. 480-487, 2021.

[19] T. Wen, Y. Liu, Y. he Bai, and H. Liu, "Modeling and forecasting CO_2 emissions in China and its regions using a novel ARIMA-LSTM model," *Heliyon*, vol. 9, no. 11, 2023.

[20] W. Cheevachaipimol, B. Teinwan, and P. Chutima,, "Flight delay prediction using a hybrid deep learning method," *Engineering Journal*, vol. 25, no. 8, pp. 99-112, 2021.

[21] K. Senneset and M. Gultvedt, "Something old, something new: A hybrid approach with ARIMA

and LSTM to increase portfolio stability," master's thesis, Norwegian School of Economics, 2020.
[22] Y. Deng, H. Fan, and S. Wu, "A hybrid ARIMA-LSTM model optimized by BP in the forecast of outpatient visits," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-11, 2020.
[23] Z. Hajirahimi and M. Khashei, "Hybrid structures in time series modeling and forecasting: A review," *Engineering Applications of Artificial Intelligence*, vol. 86, pp. 83-106, 2019.
[24] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the royal statistical society*, vol. 39, no. 1, pp. 1-22, 1977.
[25] D. B. Rubin, "Multiple imputation after 18+ years," *Journal of the American statistical Association*, vol. 91, no. 434, pp. 473-489, 1996.
[26] S. S. Kumari, "Multicollinearity: Estimation and elimination," *Journal of Contemporary Research in Management*, vol. 3, no. 1, pp. 87-95, 2008.
[27] C. Thongdonnoi, P. Chutima, A. Jiamsanguanwong, O. Kittithreerapronchai, and M Swangnetr Neubert, "Application of collaborative robots for increasing productivity in an eyeglasses lenses manufacturer," *Engineering Journal*, vol. 27, no.10, pp. 93-112, 2023.
[28] B. Willians, A. Onsman, and T. Brown, "Exploratory factor analysis: A five-step guide for novices," *Australasian Journal of Paramedicine*, vol. 8, no. 3, pp. 1-13, 2010.
[29] T. Kyriazos and M. Poga, "Dealing with multicollinearity in factor analysis: The problem, detections, and solutions," *Open Journal of Statistics*, vol. 13, no. 3, pp. 404-424, 2023.
[30] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85-117, 2015.
[31] W. Khrakhuean and P. Chutima, "Real-time induction motor health index prediction in a petrochemical plant using machine learning," *Engineering Journal*, vol. 26, no. 5, pp. 91-107, 2022.
[32] C. Tian, J. Ma, C. Zhang, and P. Zhan, "A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network," *Energies*, vol. 11, no. 12, 2018.
[33] C. A. Sims, "Comment on Glenn Rudebusch's "Do measures of monetary policy in a VAR make sense?"," *International Economic Review*, vol. 39, no. 4, pp. 933-941, 1998.
[34] X. Yan and X. Su, "Linear regression analysis: Theory and computing," *World Scientific*, 2009.
[35] S. Sharma and S. Sharma, "Activation functions in neural networks," *International Journal of Engineering Applied Sciences and Technology*, vol. 4, no. 12, pp. 310-316, 2020.
[36] C. Perlich, "Learning curves in machine learning," IBM T.J. Watson Research Center, 2010.

Techin Arnonwattana received a B.Eng. in Industrial Engineering from King Mongkut's University of Technology North Bangkok, Bangkok, Thailand. He obtained an M.Eng. in Industrial Engineering from Chulalongkorn University, Bangkok, Thailand.

Professor Parames Chutima received a Bachelor of Engineering from Chulalongkorn University, Master's degrees from Chulalongkorn University and Asian Institute of Technology, and a PhD in Manufacturing Engineering and Operations Management from the University of Nottingham, UK. Currently, he is a full Professor in the Faculty of Engineering at Chulalongkorn University, Thailand, and the Director of the Regional Centre for Manufacturing Systems Engineering, Chulalongkorn University, Thailand. His research interests include multi-objective optimisation in operations management, production planning and control of assembly lines, just-in-time production systems, lean & six Sigma construction management, and simulation modelling. He is the author of many books and articles in prestigious international journals and international conferences.