WSB Journal of Business and Finance
Year 2025, Vol. 59, No.1
eISSN 2657-4950

Application Of Artificial Neural Network Model To Forecast Growth Rate Of Service Sector's Value In Ho Chi Minh City

Le Hoang Anh[a], Nguyen Van Hao[a]

Ho Nguyen Thai Bao, Vo Huynh Hung Thinh, Nguyen Truc Van[b,]

[a]Ho Chi Minh University of Banking, Ho Chi Minh city, Vietnam
[b]Centre for Socioeconomic Simulation and Forecast of Ho Chi Minh City, Ho Chi Minh city, Vietnam

DOI 10.2478/WSBJBF-2025-0005

Abstract

Ho Chi Minh City has a trade-service sector structure accounting for over 60% and is also strongly affected by domestic and international macroeconomic factors. Accurate forecasting methods support policy planning and economic management in increasingly volatile global and national economies. The Artificial Neural Network (ANN) model has proven to be highly effective in forecasting macroeconomic indicators such as GDP, unemployment rate, inflation, and export revenue due to its ability to process complex data and detect nonlinear relationships. This study presents the analysis and forecasting of the time series data of the quarterly growth rate of trade services in Ho Chi Minh City from 2011 to 2024, using machine learning models including ANN and several econometric models such as SARIMA, Single moving average, Single Exponential Smooth, and Holt-Winter Additive. The results show that the artificial neural network (ANN) model has superior accuracy compared to other models. The study also provides recommendations for applying ANN in urban economic management, contributing to the sustainable growth of Ho Chi Minh City, and expanding the application of ANN in city-level economic forecasting.

Keywords: time series, forecasting, machine learning, growth rate, service sector

1. Introduction

In the context of the global and national economy facing many fluctuations, applying accurate forecasting methods to support policy decision-making and economic management is extremely important. One of the highly regarded methods for improving the accuracy of financial forecasts is the Artificial Neural Network (ANN) model (Alamsyah & Permana, 2018; Önder et al., 2013). The ANN method has proven to be exceptionally effective in forecasting macroeconomic indicators such as GDP, imports and exports, unemployment rates, inflation, and tourism revenue, thanks to its ability to process complex data and detect nonlinear relationships among factors affecting the economy (Ćetković et al., 2022). For example, a study on forecasting the share of tourism revenue in total export turnover in Turkey showed that the ANN model outperformed the traditional multiple linear regression model, with an R square value of 91.7% compared to 90.8% (Erdoğan et al., 2023). In GDP forecasting, ANNs have been used to predict future GDP values based on various macroeconomic indicators. For instance, a study on GDP forecasting in G7 countries showed that the ANN model using exchange rates, inflation, and GDP growth as inputs outperformed traditional models in forecasting accuracy (Fraz et al., 2020). Another study on GDP forecasting in the United States found that the ANN model using 10 macroeconomic variables (inflation, housing starts, interest rates, business confidence, government spending, net exports, employment levels, money supply, stock market performance, and oil prices) outperformed traditional models in forecasting accuracy (Lashgari, 2023). ANNs have also been used to forecast unemployment rates. For example, a study on the impact of COVID-19 control measures on unemployment rates showed that the ANN model using macroeconomic indicators such as GDP growth, inflation rates, export values as a percentage of GDP, and COVID-19 fiscal stimulus packages as a percentage of GDP outperformed traditional models in forecasting accuracy (Morris et al., 2022). Compared to traditional econometric models, ANNs do not require strict assumptions about the structural relationships among variables, making them more flexible in simulating real and complex economic situations (Herbrich et al., 1999).

However, most current studies on applying ANN in economic forecasting focus on the national level, using annual time series data to forecast macroeconomic indicators for the entire country. To our knowledge, few studies currently delve into the application of ANN to forecast economic indicators in large and developing cities, especially those with unique economic characteristics like Ho Chi Minh City. Most current forecasts concentrate on analyzing and predicting for countries, with annual data series. At the same time, quarterly data – which is crucial for evaluating and adjusting economic policies at the city level – has not been fully exploited. Thus, one of the major limitations of current research is the lack of attention to the specific factors of each region and city in applying the ANN model. Economic indicators in cities such as Ho Chi Minh City have unique characteristics and can be strongly influenced by local factors that macroeconomic models at the national level cannot fully reflect. This creates a gap in research and an urgent need to apply advanced models like ANN to forecast economic indicators for cities, thereby helping local policymakers make more accurate and timely decisions.

With its unique economic characteristics, Ho Chi Minh City strongly depends on macroeconomic factors, including inflation, monetary policy, and global economic fluctuations. For example, the development of the city's logistics, retail, and e-commerce sectors is directly influenced by the pace of international trade expansion and domestic consumption demand. In particular, the trade and services sector plays a crucial role as a driving force of the economy, accounting for more than 60% of the city's economic structure in 2023 (GSO, 2023). This reflects the pillar role of this sector in promoting production, consumption, and the overall development of the economy. According to research by the Ho Chi Minh City Development Research Institute, if the trade and services sector maintains an average growth rate of over 10% per year, it will contribute to achieving the national GDP growth target of 6-7% per year by 2030 (GSO, 2023).

Due to the rapid fluctuations and dependence on macroeconomic factors, forecasting and developing economic growth scenarios in this sector is essential. This helps the city not only to timely direct policies but also to ensure the sustainability of the economy. Therefore, focusing on forecasting economic development trends, especially in the trade and services sector, is significant for the city and contributes to creating growth momentum for the entire country.

Although Ho Chi Minh City's economic indicators show a rapid development trend and strong fluctuations by quarter, most studies have not considered forecasting these indicators. Using quarterly rather than annual data provides a more detailed and timely view of the city's economic situation. This is particularly important when the city needs to assess its ability to achieve the economic growth targets set for the year while also being able to adjust and implement appropriate policy responses. One of the significant gaps in current research is the lack of attention to forecasting the growth rate of the trade-service sector quarterly for Ho Chi Minh City, even though this is an essential factor that helps the city closely monitor economic development in each short-term phase. This leads to a lack of accuracy in policy decision-making for Ho Chi Minh City, especially in needing timely policy responses to short-term economic fluctuations.

Therefore, this study aims to build and apply an ANN model to forecast the quarterly growth rate of the trade-service sector in Ho Chi Minh City. Having an accurate forecasting model helps minimize risks and optimize the use of the city's economic resources. In addition, the study also aims to provide recommendations on how to apply the ANN model in economic management and administration in Ho Chi Minh City. Accurate forecasts of quarterly growth rates will help city leaders make timely and effective policy decisions. Measures to adjust budget spending, promote export activities, stimulate domestic consumption, or support important businesses and industries can be quickly implemented to maintain and boost economic growth. Furthermore, the research results will contribute to developing economic forecasting methods at the city level, expanding the application of the ANN model in economic forecasting studies at the city level.

2. Literature review

Many studies explore the potential of machine learning in the field of forecasting. Kennedy (2002) notes that artificial neural networks (ANN) often have the advantage of accuracy. That is, the difference between the ANN's forecasted and actual values is not large. It does not require any prior information about the distribution and probability of the data, can learn from past experiences, and can work with imperfect and nonlinear data.

The study by Zang et al. (2022) presents a regional economic prediction model based on artificial neural networks (ANN) integrating Bayesian Vector Neural Networks (BVNN) and the backpropagation algorithm (BP). The study's main objective is to improve the training speed and accuracy of regional economic predictions by simplifying the structure of the neural network. Data is collected from various economic regions and processed using attribute decomposition methods, importance ranking, and prediction rules. The model is compared with existing methods such as FWA-SVR and LSTM on WEO, APDREO, and AFRREO datasets. The results show that the BVNN_BP model achieves a prediction accuracy of up to 98%, surpassing previous methods. The study emphasizes that neural network technology can effectively handle nonlinear issues, especially in big data. The BVNN_BP model also minimizes prediction errors by accelerating convergence speed and optimizing the efficiency of regional economic analysis.

One approach is to use 1D CNN, which is effective in forecasting GDP growth (N'emeth et al., 2023). In fact, 1D CNN has been proposed as a "sweet spot" regarding architectural complexity, demonstrating consistently good forecasting performance in both testing phases (N'emeth et al., 2023). The study found that 1D CNN could produce accurate forecasts, with a relative RMSE of 0.624 and a relative MAE of 0.687, outperforming the benchmark model at a significance level of 5%. Another approach is to use weight-direct determination networks (WDD), which can handle regression tasks and provide advantages over traditional backpropagation algorithms (Mourtas et al., 2023). The WDD algorithm directly computes the ideal weight set, avoiding local minima and reducing computational complexity. A new multi-functional weight activation model for time series (MWASDT) has been introduced, which takes into account the unique features of the WDD-based model for binary classification and time series forecasting.

Jackie D. Urrutia et al. (2019a) used the Automatic Integrated Moving Average (ARIMA) and Bayesian Artificial Neural Network (BANN) to forecast the imports and exports of the Philippines, with the comparison of the two models being one of the main objectives of this study. Data was collected from the Philippine Statistics Authority with a total of 100 observations from the first quarter of 1993 to the fourth quarter of 2017. Furthermore, this study aims to identify the most suitable model among the forecasting models for the imports and exports of the Philippines, and the researchers will provide forecast values for imports and exports from the first quarter of 2018 to the fourth quarter of 2022 using the most appropriate model. The researchers conducted a statistical test to build and compare the statistical models of ARIMA and BANN for imports and exports, then applied forecasting accuracy measures such as MSE, NMSE, MAE, RMSE, and MAPE to compare the performance of the two models. By comparing the results, the researchers concluded that the Bayesian Artificial Neural Network is the most suitable model for forecasting the imports and exports of the Philippines. Using the paired T-test, the p-values for both imports and exports were greater than the significance level ($\alpha = 0.01$), indicating that there is no significant difference between the actual values and the predicted values for both imports and exports of the Philippines. This study may benefit the Philippine economy by considering forecasts of imports and exports that can be used in analyzing the trade deficit of the economy.

Cook and Hall (2017) used a neural network based on a single macroeconomic indicator - the monthly lag of the civilian unemployment rate to forecast the unemployment rate for 1, 3, 6, and 12 months ahead using years of unemployment data. Their model performed better than the SPF (Survey of Professional Forecasters) in the short term (1 and 3 months ahead), but did not outperform in the longer terms of 6 and 12 months.

Stone (1977) pointed out the consistency of non-parametric KNN estimation. This model is widely used for classification tasks such as object recognition, and due to its ease of implementation and interpretability, it is also used in applications such as handling missing data (Bertsimas et al., 2021) and reducing training datasets (Wauters & Vanhoucke, 2017) to better identify similar objects. KNN can identify recurring patterns in time series, and for this reason, it has been applied to financial time series models as in Ban et al. (2013). Al-Qahtani and Crone (2013) used KNN to forecast electricity demand in the UK and found that KNN outperformed other standard forecasting models. Rodríguez-Vargas (2020) found that KNN also outperformed two competing machine learning models, random forests and extreme gradient boosting, in terms of accuracy in predicting inflation. Overall, KNN has been regarded as one of the top ten algorithms in data mining (Wu et al., 2008). Furthermore, KNN is particularly suitable for cases with limited past observations, meaning very little historical information. As pointed out in Wauters and Vanhoucke (2017), artificial intelligence methods require a minimum number of observations to function normally, while for KNN, this limitation is not as strict, although a minimum number of observations is still required (Diebold & Nason, 1990). Therefore, we use the KNN model because it provides a simple methodology based on distance metrics to extract information from the past.

A Bayesian Vector Neural Network (BVNN) integrated with a Backpropagation (BP) model has also been proposed to predict regional economics (Zhang et al., 2022). This model uses a database collected based on the economy of a specific region, extracted and classified using knowledge-based computational analysis of neural networks. The proposed model reduces errors by accelerating convergence speed and accuracy for each dataset. Additionally, the Lasso backpropagation neural network method has been used to conduct financial analysis and predictions for major global economies (Shi, 2024). This model analyzes and classifies the real Gross Domestic Product of the top 30 countries in the global ranking and uses multi-layer hidden variable analysis of neural networks to facilitate the analysis and prediction of national economic trends.

Meanwhile, the study by Munka and Kyryliuk (2022) uses artificial neural networks (ANN) to predict economic indicators of Ukraine during the period of 2022-2023. The prediction model is built based on a backpropagation neural network with a sigmoid activation function. The accuracy of the model is evaluated through Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) metrics. The forecast results indicate that Ukraine's GDP may slightly decrease, and the role of the private sector in the country's fixed asset structure will increase, along with an increase in investment capital and export revenue. However, state investment and average wages are likely to decrease. The labor force is predicted to remain stable. The study suggests that using artificial neural networks in economic forecasting not only provides high accuracy but also offers a powerful tool for analysis and planning in the context of global economic fluctuations.

Jackie D. Urrutia et al. (2019b) aimed to forecast the Gross Domestic Product (GDP) of the Philippines from the first quarter of 2018 to the fourth quarter of 2022. Furthermore, this study identifies the most suitable model between the Automatic Integrated Moving Average and the Bayesian Artificial Neural Network that can forecast the GDP of the Philippines. The researcher used data from the first quarter of 1990 to the fourth quarter of 2017 with a total of 112 observations. Statistical tests were conducted in the study to form and compare the statistical models of ARIMA and Bayesian ANN. The study concluded that ARIMA (1,1,1) and Bayesian ANN can forecast the GDP of the Philippines. The researcher used forecasting accuracy measures such as MSE, NMSE, MAE, RMSE, and MAPE to compare the performance of the two models. In this paper, the most suitable model obtained was the Bayesian ANN. The paired T-test concluded that there is no significant difference between the actual values and the predicted values. This study aids economics specifically in economic forecasting and analysis.

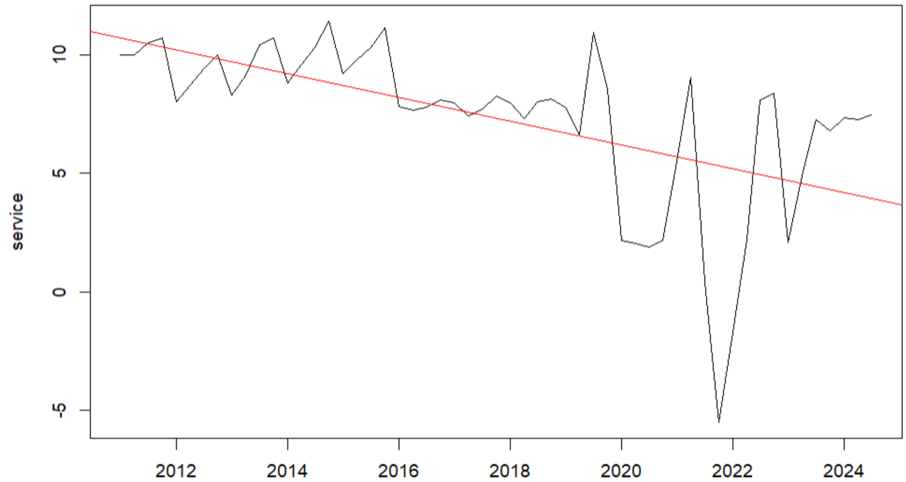
The research by Huang et al. (2007) focuses on the role of artificial neural networks (ANN) in financial and economic forecasting, which is a significant challenge due to the nonlinear, complex, and volatile nature of the related data. Traditional forecasting methods, such as time series analysis, do not always achieve high effectiveness in complex cases. The research data consists of financial and economic data from various sources, including exchange rates, stock market indices, and economic growth indices. This data is often organized in univariate (single variable) or multivariate (multiple variables) formats. The research methods employed include various neural network architectures such as multilayer perceptron (MLP), recurrent neural networks (RNNs), and radial basis function networks (RBFNs). An integrated approach combining ANN with other technologies, such as nonlinear ensemble methods, is also proposed to improve forecasting performance. Results from ANN applications demonstrate superior effectiveness in predicting exchange rates, stock market index values, and economic growth. However, the performance of ANN depends on the network architecture, input variables, and training methods. Some studies have noted that ANN combined with other predictive techniques, such as linear statistics, can enhance predictive capabilities.

The research by Ugulava (2019) emphasizes the role of ANN in forecasting regional economic indicators, particularly in nonlinear, dynamic, and unstable economic environments. In the context of the regional economy, ANN offers significant potential to improve the accuracy and effectiveness of economic forecasts. Using data from the Imereti region of Georgia, including regional gross domestic product (RGDP), foreign direct investment (DFI), fixed asset investment (FAI), labor force (EMP), business turnover (BT), and consumer price index (CPI). The data was collected during the period from 2006 to 2017 and was standardized for use in ANN models. The study utilized a three-layer perceptron neural network, with an 8-4-2 node structure in the hidden layer, programmed in R language. The results from ANN were compared with linear regression models to test accuracy and fit. The results showed that ANN had high accuracy (98.48%), outperforming linear regression. ANN demonstrated superior capability in predicting nonlinear and dynamic indicators, despite the "overfitting" issue in training. The study concludes that ANN is a useful and reliable tool for regional economic research, although further testing with larger datasets is needed.

3. Research Methodology

3.1. Data Description

The data on the growth rate of value-added services in Ho Chi Minh City is collected quarterly, semi-annually, every nine months, and annually from 2011 to 2024. The data used to apply the model will be collected for up to nine months in 2024. The 12-month growth rate data for the value-added services sector in Ho Chi Minh City has been estimated by the General Statistics Office and is used for in-sample testing.



Source: Ho Chi Minh City Statistics Office

Fig. 1. Growth rate of value-added in the service sector of Ho Chi Minh City1

Table 1. Descriptive statistics of the GRDP growth rate data series of Ho Chi Minh City1

	N Statistic	Range Statistic	Minimum Statistic	Maximum Statistic	Sum Statistic	Mean		Std Deviation Statistic	Variance Statistic
						Statistic	Std. Error		
Service Growth (%)	55	16,900	-5,500	11,400	401,880	7,307	0,461	3,419	11,694
Valid N (listwise)	55								

Source: From data processing results

The relatively limited period of quarterly data from 2011 to 2024 does not significantly diminish the value of this study, particularly given the specific context and objectives of forecasting service-sector growth for Ho Chi Minh City. Firstly, this dataset represents the longest and most comprehensive series currently available for the city's service sector at the required frequency, making it the most practical and relevant choice. Secondly, the ANN model is particularly effective in capturing non-linear dynamics even with moderately sized datasets, thereby alleviating concerns about limited historical range. Additionally, the inclusion of the period covering significant economic disruptions, such as COVID-19, actually strengthens the model's adaptability to future shocks and economic variability. Lastly, through rigorous validation techniques such as cross-validation and sensitivity analysis, the research ensures robust predictions despite the relatively constrained time span of the available data.

3.2. Testing the stationarity of the data

According to Fig. 1, it can be seen that this time series data is non-stationary. Therefore, it is necessary to take the first difference of this data series to examine the stationarity of the first difference series. Taking the difference in the time series will help eliminate trends, seasonality, or cycles in the data, allowing the data to revolve around the mean value of the series.

In addition, the ACF graph can be used to determine the stationarity of the data series. For stationary time series, the ACF will decrease to 0 relatively quickly, while for non-stationary time series, decreasing to 0 occurs slowly. Furthermore, for non-stationary series, the autocorrelation value r1 is often positive and significant.

The Augmented Dickey-Fuller (ADF) test results for the first difference series of the variable of interest were conducted. The test results show that the p-value is less than 0.05. Thus, we can reject the null hypothesis H0. This implies that the time series is stationary. Simply put, we can say that the first difference series of the growth rate of value-added in the service sector of Ho Chi Minh City has a structure that is time-independent and possesses a variance that does not change over time.

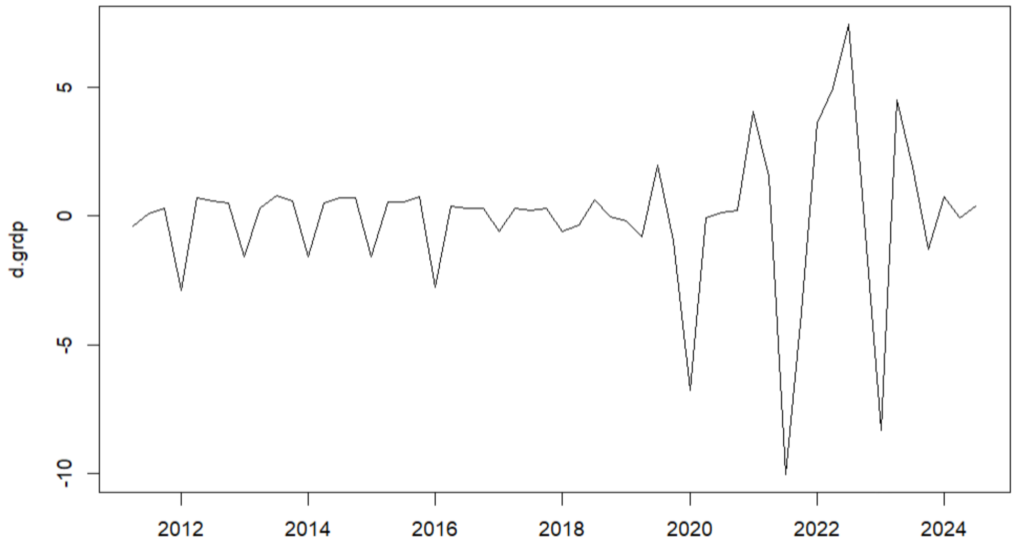


Fig. 2. First difference in the growth rate of value-added in the trade-service sector2

3.3. Applying the ANN model

3.3.1 Data Structure Selection Plan

The data is divided into two sets: 80% for training the model and 20% for testing the model's forecasting ability. This helps ensure the generalizability of the model when applied in practice.

3.3.2. Neural network design

The data on the growth rate of value-added in the service sector of Ho Chi Minh City is designed with 3 inputs and 1 output at a minimal level to help the model generalize better on unseen data while also avoiding issues such as overfitting.

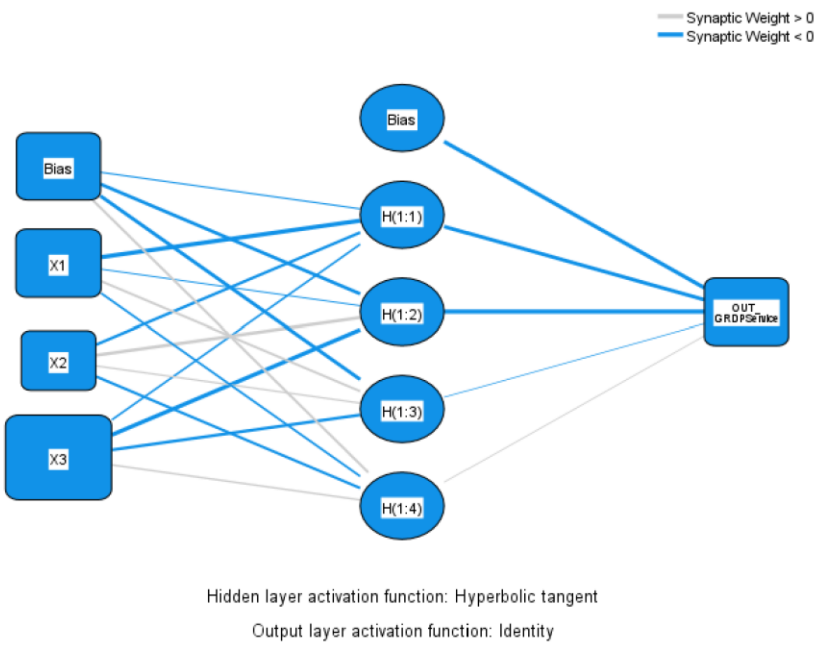
Theoretically, the Universal Approximation Theorem supports the construction of an ANN architecture consisting of one input layer, a single hidden layer, and one output layer. According to Tambe et al. (1996), this theorem establishes that an artificial neural network containing only one hidden layer—with a sufficiently large number of neurons—can approximate virtually any nonlinear relationship between input and output structures with arbitrary precision. Therefore, adding additional hidden layers does not necessarily enhance the approximation capability significantly; instead, it could increase unnecessary complexity and heighten the risk of model overfitting. Guided by these theoretical insights from Tambe et al. (1996), this study intentionally adopts a single-hidden-layer ANN structure to effectively capture the nonlinear characteristics inherent in economic growth data, while also maintaining simplicity and computational efficiency in practical forecasting scenarios. This design choice aligns closely with the study's objective of forecasting service-sector growth for Ho Chi Minh City, where nonlinear interactions among variables are clearly evident. In this hidden layer, the number of neurons is determined according to the formula of Fang and Ma (2009), specifically:

$$k = \log_2 n$$

Where n is the number of neurons in the input layer, which is 3 here. Thus, it will take the value of 1.6. However, to ensure objectivity, we will allow the number of neurons in the hidden layer to fluctuate within the range [1,4] and choose the model with the highest forecasting accuracy.k

Finally, the ANN model has one output layer representing the growth of the value-added services in Ho Chi Minh City. The hidden layer uses an activation function to optimize the learning process of the model.

Finally, the ANN model has one output layer representing the growth of the value-added services sector in Ho Chi Minh City. The hidden layer uses an activation function to optimize the learning process of the model.



Source: From data processing results

Fig 3. Structure of the network for the data on the growth rate of value-added services in Ho Chi Minh City1

3.3.3. Training the network

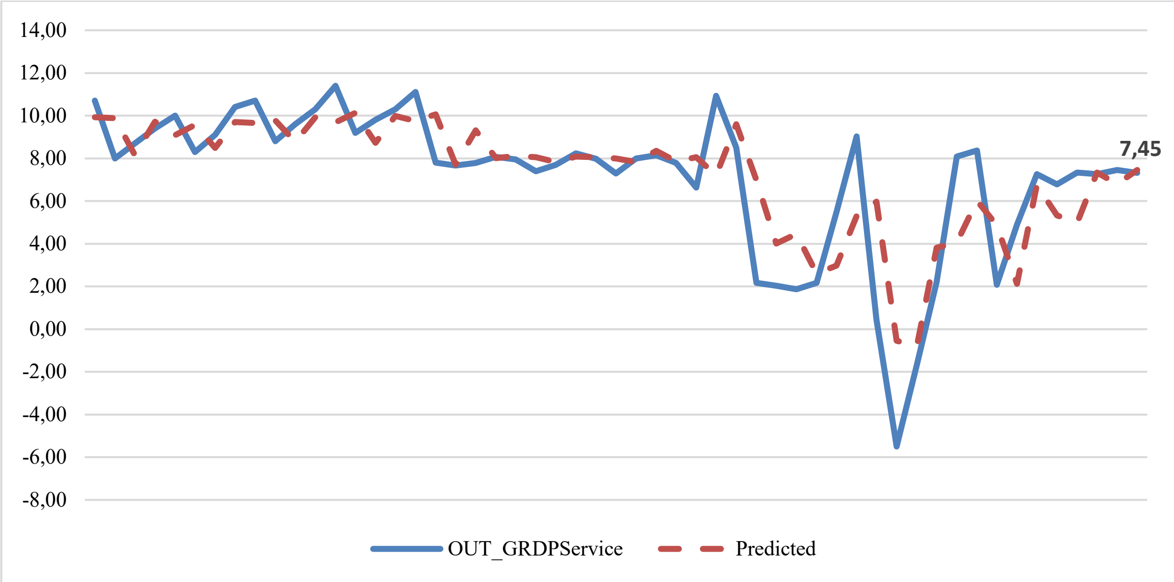
Table 2: Training the network for the data on the growth rate of value-added services in Ho Chi Minh City2

Predictor		Predicted				
		Hidden Layer 1				Output Layer OUT_GRDPService
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	
Input Layer	(Bias)	-0,171	-0,640	-0,685	0,452	
	X1	-1,067	-0,128	0,396	-0.360	
	X2	-0,486	0,569	0,232	-0,479	
	X3	-0,345	-0,821	-0,510	0,314	
Hidden Layer 1	(Bias)					-0.791
	H(1:1)					-0,705
	H(1:2)					-1,273
	H(1:3)					-0,023
	H(1:4)					0,040

Source: From data processing results

3.3.4. Model validation

The forecasted growth rate of value-added services for 12 months in 2024, according to the ANN model, is 7.45%.



Source: From data processing results

Fig. 4. Forecast results and actual values of the data on the growth rate of value-added services in the trade sector2

Table 3. Validation values for the forecast of the growth rate of value-added services in Ho Chi Minh City3

Validation criteria	MAPE	RMSE
Value	65,27	0,638

Source: From data processing results

On the other hand, based on the data on the growth rate of value-added services for 12 months in 2024 published by the General Statistics Office, which reached 7.32%, the forecast result has a negligible error. Currently, the General Statistics Office estimates the economic growth of Ho Chi Minh City for 12 months in 2024 to be 7.17; however, the General Statistics Office has not published the growth rate of value-added services in Ho Chi Minh City. Therefore, the research team uses the data published in July 2024 to ensure data consistency.

3.3.5. Applying econometric models

The forecasted growth rate of value-added services for 12 months in 2024 according to the Single Exponential Smooth model, SARIMA model, Single Moving Average model, and Holt-Winter's Additive model is presented in the following table:

Table 4. Forecast results for the growth rate of value-added services in Ho Chi Minh City for 12 months in 20244

Model/Validation criteria	**MAPE (test dataset)**	**RMSE**	**Forecast results according to the model**
Single Exponential Smooth	65,89	1,18	7,46
Single Moving Average	90,49	1,66	7,46
SARIMA	89,59	1,51	7,08
Holt-Winter's Additive	93,66	2,04	7,51

Source: From data processing results

4. Comparing model results and selecting a model

Although the forecast results of both models do not differ much, based on the testing criteria, the ANN model has a higher accuracy in forecasting.

Table 5. Comparison of testing criteria and forecast results of the models5

Model/Validation criteria	**MAPE (test dataset)**	**RMSE**	**Forecast results according to the model**
Single Exponential Smooth	65,89	1,18	7,46
Single Moving Average	90,49	1,66	7,46
SARIMA	89,59	1,51	7,08
Holt-Winter's Additive	93,66	2,04	7,51
ANN	**65,27**	**0,638**	**7,45**

Source: From data processing results

The forecast results are consistent with previous studies, indicating that the ANN model provides more accurate forecast values.

5. Conclusion

The study has modeled and built a neural network, applying some econometric models to forecast the growth rate of value-added in the trade-service sector of Ho Chi Minh City on a quarterly, semi-annual, nine-month, and annual basis to test the reliability and accuracy of the forecast results. At the same time, the research results will also provide a basis for the city leadership to consider the possibility of achieving the growth targets set for the year, thereby making appropriate policy responses and proposing solutions to boost economic growth drivers to achieve the planned economic growth targets.

Additionally, the research results also show that in the context of economic shocks such as economic crises, epidemics, political conflicts, etc., traditional forecasting models will not be effective due to the unusual behavioral changes of economic agents. Therefore, the ANN model will provide better forecasts in cases of economic shocks as it is developed not based on economic theories and can be adjusted according to real contexts. Moreover, a significant advantage of the ANN model is its ability to learn and adjust forecast results to align with reality without relying on subjective opinions.

Finally, this study acknowledges that its geographic scope, specifically focusing on Ho Chi Minh City, might limit findings' direct applicability and scalability to other regions or cities with distinct economic structures. Although the ANN model developed demonstrates effectiveness in capturing the unique dynamics of the city's service-sector growth, caution is necessary when generalizing these results to broader contexts. Future research could address this limitation by extending similar methodologies to other regions or by incorporating comparative analyses across multiple cities, thereby enhancing the robustness and broader relevance of the forecasting approach.

References

Aaron Kreiner (2019). Can Machine Learning on Economic Data Better Forecast the Unemployment Rate?. Oberlin College and Nomura Securities, May 17, 2019.

Alamsyah, A., & Permana, M. F. (2018, August). Artificial neural network for predicting indonesian economic growth using macroeconomics indicators. In 2018 International Symposium on Advanced Intelligent Informatics (SAIN) (pp. 15-19). IEEE.

Al-Qahtani, F. H., & Crone, S. F. (2013, August). Multivariate k-nearest neighbour regression for time series data—A novel algorithm for forecasting UK electricity demand. In The 2013 international joint conference on neural networks (IJCNN) (pp. 1-8). IEEE.

Ban, T., Zhang, R., Pang, S., Sarrafzadeh, A., & Inoue, D. (2013). Referential k NN regression for financial time series forecasting. In Neural Information Processing: 20th International Conference, ICONIP 2013, Daegu, Korea, November 3-7, 2013. Proceedings, Part I 20 (pp. 601-608). Springer Berlin Heidelberg.

Bertsimas, D., Delarue, A., & Pauphilet, J. (2021). Prediction with missing data. stat, 1050, 7.

Ćetković, J., Knežević, M., & Žarković, M. (2022). Use of ANN model in economies. In E3S Web of Conferences (Vol. 363, p. 04058). EDP Sciences.

Diebold, F. X., & Nason, J. A. (1990). Nonparametric exchange rate prediction?. Journal of international Economics, 28(3-4), 315-332.

Fraz, T. R., & Fatima, S. (2020). Are Neural Network Models Truly Effective at Forecasting? An Evaluation of Forecast Performance of Traditional Models with Neural Network Model for the Macroeconomic Data of G-7 Countries. International Journal of Economic and Environmental Geology, 11(3), 49-52.

General Statistics Office of Vietnam (2023). Statiscal Yearbook of Viet Nam 2023. Retrieved from https://www.gso.gov.vn

Herbrich, R., Keilbach, M., Graepel, T., Bollmann-Sdorra, P., & Obermayer, K. (1999). Neural networks in economics: Background, applications and new developments. In Computational techniques for modelling learning in economics (pp. 169-196). Boston, MA: Springer US.

Holt, C. C. (2004). Forecasting seasonals and trends by exponentially weighted moving averages. International journal of forecasting, 20(1), 5-10. https://doi.org/10.1016/j.ijforecast.2003.09.015

Huang, W., Lai, K. K., Nakamori, Y., Wang, S., & Yu, L. (2007). Neural networks in finance and economics forecasting. International Journal of Information Technology & Decision Making, 6(01), 113-140.

Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.

Jackie D. Urrutia, Alsafat M. Abdul and Jacky Boy E. Atienza (2019b). Forecasting Philippines imports and exports using Bayesian artificial neural network and autoregressive integrated moving average. AIP Conference Proceedings 2192, 090015 (2019).

Jackie D. Urrutia, Paul Ryan A. Longhas , and Francis Leo T. Mingo (2019a). Forecasting the Gross Domestic Product of the Philippines using Bayesian artificial neural network and autoregressive integrated moving average. AIP Conference Proceedings (2019).

Kayakuş, M., Erdoğan, D., & Terzioğlu, M. (2023). Predicting the share of tourism revenues in total exports. Alphanumeric Journal, 11(1), 17-30.

Krispin, R. (2019). Hands-On Time Series Analysis with R: Perform time series analysis and forecasting using R. Packt Publishing Ltd.

Lashgari, A. (2023). Harnessing the Potential of Volatility: Advancing GDP Prediction. arXiv preprint arXiv:2307.05391.

Morris, W., Correa, A., & Leiva, R. (2023). Impact of COVID-19 containment measures on unemployment: A multi-country analysis using a difference-in-differences framework. International Journal of Health Policy and Management, 12.

Mourtas, S. D., Drakonakis, E., & Bragoudakis, Z. (2023). Forecasting the gross domestic product using a weight direct determination neural network. AIMS Math, 8, 24254-24273.

Munka, S., & Kyryliuk, Y. (2022). Forecasting Indicators of Economic Development of Ukraine Using an Artificial Neural Network. Path of Science, 8(1), 3018-3024.

National Center for Socio-Economic Information and Forecasting (2016), Project "Research on Medium-Term Socio-Economic Forecasting Methods in the Russian Federation and Their Applicability in Vietnam".

N'emeth, K., & Hadházi, D. (2023). GDP nowcasting with artificial neural networks: How much does long-term memory matter?. arXiv preprint arXiv:2304.05805.

Önder, E., Bayır, F., & Hepsen, A. (2013). Forecasting macroeconomic variables using artificial neural network and traditional smoothing techniques. Journal of Applied Finance and Banking, 3(4), 73-104.

Rodríguez-Vargas, A. (2020). Forecasting Costa Rican inflation with machine learning methods. Latin American Journal of Central Banking, 1(1-4), 100012.

Shi, J. (2024). Establishment of Economic Analysis Model Based on Artificial Intelligence Technology. International Journal of Advanced Computer Science & Applications, 15(5).

Stone, C. J. (1977). Consistent nonparametric regression. The annals of statistics, 595-620.

Thomas R. Cook and Aaron Smalter Hall (2017), Macroeconomic Indicator Forecasting with Deep Neural Networks. Kcfred Research Working Paper, September 2017, ISSN 1936-5330.

Ugulava, G. (2019). USE OF ARTIFICIAL NEURAL NETWORKS TO PREDICT TERRITORIAL ECONOMIC INDICATORS. Globalization and Business, 4(8), 143-146.

Wauters, M., & Vanhoucke, M. (2017). A nearest neighbour extension to project duration forecasting with artificial intelligence. European Journal of Operational Research, 259(3), 1097-1111.

Wu, X., Kumar, V., Ross Quinlan, J., Ghosh, J., Yang, Q., Motoda, H., ... & Steinberg, D. (2008). Top 10 algorithms in data mining. Knowledge and information systems, 14, 1-37.

Zhang, Q., Yan, L., Hu, R., Li, Y., & Hou, L. (2022). Regional economic prediction model using backpropagation integrated with bayesian vector neural network in big data analytics. Computational Intelligence and Neuroscience, 2022(1), 1438648.

Zhang, Q., Yan, L., Hu, R., Li, Y., & Hou, L. (2022). Regional economic prediction model using backpropagation integrated with bayesian vector neural network in big data analytics. Computational Intelligence and Neuroscience, 2022(1), 1438648.