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FORECASTING ECONOMIC GROWTH AND INFLATION IN VIETNAM: A COMPARISON BETWEEN THE VAR MODEL, THE LASSO MODEL, AND THE MULTI - LAYER PERCEPTRON MODEL

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Economic growth and inflation are two critical indicators of any economy in the world. Because of the importance of these two indicators to the economies, the forecast of economic growth and inflation has become an important issue and always has been paid attention from the national governments. This paper aimed to provide a comparison between economic growth and inflation by common current methods. Specifically, the forecasting model of economic growth and inflation is developed and estimated through 3 models: VAR, LASSO, and MLP. Given the data obtained in the period from 1996 to 2020, the empirical results show that according to all three indicators, RMSE, MAPE, and MSE, the forecasting model of economic growth by LASSO model is the most accurate while the forecasting model of inflation by VAR model is the most accurate. Even though the MLP model has not shown high predictive efficiency in this paper, it is still a productive tool of the future because it describes the nonlinear relationships between variables in the model and can visually map these nonlinear relationships.

Keywords: *VAR, LASSO, MLP.*

JEL Classifications: *C53, C63, E31*

1. Introduction

Economic growth and inflation are two critical indicators of any economy in the world. Economic growth reflects the development of a country, helping to enhance its status and attract investment into that country. Economic growth affects implementing social policies, changing the structure of economic sectors, forming new industries, and creating many new jobs for the residents. Contrary to economic growth, high inflation causes macroeconomic instability by affecting consumption, investment, saving, and every corner of an economy. Furthermore, high inflation in a country reduces public trust in that country's national currency.

Although they are considered two macroeconomic indicators that deeply affect socio-economic life, inflation and economic growth have a connection. This relationship has been indicated in many

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theories and empirical studies. Specifically, Keynes' theory shows that countries have to accept a certain inflation level to grow the economy in the short term. However, this positive relationship does not exist forever. When inflation exceeds a threshold, economic growth decreases (Stockman, 1981; Ocran and Biekpe, 2007). In the long term, when economic growth has reached the optimal level, inflation will not affect the economic growth, but now inflation is the result of excessively supplying money to the economy.

Due to the importance of two variables to the economy, forecasting economic growth and inflation have become an important issue and always received national governments' attention. Because sustainable economic growth is the goal that all governments aim to stabilize the macroeconomy, improve labor qualification, apply advanced science and technology, improve organizations and production management, increase the efficiency of labor materials, and effectively take advantage of the associated natural resources with environmental protection. Besides, high inflation in any situation and any country reveals the government's limited ability to operate and manage the economy. Therefore, forecasting inflation has become a core business that any central bank in any country also has to perform. Accurate inflation forecasting will help the central bank implement the monetary policy to ensure economic growth and stabilize the value of the domestic currency.

Many methods of forecasting economic growth and inflation have been developed. Macroeconomy forecasting is a highly complex business. Over the past decades, by applying increasingly mathematical tools to economic research, economic forecasting methods have developed continuously. Mathematical and econometric models have been thoroughly applied in the forecasting business. Up to now, the forecasting methods of economic growth and inflation can be divided into quantitative methods and qualitative methods. The quantitative methods can be divided into causal methods (multivariate regression, quantile regression, logit regression, probit regression, etc.), time series methods (Moving average, trend and seasonal analysis, vector autoregressive, ARIMA analysis, etc.). The qualitative methods are divided into the Delphi method, the Exploratory analysis, and the Expert opinion collection.

However, so far, the accuracy of economic forecasting models is limited. International organizations such as Work Bank (WB) and International Monetary Fund (IMF) all have complex and meticulous forecasting models, but their forecasting results are always different from reality. Although forecasting is difficult, government authorities, policymakers, firms, etc., always need the economic forecasts as a basis for policy administration. The forecasts are not completely accurate but also reflecting the trend of economic fluctuations. In this paper, we forecast economic growth and inflation through vector autoregressive model (VAR), least absolute shrinkage and selection operator model (LASSO), multi-layer perceptron model (MLP).

2. Methodology

2.1. Forecasting Methods

2.1.1. Vector Autoregressive Model (VAR)

The Vector Autoregressive Model (VAR) is an econometric technique used to forecast and analyze an economy. The basic assumption of VAR is the present values of variables can be explained by past values of variables involved (Lütkepohl, 2009). The VAR(p) model has the following form:

$y_t = v + A_1 y_{(t+1)} + ... + A_t y_{(t-p)} + u_t$ (1)

where $y_t = (y_{1t},...,y_{Kt})^T$ is a (Kx1) random vector, A_i is fixed (KxK) coefficient matrix, $v = (v_1,...,v_K)^T$ is a fixed (Kx1) vector of intercept coefficients, $u_t=(u_{1t},...,u_{Kt})^T$ is a K-dimensional vector of white noise.

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The VAR model is performed in the following order: (i) Testing stationarity of time series, (ii) determining the optimal lag p for the VAR model, (iii) estimate the VAR model with the optimal lag p. In this paper, the Augmented Dickey-Fuller test (ADF) is used for testing stationarity. Determining the optimal lag p is based on the criterions such as Likelihood-Ratio statistic (LR), Akaike information criteria (AIC), Hannan-Quinn information criteria (HQ), Schwarz information criteria (SC), Final Prediction Error (FPE) criterion.

The VAR model has some advantages, namely (i) no need to determine endogenous and exogenous variables in the model; (ii) estimating a system of simultaneous equations will give better estimates than estimating each equation separately, (iii) the method to build and estimate the VAR model is simple, and variables in the model can be endogenous variables which are performed through the lagged variables of themselves or other variables in the model. Besides of advantages, the VAR model has some disadvantages are (i) the variables in the model must be stationary so that there is no spurious regression occurring when estimating the parameters in the model; (ii) unlike simultaneous equation models, the VAR model is still based on theories and uses less a priori information, the exclusion or inclusion of new variables plays an important role in determining model.

2.1.2. Least Absolute Shrinkage and Selection Operator Model (LASSO)

$$y_i = \beta_0 + \sum_{j=1}^{p} x_{ij}\,\beta_j \qquad (2)$$

where y_i is dependent variable and p is the number of explanatory variables $x_i = (x_{i1},\ldots,x_{ip})$. With xi and yi are belong to the set Rp and set R, respectively. $\beta=(\beta_1,\ldots,\beta_p)^T$ is the weight vector belong to the set R^p and intercept coefficient β_0 in the set R.

The pair (β_0,β) is estimated by the OLS model based on minimizing squared error as follows:

$$\underset{\beta_0,\beta}{\text{minimize}}\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{p}x_{ij}\,\beta_j\right)^2\right\}=\frac{1}{N}\|y-\beta_0 1-X\beta\|^2 \quad (3)$$

where: $y=(y_1,\ldots,y_N)^1$, X is an Nxp matrix and $1=(1,\ldots,1)^T$. Equation (3) can be explained as follows:

$\beta=(X^T X)^{(-1)} X^T y$

With the OLS model, the pair (β0, β) calculated as above will be unbiased estimates. However, the variances of coefficient estimators will be large. Therefore, the efficiency of forecasts based on the OLS model will not be high. To increase the accuracy of the forecast, Hastie et al. (2015) suggest that it is possible to reduce the number of regression coefficients or set certain coefficients to 0. This way may lead to bias in estimating regression coefficients but will reduce variances of expected values and, therefore, increase the forecast's accuracy. This idea allows the modification of the OLS model to the LASSO model, which is implemented as follows:

$$\underset{\beta_0,\beta}{\text{minimize}}\left\{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\beta_0-\sum_{j=1}^{p}x_{ij}\,\beta_j\right)^2+\lambda\sum_{j=1}^{p}\beta_j\right\}=\frac{1}{N}\|y-\beta_0 1-X\beta\|^2+\lambda\,\|\beta\|$$

The main problem in the LASSO algorithm is to choose the optimal value of lambda. There are many methods to choose the optimal lambda value, such as Cross-validation, Theory-driven, and Information Criteria. In this paper, we use the Cross-validation method to select the optimal lambda value.

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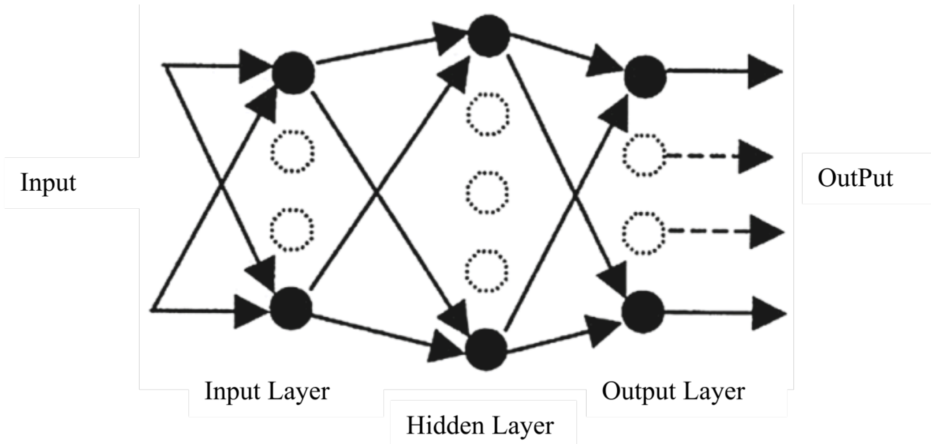
The least absolute shrinkage and selection operator model (LASSO) has some advantages, namely (i) determining the independent variables in the model that mainly impact on the dependent variable, and the other independent variables have no significant impact, their regression coefficients will be approximated 0; (ii) This method will minimize the variances of estimators, thus giving more accurate forecasting results than other methods. However, a disadvantage of this method is the estimators of regression coefficients obtained will be biased. Therefore, this method will be best suited for forecasting purposes.

2.1.3. Multi-layer perceptron model (MLP).

Artificial Neural Networks - ANNs are computational tools that simulate neural networks in the human brain and can map nonlinear relationships between inputs and outputs. The analytical efficiency of ANNs has remarkable results in many different fields, and artificial neural networks are increasingly being used in statistical scientific research (Movagharnejad et al., 2011).



Source: Boroushaki et al., (2003)

Figure 1: *A Typical MLP Neural Network*

Figure 1 shows that a typical MLP model has one input layer, one hidden layer, and one output layer. The data stream from the input layer to the output layer through the hidden layer (s), and the weights are then determined by the learning process performed by the back-propagation algorithm. This algorithm optimizes the quadratic cost function. The independent variables determine the number of neurons in the input layer, and the number of neurons in the output layer represents the number of dependent variables (Boroushaki et al., 2003).

The MLP models have some advantages such as (i) the ability to continuously adapt the model to each research objective based on the given input and output data; (ii) a great advantage of the MLP model is that the building and estimation of the model are not based on economic theories about the relationship between the variables in the model, so when the economy has large fluctuations that change economic theories, the evaluation and analysis based on the MLP model will not be affected; (iii) according to the universal approximation theorem, the MLP model with hidden layers and neurons in each layer can represent any continuous function. Besides the advantages, the MLP model also has an outstanding disadvantage. There is no specific rule and formula for determining the number of hidden layers in the network and the number of neurons in each hidden layer.

This paper develops the MLP model with the input layer, including the explanatory variables for the output layers' fluctuations: economic growth and inflation, respectively. In theory, there could be one or several hidden layers, but the universal approximation theorem suggests that the MLP model with a single hidden layer with a sufficiently large number of neurons can represent any input-output structure (Tambe et al., 1996). Therefore, the proposed MLP model has a single hidden layer.

2.2. The forecasting model of economic growth and inflation

Many different macroeconomic variables can explain inflation and economic growth. Many domestic and foreign researches have shown that economic growth and inflation can be explained through variables such as industrial output, money supply (Vo Tri Thanh et al., 2001; Vinh and Fujita, 2007), labor force (Akinboade et al., 2004; Kim, 2001), foreign investment capital (Kim, 2001), trade value (Camen, 2006; Vinh and Fujita, 2007). In this paper, we use these variables to forecast economic growth and inflation in Vietnam. The data is collected in the period from 1996 to 2019 from reliable sources such as the International Monetary Fund (IMF), the State Bank of Vietnam.

The proposed research model has the following form:

$y_t = v + A_1 y_{(t-1)} + ... + A_p y_{(t-p)} + u_t$

Where: $y_t = (y_{1t},...,y_{Kt})^T$ is a (7x1) vector of the variables namely economic growth year t (GDP_t), inflation year t (INF_t), trade-to-GDP ratio year t ($TRADE_t$), the growth rate of labor force (H_t), industrial output to GDP ratio year t (IND_t), the growth rate of total liquidity year t (Mt), the foreign direct investment capital year t (FDI_t). A_i is the fixed (7x7) coefficient matrix, $v=(v_1,...,v_{tK})^T$ is a vectors of intercept coefficients, $u_t=(u_{1t},...,u_{Kt})^T$ is a vector of white noise.

Table 1: *The Variables in the forecasting model*

Notation	Descriptions	Source
GDP_t	Economic growth year t	Monetary Fund (IMF)
INF_t	Inflation year t	Monetary Fund (IMF)
$TRADE_t$	Trade-to-GDP ratio year t	Monetary Fund (IMF)
H_t	Growth rate of labor force year t	Monetary Fund (IMF),
IND_t	Industrial output to GDP year t	Monetary Fund (IMF)
M_t	Growth rate of total liquidity year t	The State Bank of Vietnam
FDI_t	Foreign direct investment capital year t	Monetary Fund (IMF)

Source: Proposed by the author.

Besides, to forecast economic growth and inflation in Vietnam in 2021, we use the estimated values year 2020 of the variables in the research model (taking into account the impact of COVID -19 pandemic) that are collected from the General Statistics Office of Vietnam

Table 2: *Figures for 2020 (expected) under the impact of COVID-19*

Indicators	Number
Economic growth	2.91%
Foreign Direct Investment Capital	USD 19.97 billions
Growth rate of labor force	1.14%
Industrial output (%GDP)	29.31%
Inflation	2.31%
The growth rate of total liquidity	8.63%

Source: General Statistics Office of Vietnam.

Due to the limitation of research data in Vietnam, in this paper, we use the optimal lag p = 1 to estimate the VAR model as well as the LASSO and MLP models.

This paper forecasts Vietnam's inflation and economic growth in 2021 according to 3 models VAR, LASSO, and MLP. The best forecasting method will be chosen based on three indicators, namely RMSE, MAPE, and MSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}}$$

$$MAPE = \frac{\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{y_i}}{N}$$

$$MSE = \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}$$

Where y_i is the real output value, $\hat{y}_i$ is the forecasting values obtained from the VAR model, the LASSO model, and the MLP model.

3. Empirical Result

3.1. The Estimated Result of the VAR Model

Before estimate the VAR model, we test the stationarity of the time series in the research model. The result is shown in Table 3.The result of the stationarity test shows that most of the time series in the research model is not stationary at level but stationary at the first difference. Therefore, the first differences of the time series will be used for the VAR model.

The result of the stationarity test indicates that all of the time series in the forecasting model is stationary at the first difference. Therefore, we use the first differences to estimate the VAR model with the optimal lag of 1. Table 4 represents the result of the VAR estimation.

3.2. The Estimated Result of the LASSO model

Next, we estimate the LASSO model with the dependent variables being economic growth and inflation, respectively. The lambda coefficients in the models are chosen by the Cross-Validation (CV) method. The estimated result represents in Table 5.

Table 5 shows that the chosen lambda value is 0.08687, with the CV mean prediction error is 1.02354. Besides, at this lambda value, there are five variables with their coefficients different from 0. They are D(TRADE), D(H), D(IND), D(FDI), and D(M).

Table 6 shows that the chosen lambda value is 0.98038, with the CV mean prediction error is 1.02354. In addition, at this lambda value, there are two variables with their coefficients with non-zero values. They are D(H) and D(GDP).

Table 3: *The Result of Stationarity Test*

Variables	T Statistic (p-value)	Variables	T Statistic (p-value)
FDI	0.7513 (0.9906)	**ΔFDI**	-3.7315 (0.0109)
GDP	-3.8468 (0.0081)	**ΔGDP**	-5.3654 (0.0003)
H	-3.1564 (0.0392)	***ΔH***	-4.2479 (0.0049)
IND	-2.0729 (0.2564)	***ΔIND***	-4.2366 (0.0035)
INF	-2.9632 (0.0536)	***ΔINF***	-5.8548 (0.0001)
M	-4.4188 (0.0022)	***ΔM***	-6.5853 (0.0000)
TRADE	-0.1748 (0.9639)	***ΔTRADE***	-6.1028 (0.0001)

Source: Author's calculation

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Table 4: *The VAR Estimation Result*

	D(FDI)	D(GDP)	D(H)	D(IND)	D(INF)	D(TRADE)	D(M)
D(FDI(-1))	0.052904	-1.74E-10	-7.54E-13	-6.66E-11	1.44E-09	-2.02E-09	-5.20E-09
	(0.25448)	(1.9E-10)	(1.9E-12)	(2.5E-10)	(1.1E-09)	(1.6E-09)	(2.5E-09)
	[0.20789]	[-0.91888]	[-0.39843]	[-0.27090]	[1.31957]	[-1.27420]	[-2.07270]
D(GDP(-1))	-2.75E+08	0.260420	0.001818	-0.087113	0.825830	-0.637420	-4.903124
	(5.0E+08)	(0.36903)	(0.00368)	(0.47910)	(2.12007)	(3.07971)	(4.88490)
	[-0.55395]	[0.70568]	[0.49346]	[-0.18183]	[0.38953]	[-0.20697]	[-1.00373]
D(H(-1))	1.42E+10	5.435762	0.794292	-15.55002	-57.63301	-33.55718	-50.22842
	(7.9E+09)	(5.87484)	(0.05865)	(7.62706)	(33.7505)	(49.0275)	(77.7653)
	[1.79510]	[0.92526]	[13.5432]	[-2.03880]	[-1.70762]	[-0.68446]	[-0.64590]
D(IND(-1))	1.87E+08	0.071538	-0.001056	-0.095331	-1.894747	-2.855632	-4.303367
	(2.3E+08)	(0.16793)	(0.00168)	(0.21802)	(0.96475)	(1.40144)	(2.22290)
	[0.83060]	[0.42600]	[-0.63014]	[-0.43726]	[-1.96398]	[-2.03764]	[-1.93593]
D(INF(-1))	-81081685	0.006983	0.000608	0.081004	-0.762704	-1.080124	0.360751
	(6.9E+07)	(0.05165)	(0.00052)	(0.06706)	(0.29675)	(0.43107)	(0.68375)
	[-1.16890]	[0.13519]	[1.17955]	[1.20792]	[-2.57018]	[-2.50566]	[0.52761]
D(TRADE(-1))	58022562	-0.025592	-0.000291	0.052261	0.194807	0.188160	0.374043
	(5.2E+07)	(0.03838)	(0.00038)	(0.04982)	(0.22047)	(0.32026)	(0.50798)
	[1.12591]	[-0.66687]	[-0.75950]	[1.04896]	[0.88362]	[0.58753]	[0.73634]
D(M(-1))	20072543	0.024188	0.000202	0.026056	-0.021061	0.244767	-0.433664
	(2.0E+07)	(0.01525)	(0.00015)	(0.01980)	(0.08764)	(0.12731)	(0.20193)
	[0.97985]	[1.58562]	[1.32605]	[1.31565]	[-0.24032]	[1.92267]	[-2.14763]
C	5.66E+08	0.354493	0.002669	-0.487675	-2.982052	5.371239	0.468620
	(4.1E+08)	(0.30679)	(0.00306)	(0.39829)	(1.76247)	(2.56024)	(4.06094)
	[1.37506]	[1.15550]	[0.87159]	[-1.22443]	[-1.69197]	[2.09794]	[0.11540]
R-squared	0.409773	0.335334	0.966023	0.600332	0.513326	0.600452	0.562840
Adj. R-squared	0.114660	0.003000	0.949035	0.400497	0.269989	0.400678	0.344260
Sum sq. resids	2.15E+19	11.90765	0.001187	20.07000	393.0021	829.3035	2086.435
S.E. equation	1.24E+09	0.922251	0.009207	1.197319	5.298262	7.696490	12.20783
F-statistic	1.388528	1.009028	56.86402	3.004148	2.109528	3.005657	2.574983
Log likelihood	-486.8621	-24.46417	76.88702	-30.20667	-62.92714	-71.14163	-81.29051
Akaike AIC	44.98746	2.951288	-6.262456	3.473334	6.447922	7.194694	8.117319
Schwarz SC	45.38420	3.348031	-5.865713	3.870076	6.844665	7.591436	8.514062
Mean dependent	6.32E+08	-0.051575	-0.019525	0.109751	-0.018805	5.474394	0.520352
S.D. dependent	1.32E+09	0.923637	0.040783	1.546373	6.201100	9.941745	15.07553

Source: Author's calculation

Table 5: *The estimated result of the LASSO model with the economic growth as the dependent variable*

ID	Description	lambda	No. of nonzero coef.	Out-of-sample R-squared	CV mean prediction error
2	first lambda	3.270688	0	0.1019	1.064068
40	lambda before	.0953423	5	-0.0605	1.024056
* 41	selected lambda	.0868723	5	-0.0599	1.02354
42	lambda after	.0791548	5	-0.0601	1.023693
90	last lambda	.0009101	6	-0.1813	1.14074

* lambda selected by cross-validation in final adaptive step.

	active
trade	x
h	x
ind	x
fdi	x
m	x
_cons	x

Legend:
b - base level
e - empty cell
o - omitted
x - estimated

Source: Author's calculation

Table 6: *The estimated result of the LASSO model with the inflation as the dependent variable*

ID	Description	lambda	No. of nonzero coef.	Out-of-sample R-squared	CV mean prediction error
1	first lambda	1.713237	0	0.1892	35.24454
6	lambda before	1.075962	2	-0.1541	34.20673
* 7	selected lambda	.9803769	2	-0.1528	34.16797
8	lambda after	.893283	2	-0.1543	34.21272
76	last lambda	.0015978	6	-0.2364	36.64582

* lambda selected by cross-validation.

	active
h	x
gdp	x
_cons	x

Legend:
b - base level
e - empty cell
o - omitted
x - estimated

Source: Author's calculation

3.3. The Estimated Result of the MLP model

We estimate the MLP model with the output variables being economic growth and inflation, respectively. We estimate the MLP model with three layers the input layer (independent variables in the model), the hidden layer, and the output layer (economic growth and inflation, respectively). In theory, the MLP model has one input layer, one output layer, and several hidden layers. However, the universal approximation theorem suggests that an MLP neural network with a single hidden layer with a sufficiently large number of neurons can represent any input-output structure (Tambe et al., 1996). In this paper, for convenience, we use three neurons in one hidden layer. The estimated results are shown in Figure 2.

3.4. Forecasting results of economic growth in 2021 using models

The research results show that forecasting economic growth by the LASSO model is the most accurate. Specifically, according to all three indicators such as RMSE, MAPE, and MSE, the LASSO model has more accurate forecasting results than the VAR and MLP models (see Table 7).

Next, we forecast the economic growth in 2021 by using all three models, VAR, LASSO, and MLP. The forecasting result represents in Figure 4.

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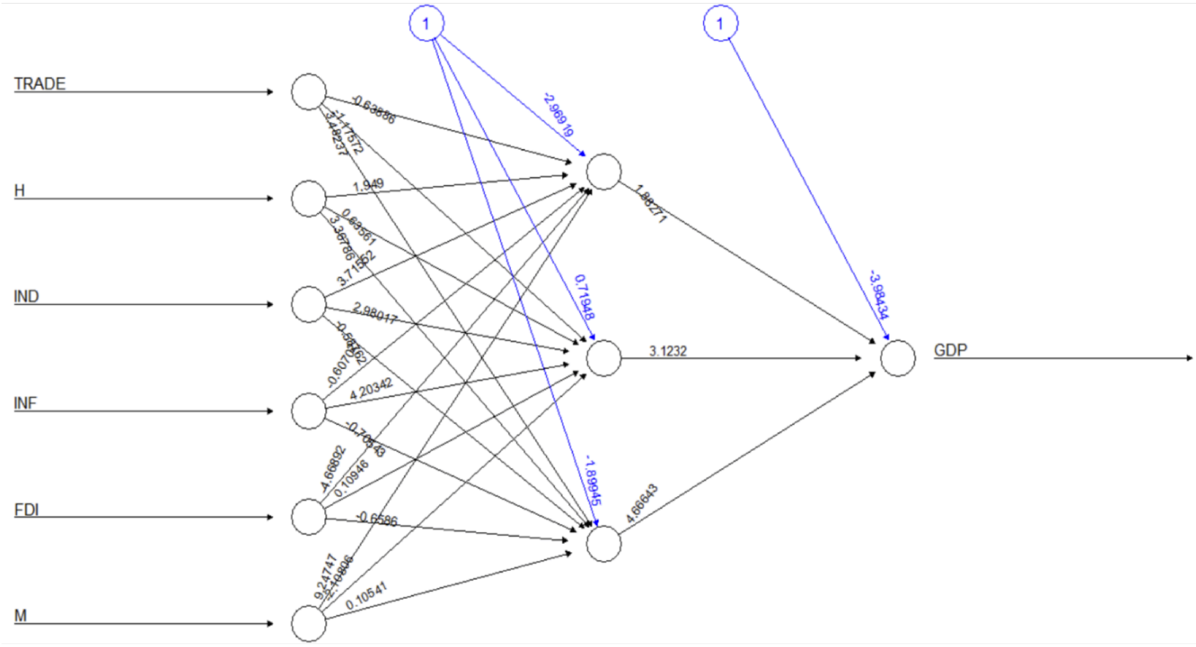
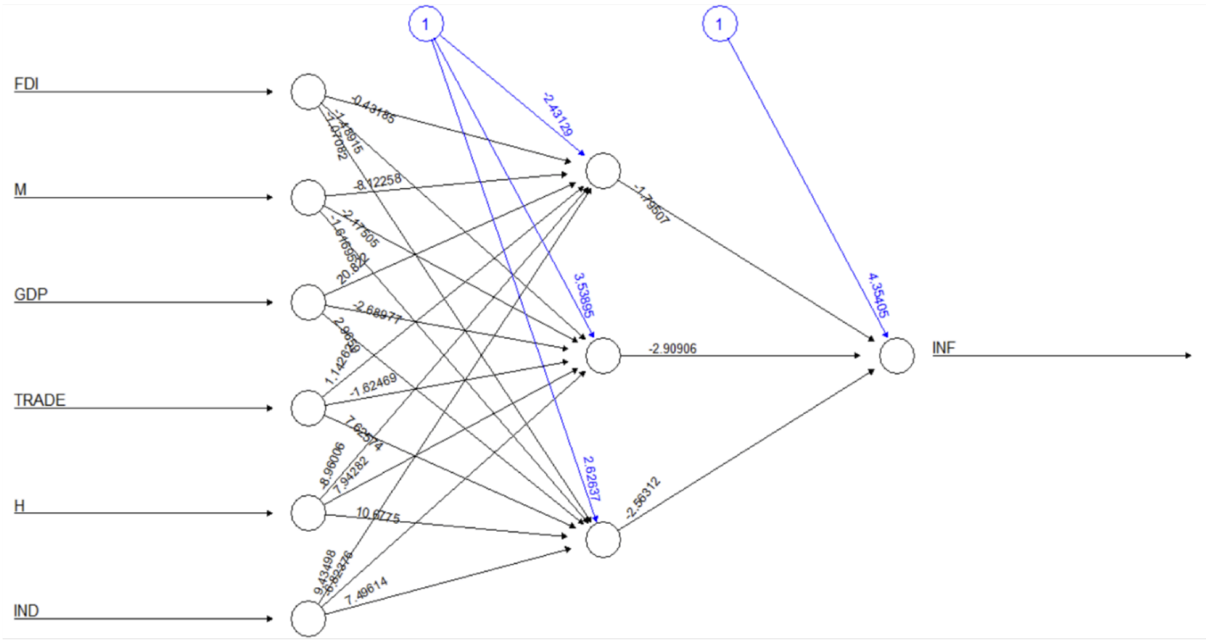


Source: Author's calculation

Figure 2: *The estimated result of the MLP model with the economic growth as the output variable*



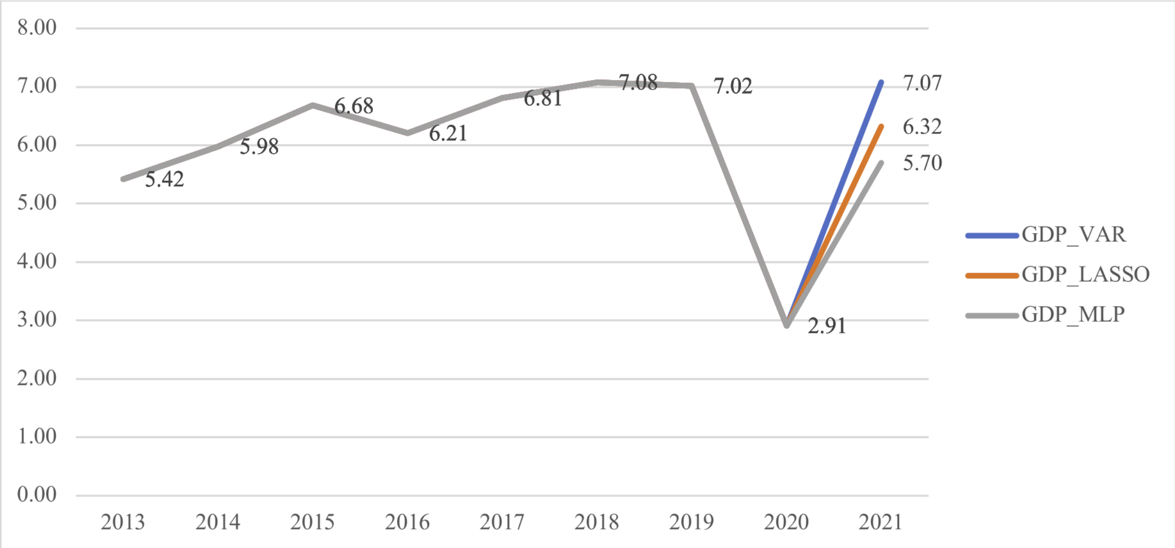
Source: Author's calculation

Figure 3: *The estimated result of the MLP model with the inflation as the output variable*

Table 7: *The result of RMSE, MAPE, and MSE indicators in the economic growth forecasting models*

Indicator	VAR	LASSO	MLP
RMSE	0.006135	0.006053	0.02308
MAPE	0.000737	0.000725	0.003436
MSE	0.003764	0.003664	0.053267

Source: Author's calculation



Source: Author's calculation

Figure 4: *Forecasting results of economic growth in 2021 using VAR, LASSO, and MLP models*

3.5. Forecasting results of inflation in 2021 using models

The research results show that forecasting inflation by the VAR model has the highest accuracy. Specifically, according to all three indicators such as RMSE, MAPE, and MSE, the VAR model will give higher accurate forecasting results than the VAR and MLP models (see Table 8)

Table 8: *The result of RMSE, MAPE and MSE indicators in the inflation forecasting models*

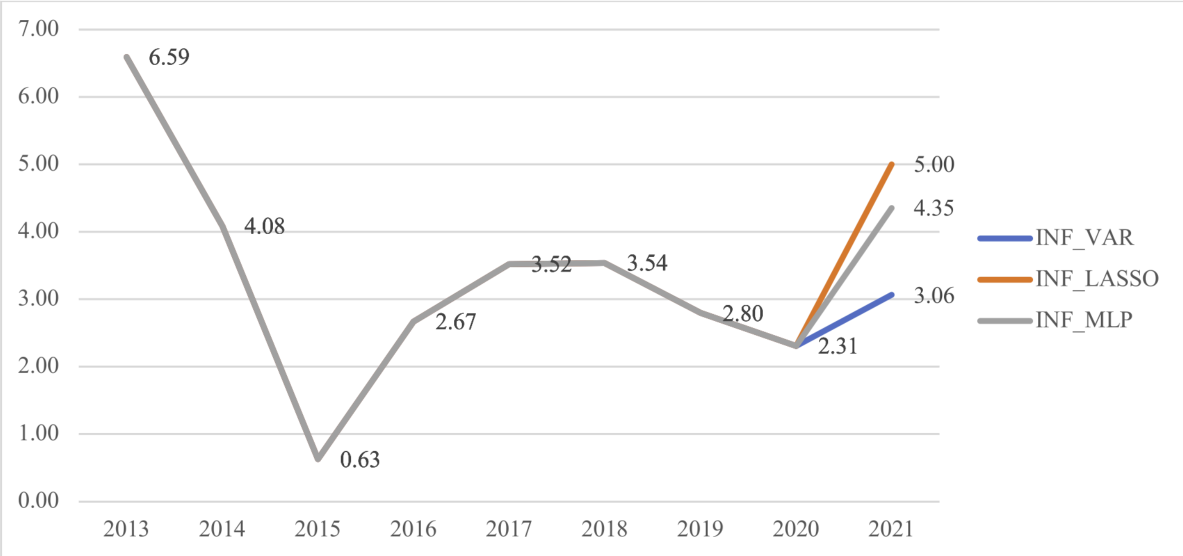
Indicator	VAR	LASSO	MLP
RMSE	0.015972	0.033199	0.019355
MAPE	0.008482	0.019292	0.025004
MSE	0.02551	0.11022	0.037462

Source: Author's calculation

Next, we make the inflation forecast for 2021 by using all three models, VAR, LASSO, and MLP. The forecasting result represents in Figure 5.

4. Conclusion

Economic growth and inflation are the basic indicators of the national economies. Therefore, many analysts, policymakers, and government authorities of countries have taken part in analyzing the situations, influencing factors, and forecasting the fluctuations of the two indicators.



Source: Author's calculation

Figure 5: *Forecasting results of inflation in 2021 using VAR, LASSO, and MLP models*

With the volatile and nonlinear nature of inflation and economic growth, in this paper, the MLP neural model as an effective tool to describe the nonlinear mapping relationship is developed to forecast the two variables. In addition, we also use other popular forecasting models such as the VAR model and the LASSO model. The forecasting results of the models are then compared to each other to find the best forecasting model. The results show that according to all three indicators, RMSE, MAPE, and MSE, forecasting economic growth by the LASSO model has the highest accuracy while forecasting inflation by the VAR model is the most accurate.

Although the MLP model has not shown high forecasting efficiency in this paper, this is still a forecasting tool of the future because it describes the nonlinear relationship between variables in the model and can visually map these nonlinear relationships. Besides, the forecasting results by the MLP model can be improved by the back-propagation algorithm. On the other hand, the reason for the low forecasting result by the MLP model in this paper also stems from the limitation of input data. Artificial Neural Networks - ANNs models in general and MLP neural models, in particular, are really effective when used with big data.

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Summary

Tăng trưởng kinh tế và lạm phát là hai chỉ tiêu quan trọng đối với bất kỳ nền kinh tế nào trên thế giới. Do tầm quan trọng của hai biến số này với nền kinh tế, việc dự báo tăng trưởng kinh tế và lạm phát trở thành vấn đề quan trọng và luôn nhận được sự quan tâm của chính phủ các quốc gia. Bài báo này nhằm cung cấp một sự so sánh về hiệu quả dự báo tăng trưởng kinh tế và lạm phát giữa các phương pháp phổ biến hiện nay. Cụ thể, mô hình dự báo tăng trưởng kinh tế và lạm phát được nhóm tác giả xây dựng và ước lượng thông qua 3 mô hình là VAR, LASSO, MLP. Với dữ liệu được thu thập trong giai đoạn 1996 - 2020, kết quả nghiên cứu cho thấy theo cả 3 chỉ số RMSE, MAPE và MSE, dự báo tăng trưởng kinh tế bằng mô hình LASSO có mức độ chính xác cao nhất trong khi dự báo lạm phát bằng mô hình VAR có mức độ chính xác cao nhất. Mặc dù mô hình nơ-ron MLP chưa cho thấy hiệu quả dự báo cao trong nghiên cứu này nhưng đây vẫn là công cụ dự báo của tương lai do mô tả được các quan hệ phi tuyến giữa các biến số trong mô hình và khả năng lập bản đồ trực quan về các mối quan hệ phi tuyến này.

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