การศึกษาการพยากรณ์ดัชนีราคาตลาดหลักทรัพย์แห่งประเทศไทย โดยใช้แบบจำลองโครงข่ายประสาทเทียม

SET INDEX PREDICTION USING ARTIFICIAL NEURAL NETWORK

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บทคัดย่อ

การศึกษาครั้งนี้มีวัตถุประสงค์เพื่อศึกษาความสามารถของโครงข่ายประสาทเทียมในการพยากรณ์ดัชนีราคาตลาดหลักทรัพย์แห่งประเทศไทย แบบจำลองประเภท NARX จำนวน 100 แบบจำลอง ที่มีการกำหนดกลุ่มของแบบจำลองออกเป็น 2 กลุ่ม โดยจำแนกตามการใช้ข้อมูลย้อนหลังคือ แบบ 5 วันย้อนหลัง และ 10 วันย้อนหลัง ได้ถูกนำมาใช้ในการทดลองและพิจารณา ในส่วนของกรรมวิธีในการวิจัยจะใช้วิธีแบ่งการทดสอบออกเป็น 4 รอบการทดสอบแบบมีผลต่อเนื่อง โดยแต่รอบของการทดสอบจะมีวัตถุประสงค์ในการทดสอบที่แตกต่างกัน นั่นคือ จะเริ่มทดสอบจากลักษณะโครงสร้างของโครงข่าย อัลกอริทึมที่ใช้ในการสอนแบบจำลอง รูปแบบของฟังก์ชั่นที่ใช้สำหรับเลเยอร์ชั้นใน และ รอบสุดท้ายจะเป็นการทดสอบรูปแบบฟังก์ชั่นที่ใช้สำหรับเลเยอร์ชั้นนอกสุด. ในส่วนของข้อมูลที่นำมาใช้ในการศึกษาครั้งนี้จะใช้ข้อมูลรายวันตั้งแต่วันที่ 27 มกราคม 2548 จนถึง 22 พฤษภาคม 2560 ด้วยจำนวนข้อมูลทั้งสิ้น 2920 ข้อมูล โดยข้อมูล 2828 แรกจะถูกนำมาใช้เป็นฐานข้อมูลสำหรับการสอนแบบจำลองและข้อมูลในส่วนที่เหลือจะถูกนำมาใช้สำหรับการทดสอบความสามารถของแบบจำลองในการพยากรณ์ดัชนีราคาตลาดหลักทรัพย์แห่งประเทศไทย

จากผลการศึกษาสามารถสรุปได้ว่าแบบจำลองประเภท NARX สามารถนำมาใช้พยากรณ์ดัชนีราคาตลาดหลักทรัพย์แห่งประเทศไทยได้อย่างเหมาะสมและมีประสิทธิภาพ เมื่อใช้กับข้อมูลเข้า 5 แบบดังนี้ ยอดซื้อขายสุทธิสิ้นวันของนักลงทุนสถาบันไทย ยอดซื้อขายสุทธิสิ้นวันของนักลงทุนต่างประเทศ อัตราแลกเปลี่ยนเงินตราระหว่างประเทศรายวันของไทยและสหรัฐอเมริกา ดัชนีราคาน้ำมันดิบรายวันของ WTI และ ดัชนีราคาปิดรายวันของดัชนีตลาดหลักทรัพย์ดาว์นโจนของสหรัฐอเมริกา โดยค่าความแม่นยำในการพยากรณ์ของแบบจำลองที่ดีที่สุดจะมีค่าสูงสุดอยู่ที่ 90.493%.

คำสำคัญ: โครงข่ายประสาทเทียม, NARX

ABSTRACT

In this study the ability of artificial neural network (ANN) in forecasting the daily SET stock exchange rate is investigated. 100 Non-linear Autoregressive Network with Exogenous Inputs (NARX) models along with two

groups of five-prior days and ten-prior days have been assessed. The series of testing for 4 rounds of 4 different testing objectives, network architecture, training algorithm, hidden transfer function and output transfer function, are the methodology used in this study. The period of dataset is from January 27, 2005 till May 22, 2017 with totally 2920 time-step observations and the first 2828 observations are treated as training dataset and the next observations are treated as prediction dataset for testing the model prediction ability.

The results of study show that NARX can be used to forecast SET index accordingly and effectively along with 5 input parameters: daily net buy/sell of Thai institute investors, daily net buy/sell of foreign investors, daily Thai-US currency exchange rate (THB/USD), daily closing price of WTI price index (WTI) and daily closing price of US Dow Jones industrial stock index, and the model performance for prediction is 90.493% of the value of the coefficient of determination for regression plot.

Keywords: Neural Network, NARX

1. Introduction

In studying some phenomenon, developing a mathematical model to simulate the non-linear relations between inputs and outputs is a hard task due to complicated nature of that phenomenon. Artificial intelligent systems such as artificial neural networks (ANN), fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) have been applied to model a wide range of challenging problems in science and engineering. ANN displays better performance in bankruptcy prediction than conventional statistical methods such as discriminant analysis and logistic regression. Investigations in credit rating process showed that ANN has better prediction ability than statistical methods due to complex relation between financial and other input variables. Bankruptcy prediction, credit risk assessment and security market applications are the other economical area that ANN has been widely applied.

1.1 Implementations

There are 4 areas of implementation that ANN can be applied

- Function Approximation / Input-Output and Curve Fitting / Non-linear Regression
- Pattern Recognition / Classification
- Data Clustering / Feature Extraction / Data Dimension Reduction
- Time Series Prediction / Dynamic Modeling / Non-linear Autoregression

1.2 Time Series NARX Feedback Neural Networks

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling. The defining equation for the NARX model is

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u))$$

where the next value of the dependent output signal y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. (Amin Hedayati Moghaddam, Moein Hedayati Moghaddam and Morteza Esfandyari, 2016: 89-93)

1.3 **Training Algorithms**

Below are the training algorithms which are used in this study

- Levenberg (trainlm)
- Bayesian Regularization (trainbr)
- BFGS Quasi-Newton (trainbfg)
- Resilient Backpropagation (trainrp)
- Scaled Conjugate Gradient (trainscg)
- Conjugate Gradient with Powell/Beale Restarts (traincgb)
- Fletcher-Powell Conjugate Gradient (traincgf)
- Polak-Ribiere Conjugate Gradient (traincgp)
- One Step Secant (trainoss)
- Variable Learning Rate Gradient Descent (traingdx)
- Gradient Descent with Momentum (traingdm)
- Gradient Descent (traingd)
- Gradient Descent with adaptive learning rate (traingda)

1.4 **Transfer Functions**

Below are the transfer functions which are used in this study

Table 1 List of Transfer Functions

Name	Input/Output Relation	Icon	MATLAB Function
Hard Limit	$a = 0 \quad n < 0$ $a = 1 \quad n \geq 0$		hardlim
Symmetrical Hard Limit	$a = -1 \quad n < 0$ $a = +1 \quad n \geq 0$		hardlims
Linear	$a = n$		purelin
Saturating Linear	$a = 0 \quad n < 0$ $a = n \quad 0 \leq n \leq 1$ $a = 1 \quad n > 1$		satlin
Symmetric Saturating Linear	$a = -1 \quad n < -1$ $a = n \quad -1 \leq n \leq 1$ $a = 1 \quad n > 1$		satlins
Log-Sigmoid	$a = \frac{1}{1+e^{-n}}$		logsig
Hyperbolic Tangent Sigmoid	$a = \frac{e^{n}-e^{-n}}{e^{n}+e^{-n}}$		tansig
Positive Linear	$a = 0 \quad n < 0$ $a = n \quad 0 \leq n$		poslin
Competitive	$a = 1$ neuron with max n $a = 0$ all other neurons	C	compet

2. Objectives of Study

1. To study how to use artificial neural network for predicting stock market index
2. To apply neural network approach for forecasting SET index

3. Empirical Methodologies

3.1 **Scope of Empirical Study**

This study will concern and focus only about quantitative analysis through artificial neural networks and the criteria for choosing models is considered by the quantitative R-measure which is the linear correlation between actual data and network outputs. Specifically, all total 100 models of time series NARX feedback neural networks will be assessed and each model will be trained and tested iteratively at least 3 times in order to make sure that all models are trained properly and give the reliable and stable testing results.

3.2 **Input Data**

- Daily Net Buy/Sell of Thai Institute Investors

This information can represent as the investment view of marginal investors.

- Daily Net Buy/Sell of Foreign Investors

This information represents as the foreign investor's investment view toward Thailand's economic perspectives.

- Daily Thai-US Currency Exchange Rate

This information represents as the foreign investor's investment view toward Thailand's economic perspectives.

- Daily closing price of WTI Price Index

The mainly reason to use this information as of input data because the majority of market cap of SET are crude oil companies.

- Daily closing price of US Dow Jones Industrial Stock Index

This information can represent as the investment momentum perspectives.

All input and output data have been collected from January 27, 2005 till May 22, 2017 with totally 2920 time-step observations.

3.3 **Dataset**

- Training / Validation / Test Dataset

The purpose of this dataset is to do model quantitative analysis with training, validating and testing dataset and the ratio of dividing is 0.7, 0.15 and 0.15 for training, validation and testing dataset respectively. This group of dataset covers data period from January 27, 2005 to December 30, 2016, with totally 2828 time-step observations

- Prediction Dataset

The purpose of this dataset is to do model forward testing. For this stage, the regression plot of this testing, R-measure, will be consider as the model key performance indicator. This dataset covers data period from January 4, 2017 to May 22, 2017, with totally 92 time-step observations.

3.4 **Key Model's Performance Indicator (R-measure)**

In this studying will use a regression plot for prediction dataset as a key model performance indicator, R-measure. R-measure is the linear correlation between actual data and network outputs as shown in below figure

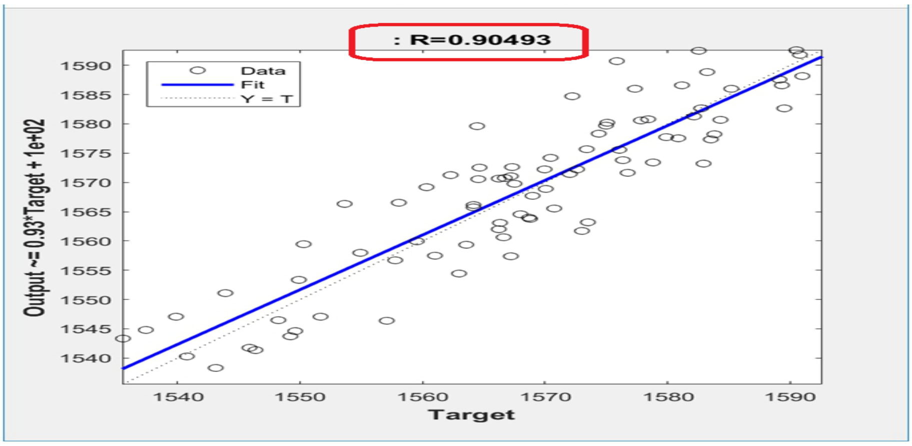

Figure 1 The value of R-Measure = 90.493%

From this regression plot, it shows the linear relationship between targets (T: actual data) and outputs of the testing model (Y) and in this case R-measure is 90.493%. The blue dark line represents the degree of model fitting.

3.5 **Empirical Topologies**

This study designs to do testing iteratively with 4 rounds of different objective testing.

- Round 1 – Neural Network Architecture

This round will cover 2 groups of models, 5-lag of time (t-5) and 10-lag of time (t-10) for both input and output time-series data, and each group will be conducted with many simulations of the neural network architecture. Totally 48 models will be assessed in this round.

- Round 2 – Neural Network Algorithm

This round still maintains 2 groups of models (t-5 and t-10) but only the best performance model of each group from the previous round will be further evaluated with many algorithms. Totally 24 models will be assessed in this round.

- Round 3 – Hidden Layer Transfer Function

This round will maintain only one the best performance model form the previous round and the model will be further investigated with many hidden layer transfer functions. Totally 14 models will be assessed in this round.

- Round 4 – Output Layer Transfer Function

This round will maintain only one the best performance model form the previous round and the model will be further investigated with many output layer transfer functions. Totally 14 models will be assessed in this round.

4. Empirical Results

Below are the testing results for round-1, round-2, round-3 and round-4.

Table 2 Empirical Result for Round-1

Models						R(%)	
Architecture			Algorithm	Transfer Function		Group	
No.	Layers	Neurons		Hidden	Output	t-5	t-10
1	1	10-1	trainlm	tansig	purelin	80.58	77.333
2		20-1	trainlm	tansig	purelin	81.856	64.216
3		30-1	trainlm	tansig	purelin	79.929	85.974
4		40-1	trainlm	tansig	purelin	85.609	67.256
5		50-1	trainlm	tansig	purelin	83.952	57.533
6		60-1	trainlm	tansig	purelin	88.231	75.616
7		70-1	trainlm	tansig	purelin	85.76	41.866
8		80-1	trainlm	tansig	purelin	77.493	66.411
9		90-1	trainlm	tansig	purelin	64.751	55.469
10	2	5-5-1	trainlm	tansig	purelin	87.029	87.71
11		10-10-1	trainlm	tansig	purelin	83.132	81.2
12		15-15-1	trainlm	tansig	purelin	54.745	74.351
13		20-20-1	trainlm	tansig	purelin	73.093	79.04
14		25-25-1	trainlm	tansig	purelin	50.306	50.639
15		30-30-1	trainlm	tansig	purelin	30.317	58.106
16	3	5-5-5-1	trainlm	tansig	purelin	88.489	89.309
17		10-10-10-1	trainlm	tansig	purelin	86.593	80.903
18		15-15-15-1	trainlm	tansig	purelin	81.161	77.34
19		20-20-20-1	trainlm	tansig	purelin	61.536	62.354
20	4	5-5-5-5-1	trainlm	tansig	purelin	89.046	89.533
21		10-10-10-10-1	trainlm	tansig	purelin	73.383	81.416
22	5	5-5-5-5-5-1	trainlm	tansig	purelin	89.073	89.893
23	6	5-5-5-5-5-5-1	trainlm	tansig	purelin	88.556	88.626
24	7	5-5-5-5-5-5-5-1	trainlm	tansig	purelin	87.671	86.506

From this testing result, the selected models for this round is Model No. 22 - 5 layers and each layer contains 5 neurons (5-5-5-5-5-1) for both groups of t-5 and t-10 with %R=89.073% and 89.893% respectively.

Table 3 Empirical Result for Round-2

Models						R(%)	
Architecture			Algorithm	Transfer Function		Group	
No.	Layers	Neurons		Hidden	Output	t-5	t-10
1	5	5-5-5-5-5-1	trainlm	tansig	purelin	89.073	89.893
2			trainbr	tansig	purelin	87.732	78.275
3			trainbfg	tansig	purelin	56.443	38.088
4			trainrp	tansig	purelin	38.871	65.65
5			trainscg	tansig	purelin	78.663	77.553
6			traincgb	tansig	purelin	84.837	86
7			traincgf	tansig	purelin	85.107	71.476
8			traincgp	tansig	purelin	80.503	48.697
9			trainoss	tansig	purelin	70.528	85.53
10			traingdx	tansig	purelin	-3.4283	11.497
11			traingdm	tansig	purelin	15.007	45.131
11			traingd	tansig	purelin	-24.772	-6.5819
12			traingda	tansig	purelin	-9.046	-34.547

From this testing result, the selected models for this round is Model No. 1 - 5 layers and each layer contains 5 neurons (5-5-5-5-5-1) for group of t-10 with %R=89.893%.

Table 4 Empirical Result for Round-3

Models						R(%)
Architecture			Algorithm	Transfer Function		Group
No.	Layers	Neurons		Hidden	Output	t-10
1	5	5-5-5-5-5-1	trainlm	tansig	purelin	89.893
2			trainlm	logsig	purelin	89.803
3			trainlm	hardlim	purelin	23.125
4			trainlm	hardlims	purelin	0.00*
5			trainlm	netinv	purelin	11.433
6			trainlm	poslin	purelin	87.028
7			trainlm	purelin	purelin	90.493
8			trainlm	radbas	purelin	53.638
9			trainlm	radbasn	purelin	84.192
10			trainlm	satlin	purelin	88.699
11			trainlm	satlins	purelin	89.549
12			trainlm	softmax	purelin	84.495
13			trainlm	tribas	purelin	81.956
14			trainlm	elliotsig	purelin	89.025
15			trainlm	compet	purelin	0.00*

0.00* is not equal to zero but it is very very less value

From this testing result, the selected models for this round is Model No. 7 - 5 layers and each layer contains 5 neurons (5-5-5-5-5-1) for group of t-10 along with hidden transfer function 'purelin' with %R=90.493%.

Table 5 Empirical Result for Round-4

Models						R(%)
Architecture			Algorithm	Transfer Function		Group
No.	Layers	Neurons		Hidden	Output	t-10
1	5	5-5-5-5-5-1	trainlm	purelin	tansig	76.803
2			trainlm	purelin	logsig	81.689
3			trainlm	purelin	hardlim	0.00*
4			trainlm	purelin	hardlims	0.00*
5			trainlm	purelin	netinv	-15.413
6			trainlm	purelin	poslin	89.769
7			trainlm	purelin	purelin	90.493
8			trainlm	purelin	radbas	-2.1072
9			trainlm	purelin	radbasn	0.00*
10			trainlm	purelin	satlin	88.218
11			trainlm	purelin	satlins	90.343
12			trainlm	purelin	softmax	0.00*
13			trainlm	purelin	tribas	0.00*
14			trainlm	purelin	elliotsig	64.607
15			trainlm	purelin	compet	0.00*

0.00* is not equal to zero but it is very very less value

From this testing result, the selected models for this round is Model No. 7 - 5 layers and each layer contains 5 neurons (5-5-5-5-5-1) for group of t-10 along with hidden transfer function 'purelin' and output transfer function 'purelin' with %R=90.493%.

Finally, the best model of this studying is the model of 5-5-5-5-5-1 neurons along with the same transfer function (purelin) for both of hidden and output layers.

5. Summary and Suggestions

From the empirical study and results, it can be summarized that the top three performances, R-measure, are 90.493%, 90.343% and 89.893% as it is shown in Table 5.

Table 6 The best top three models.

Performance:R	Model				
	Architecture		Transfer Function		Algorithm
	Layer	Neurons	Hidden	Output	
90.493%	5	5-5-5-5-5-1	purelin	purelin	trainlm
90.343%			purelin	satlins	
89.893%			tansig	purelin	

5.1 **Prediction Test – Regression Plot**

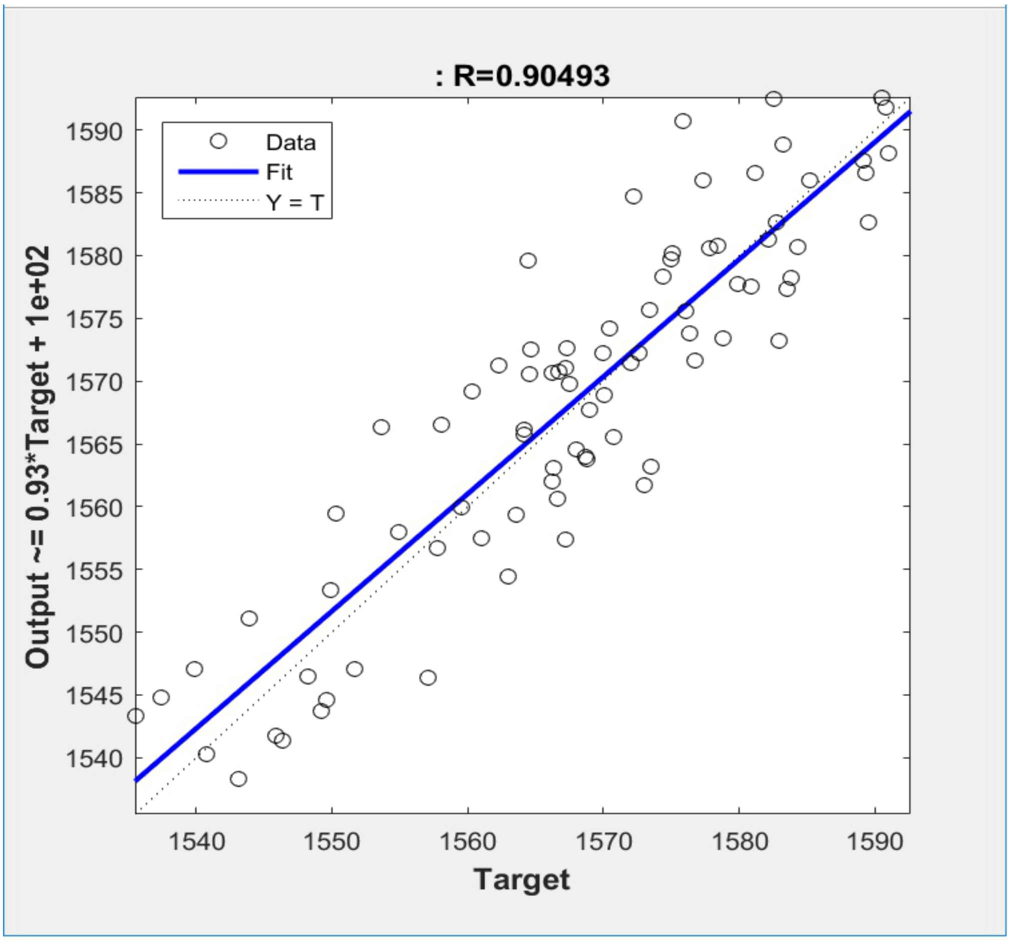

Figure 2 Regression Plot for prediction dataset

From this figure of regression plot for prediction dataset, R-measure value is 90.493%.

5.2 **Prediction Test – Time Series Response**

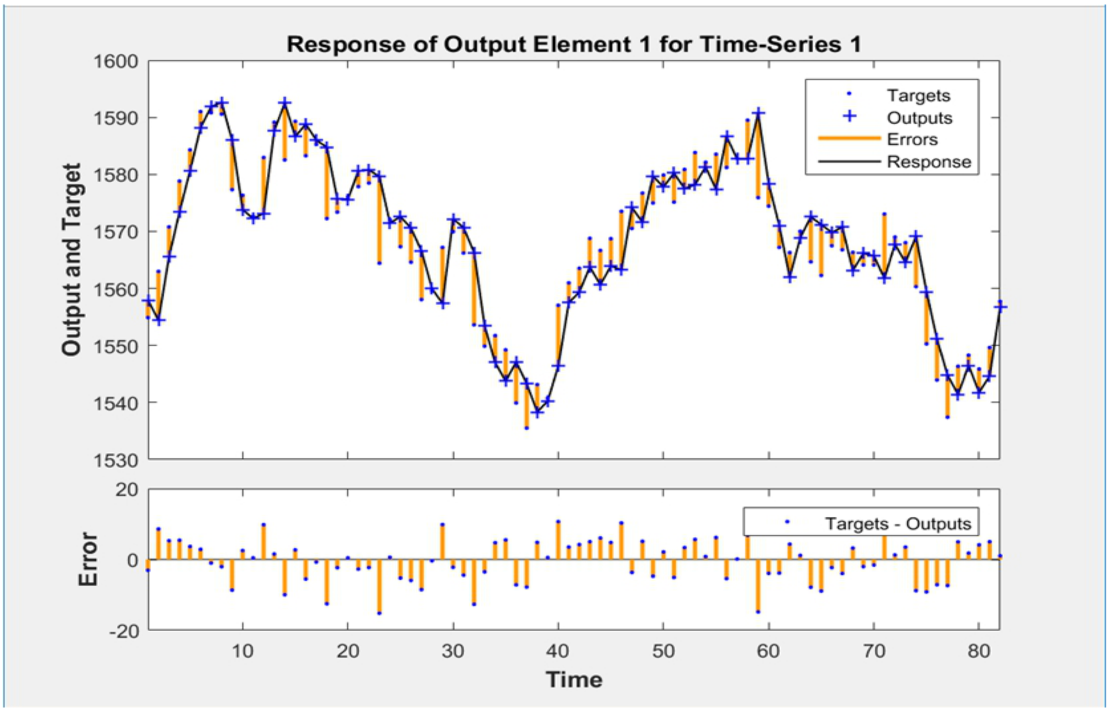

Figure 3 Time Series Response for prediction dataset

This figure shows time-series response of the network's output and network's error for whole period of prediction dataset from January 4, 2017 to May 22, 2017, with totally 92 observations.

5.3 **Prediction Test – Error Histogram**

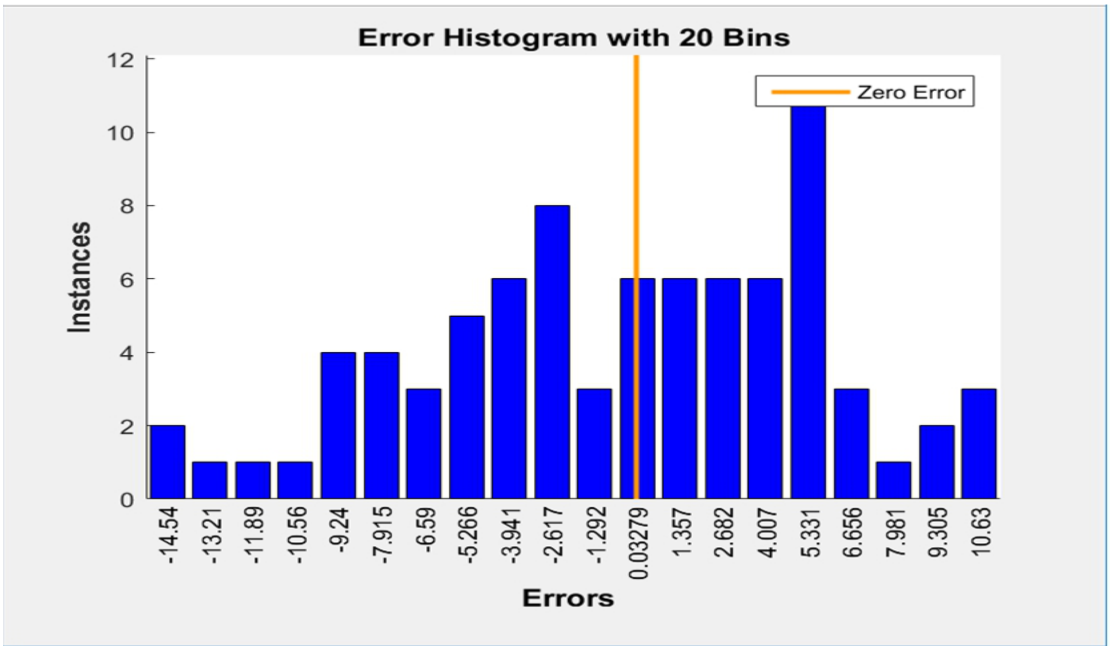

Figure 4 Error Histogram for prediction dataset

From this error histogram shows that the range of error is [-14.54, 10.63] points, the mode of error is 5.331 points and the mean of error is about -0.517 point.

5.4 **Suggestion**

As you can see all input data are time-series data so it can be positive to do time-series analysis to find out proper the number of lag and bring more inputs that can capture SET index movement significantly.

6. Conclusion and Benefits

From the theoretical studying of artificial neural network for predicting stock market index and from the empirical results, NARX can be used to forecast SET index accordingly and effectively along with 5 input parameters: Net Inst, Net Foreign, THB/USD, WIT and DJI.

All local and foreign investors can apply this study to forecast Stock Exchange of Thailand Index for making their decision plans or their investment views in the way of quantitative analysis perspectives.

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Reference

[1] Mark Hudson Beale, Martin T. Hagan, Howard B. Demuth, 2014. Neural Network Design 2nd Edition

[2] Mark Hudson Beale, Martin T. Hagan, Howard B. Demuth, 2016. Neural Network Toolbox User's Guide.

[3] Amin Hedayati Moghaddam, Moein Hedayati Moghaddam and Morteza Esfandyari (2016). NASDAQ Stock market index prediction using artificial neural network