FORECAST OF THE CANNED PINEAPPLE EXPORTS BY NONLINEAR AUTOREGRESSIVE MODEL WITH EXOGENOUS INPUT BASED ON FACTOR ANALYSIS SOLUTIONS (NARX-FA)

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**A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF SCIENCE
(INFORMATION TECHNOLOGY MANAGEMENT)
FACULTY OF GRADUATE STUDY
MAHIDOL UNIVERSITY
2015**

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entitled

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was submitted to the Faculty of Graduate Studies, Mahidol University
for the degree of Master of Science
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ACKNOWLEDGEMENTS

The success of this thesis can be succeeded by the attentive support from my major advisor Asst. Prof. Supaporn Kiattisin her valuable advice in choosing thesis topic which were so much beneficial for successful of this thesis. I would like to thank Asst. Prof. Wimol San-Um and Lect. Waranyu Wongseree for the most valuable methodology and knowledge for this thesis.

I am grateful to Co-advisor Asst. Prof. Dr. Adisorn Leelasantitham, and Dr. Sotarat Thammaboosadee who provided helpful comments on a previous draft of this thesis.

Finally, I am very grateful to my family members for attending to my study, care and love and great encouragement. This successfulness I dedicate to my parents and all the teachers who's the main source of inspiration to push me to future success. And I would like to thank all of those who I have not listed above.

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ABSTRACT

Thailand is the world's major exporting country of pineapple products including the fresh pineapple and the processed pineapples.

Each year, during the pineapple season, there are frequently unstable supplies of fresh pineapple, causing a decrease in pineapple price. To resolve the problem, this research purposes the design and development of two separate forecast models based on independent factor variables impacting the pineapple export, used as the feedback inputs for both forecast system models, given as: Nonlinear Autoregressive Model with Exogenous Inputs (NARX) and an improved NARX based on Factor Analysis Solutions (NARX-FA).

By the experimental results, both models are suitable and comparable in accuracy on the complexity and non-linear prediction problems. Furthermore, with comparisons between generic NARX and NARX-FA, the performance result of NARX-FA model has greater improvement than the generic NARX model due to an improved speedup of the network training and fast convergence. It is shown that the NARX-FA model is superior to the traditional NARX model.

KEY WORDS: NONLINEAR AUTOREGRESSIVE MODEL WITH EXOGENOUS INPUTS (NARX) / FACTOR ANALYSIS (FA) / NARX BASED ON FA SOLUTIONS (NARX-FA) / FORECASTING

94 pages

การพยากรณ์ปริมาณการส่งออกสับปะรดกระป๋องโดยใช้แบบจำลองถดถอยแบบไม่เชิงเส้นและการป้อนข้อมูลภายนอกบนพื้นฐานคำตอบของการวิเคราะห์ปัจจัย (NARX-FA)
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บทคัดย่อ

ประเทศไทยเป็นหนึ่งในประเทศผู้ส่งออกสับปะรดสดและสับปะรดแปรรูปรายใหญ่ของโลก ซึ่งในแต่ละช่วงปีของฤดูกาลสับปะรดจะมีปริมาณผลผลิตสับปะรดที่ไม่คงที่สม่ำเสมอเกิดขึ้นตลอด ด้วยเหตุนี้จึงส่งผลให้ราคาผลผลิตสับปะรดตกต่ำกว่าทุน งานวิจัยฉบับนี้ มีวัตถุประสงค์ เพื่อสร้างแบบจำลองการพยากรณ์การส่งออกสับปะรดกระป๋อง โดยใช้ข้อมูลตัวแปรอิสระที่มีผลกระทบต่อการส่งออกสับปะรดกระป๋องเป็นข้อมูลป้อนเข้าแบบจำลองในการพยากรณ์ แบ่งการสร้างแบบจำลอง เป็น 2 รูปแบบ คือ รูปแบบแรก สร้างแบบจำลองถดถอยแบบไม่เชิงเส้นและการป้อนข้อมูลภายนอก (Nonlinear Autoregressive model with Exogenous Inputs: NARX) รูปแบบที่สอง สร้างแบบจำลองถดถอยแบบไม่เชิงเส้นและการป้อนข้อมูลภายนอกบนพื้นฐานของการวิเคราะห์ปัจจัย (Nonlinear Autoregressive model with Exogenous Inputs based on Factor Analysis solutions: NARX-FA) ผลการสร้างแบบจำลอง พบว่า แบบจำลองทั้งสองรูปแบบ สามารถพยากรณ์ความซับซ้อนที่ไม่เป็นเชิงเส้นได้อย่างมีประสิทธิภาพ นอกจากนี้ แบบจำลอง NARX-FA ใช้เวลาในการประมวลผลข้อมูลได้เร็วกว่า แบบจำลอง NARX อีกด้วย

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CHAPTER 1
INTRODUCTION

1.1 Statement of Problem

Pineapple is the important economic crops in Thailand. The Export volume is more than 20000 million baht per year. Thai pineapple also is one of the country's exporter in the world market. Specifically, the canned pineapple and pineapple juice are the potential competitive Thai products in the world market. It also generates the framer does employment for both sector of the agricultural sector and industrial sector. For processing plant and industrial plant, the processing of the canned pineapple uses raw materials in the country. It is noted that the industrial added value can be created as well as pineapple.

In 2014, the Thailand has had the appropriate area for pineapple planetary for 0.542 million acres, down from last year's 2.07 percent yield of 2.07 million tons, up from last year's 0.97 percent, and yield 3,828 kg, up from last year's 2.96 percent. However, the harvested area has been declined. This is became has been planted with rubber and is not able to grow instead of pineapple and some changes to farm crops and other plants such as sugar cane and cassava. During 2013 to 2014, prices of pineapple decreased. The main reason is that pineapple farms in each cultivated area did not have enough data to form production plans. These production plans will make use of customers' demand to tell us how many fresh pineapple, and the processed pineapple products should be manufactured for each year. The yield is expected to increase. If weather and suitable climate with conditions do not suffer from drought. This resulted in an increase in overall productivity [1].

At present, Thailand, the second largest export canned pineapple one of the world has a market share of 50 percent. This canned pineapple imports in the United States, it has a larger canned pineapple imported from Thailand and the Philippines, which the country's top two ranking for the canned product [2]. This situation illustrates in Table 1.1.

Table 1.1 The volume of Canned Pineapples Imports, by Country.

Country	2010	2011	2012	Jan-May 2012	Jan-May 2013	Change 2012-13
	……………………..1,000 pounds…………………					Percent
Thailand	309,359	333,593	354,108	136,703	168,383	23
Philippines	216,908	210,219	209,660	74,057	77,467	5
Indonesia	110,395	131885	128,025	47,374	46,794	-1
China	52,744	40,577	26,153	9,624	14,822	54
Malaysia	9,071	6,067	5,473	2,696	2,370	-12
Vietnam	1,333	5,350	3,738	2,650	411	-84
Other countries	3,068	2,575	3,194	1,609	1,062	-34
World	702,879	730,351	730,351	273,105	311,310	14

Source: U.S. Department of Commerce, 2013 [2].

There are problems to consider in pineapple production. First, the regional pineapple is a seasonal fruit, with harvest period, during Apr. to Jun and Dec. to Jan. The second problem is flooding which spoils the harvest and consequently forces a decrease in the sale price of pineapple. The problem of declining pineapple price depends on production quantity as mentioned above. Therefore, there are frequently unstable supplies of fresh pineapple, causing a decrease in pineapple price.

To resolve the problem, this research purposes the design and development forecasting models input the independent factor variables, influence the pineapple export, the forecasting model stimulated by Nonlinear Autoregressive Model with Exogenous Inputs (NARX) and developed NARX based on Factor Analysis Solutions (NARX-FA). The data is used to determine the trend in pineapples prices, and is used in the decision process in business planning, selling of pineapple products including the fresh pineapple of the canned pineapple.

1.2 Objectives

1) To design the prediction model of canned pineapple export.

2) To study and analyze the experiment result taken from the comparisons of NARX model between NARX-FA model.

1.3 Scope of Work

1) To study the situation of domestic/international markets of pineapple.

2) To analyze the motivation pricing of canned pineapple exportation with historical data during 2007-2014.

1.4 Expected Result

1) To know the efficiency of forecasting models in various forms of the canned pineapple exports.

2) To develop the solution for solving the problems of oversupply of canned pineapple production with low fresh pineapples price.

3) To forecast the results as a basic for decision planning for the appropriate canned pineapple production and processed canned pineapple production over long-term period.

CHAPTER 2
LITERATURE REVIEW

The preparation of this research has assumed the related principles and theories to be applied for this research with the details as follows:

2.1 Background of Pineapples

Thailand is a tropical country with many kinds of fruit, especially for pineapple has become well known in Thailand since the era of King Narai who Ayutthaya period in 1679-1700 [3]. There are currently 27 species of pineapple in Thailand including Smooth Cayenne and Batavia or Sriracha which is well known in Thailand since 1912 are the most popular the divided container for processing a canned pineapple Smooth Cayenne is large in size with a yellow paper pulp is juicy and delicious.

Even though the pineapples are consumed fresh, but the fruits are processed for export in most many countries, however, that pineapple becomes a considerable for international market export of many countries. The pineapples are canned as whole, the flesh is scraping and making into syrup or juice. Later on canned, making by crumbling, core, and pieces of flesh which cannot be used as specified cuts, slice or squeezed into seeded fruit and canned in the light of syrup, At the same time, the canned pineapple is a product unique of Thailand.

At present, the fresh pineapples have 2 million tons of the each year, Thailand is one of plentiful manufacturer of fresh pineapple as same as the canned pineapple and pineapple juice (Figure 2.1). Annually, Thailand has volume exports fresh pineapple and processing pineapple about 60,000 tons, and 110,000 tons of pineapple juice with the value of 340 million Baht. In additional, the other processed products to export about 56,000 tons with the 2,160 million Baht. Totally, Thailand has the exports volume of pineapple with the value of 600,000 ton earning with 16,000 million Baht. Thailand is one of the exports canned pineapple and pineapple juice, especially for 40-45% of the many country demands [1].

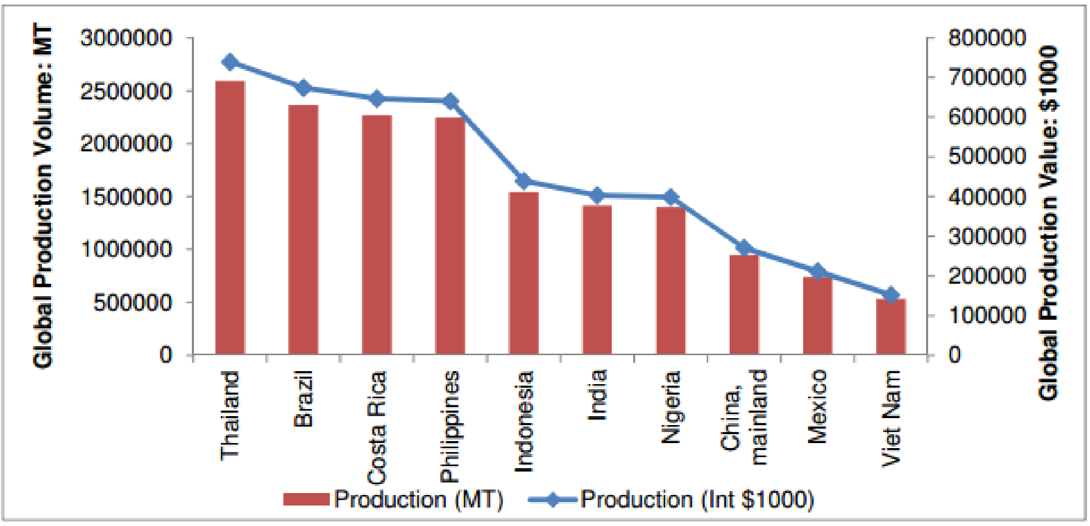

Figure 2.1 Global Pineapple Production Trends**,** FAO, 2013.

Table 2.1 Export of Pineapple in 2014**.**

Countries		**2557/2014**	
		(Value in million Baht)	**Proportion (%)**
1	U.S.A.	17273.90	33.90
2	Japan	3203.40	6.30
3	Netherland	2374.60	4.70
4	Australia	1798.60	3.50
5	Canada	1723.00	3.40
6	Russia	1719.30	3.40
7	Germany	1612.10	3.20
8	United Kingdom	1,359.00	2.70
9	China	1249.90	2.50
10	United Arab Emirates	1173.80	2.30
11	Other countries	17461.80	34.10

Source: Department of Customs, 2014.

2.1.1 Pineapple Cultivars in Thailand

In Thailand, there are about 27 species Smooth Cayenne pineapples. It has been very popular in the processing pineapple and fresh product. Each species has the following characteristics:

- Pattawia (Smooth Cayenne Group)

Many Plantation is important in Prachuap Khiri Khan Chonburi, Phetchaburi, and Lampang province planted in general to sell fresh fruit because there is a lot more water and luscious sweet. In general, there are a dark green or red, yellow when ripe with orange yellow flesh. It is a silver-gray color in the area and shape to a different weight between 2-6 kg. But it is usually around 2.5 kg. This is a very popular in Thailand.

Figure 2.2 Pattawia (Smooth Cayenne Group).

- Nang Lae (Cayenne Group)

Cultivated in Chiang Rai province, similar to the species of Batavia, but it has the shape of a circular shape rather than plants of Batavia, and raised some more skins and sweet plants is more than the old Batavia, flesh is dark yellow in color with a little dead for fresh consumption is very popular in the northern region.

Figure 2.3 Nang Lae (Cayenne Group).

- Phuket (Queen Group)

The species of Phuket being planted between rubber and coconut rows length harvest area that still young to keep the rubber for sale, in the Sawi district of Chumphon, Nakhon Si Thammarat, and Trang. The size is smaller than all, the eyes, thicker skin, crust crisp, sweet yellow flesh melt dark little fresh aroma is suitable for consumption is very popular in the south of Thailand.

Figure 2.4 Phuket (Queen Group).

- Phetchaburi (Queen)

Phetchaburi pineapple shaped stems and leaves, as well as varieties or suites Phuket by Thailand golden leaves are green and purple. It has a cylindrical shape with weighs approximately 1.8 grams. But the eye is not as flat as Batavia, the small, compact, clearly, from the original area of the stick of a rod is always yellow flesh juicy little water, than Phuket or sweet golden, but not as like as Batavia with both sweet and sour flavors. The result is a sweet 15-17% and the acid content of about 0.40 to 0.45%, as the flesh of eyes are a lot of fiber. Makes it possible to separate the sheep eating easily.

Figure 2.5 Phetchaburi (Queen).

- Trat Si Thong (Queen Group)

Trat Si Thong pineapple, species of the Trat province, it mostly for fresh consumption. The meat can be eaten to the core of the pineapple. Trat Si Thong is so characteristic of Trat is sweet, crisp, and eaten whole.

Figure 2.6 Trat Si Thong (Queen Group).

2.1.2 Pineapple Plantation

Cultivation of pineapple depends on the species and demand for consumption, a few groups such as the Cayenne Smooth and Si Racha. It grows in other areas in the region, as well as varieties of Batavia is the most popular of all, and have a large-scale and given the high-volume with productions for consumptions return with the plant. It is not only being used for the production for commercial fresh, but also the product of a large industry.

2.1.3 Harvesting

If the weather is normal, like really hot and moist pineapple or in between 60-90 ° F. Rain is between 760-2500 mm or 30-100 inches, but the duration of the pineapple. If the rain at this weather could cause dry-rot. Pineapple can be grown in all places. They do not require good soil Pineapples grow best in soil with a pH between pH 3.5-5.5 pervious or sandy. Pineapple is better than clay. If the soil and weather is normally fruits will have to change to yellowish green. Thus, if harvesting is done in the rain or hot summer season, fruits will have to be picked while still green. In Thailand, Pineapple is grown in almost any soil. In the central, which is clay, it can be grown. But it should be raised to prevent flooding. Pineapples generally tend to grow in sandy soil. For example, Chon Buri, Chachoengsao and Nakhon Si Thammarat.

Table 2.2 Production and Yield by Province in 2014.

Region/Province	Harvested Area (Rais)	Production (Tons)	Yield (Kgs. /Rai) Harvested, Yield
Whole Kingdom	511,846	1,942,508	3,795
Northern	99,722	371,374	3,724
North - Eastern	14,833	57,854	3,900
Central Plain	388,091	1,470,215	3,788
Southern	9,200	43,065	4,681
Chiang Rai	11,071	30,467	2,752
Lampang	19,575	71,958	3,676
Phitsanulok	12,560	44,688	3,558
Uttaradit	31,532	124,425	3,946
Uthai Thani	24,984	99,836	3,996
Loei	821	2,920	3,557
Nong Khai	3,787	14,781	3,903
Buangan	142	501	3,531
Nakhon Phanom	2,776	9,730	3,505
Chaiyaphum	7,307	29,922	4,095
Suphan Buri	3,870	13,530	3,496
Chachoengsao	8,805	48,612	5,521
Chanthaburi	1,256	6,152	4,898
Trat	9,456	35,649	3,770
Rayong	40,840	267,502	6,550
Chon Buri	23,517	151,238	6,431
Kanchanaburi	26,889	79,484	2,956
Ratchaburi	29,648	92,858	3,132
Phetchaburi	29,452	93,746	3,183
Prachuap Khiri Khan	214,358	681,444	3,179
Chumphon	9,200	43,065	4,681

Source: Office of Agricultural Economics, 2014.

2.2 Processing of Pineapple in Thailand

The processing has several steps of processed pineapple are produced in Thailand, wide-ranging, from canned products juice (ready drink and concentrated), frozen, dried, glace, jam, crushed or beaten, flesh in syrup, ready juice from whole fruits, wine and sweets. For manufacture, major canned (a total of 26 exist in

Thailand), [4] fruits are obtained mostly through contract farmers, either directly or through entrepreneur.

After harvest operations of fresh fruits which are obtained in the yield consist of resting on the quality and fruit stalk, then loaded with trucks, this is graded for size and quality. On the season, a more large pineapple, fresh production of approximate 5-7 % is executing since they are smaller, too large, and infected with the light brown ground, and the stand is marbled in gray on black. Fruits are processed to clean with water and remove dust and soil. The top and bottom of fresh pineapples are separated by the automatic machine, and peeling machine which takes out the core in the same processes. The flesh is of the highest quality and used as crushed pineapple. The cores of pineapple are crushed to extract in juice, the whole fruit center is passed that transports to select and provide the final processes, e.g. cut of the sector to which the eyes and peel still remain or take out those that are crushed or blemish. The slices are graded proportion to the colors and flesh quality into preferring, that variety, and formal grades, different grades are packing to choose into cans of different sizes with light syrup, purify and closed. Then last processing, the cans is labelled and packed with ready for exports.

2.3 Pineapple Marketing in Thailand

2.3.1 Domestic Markets

The pineapple markets have a many group given as: livelihood farmers group who grow pineapple as backyard or a crop grown among plants of a different kind; small farmers group who grow pineapple as income. Other group has a medium to large group of farmers who grow pineapple as the individual of income. The first group farmers generally sell their product in the domestic country market fresh pineapples for consumption while the farmers, which two organizations produce for both in the domestic country fresh pineapples consumption and processed in the factory. Regularly, traders buy the manufacture from farmers and sell production to on a large scale in the country or manufacture factories, sometimes farmers who have their own sold that can bring pineapple to the factory ours themselves. A processing of the fresh pineapple is used to determine on demand and supply in domestic and other situations.

2.3.2 International Markets

Multi-forms of products are exported canned pineapples including:

(i) Fresh fruits packed in box for sale in Singapore, Japan, the Arab countries, etc.

(ii) Canned pineapples fresh fruits, including many cuts such as slices, prices, tidbits, crush, etc. to the USA, the EU, Japan, Canada, and etc.

(iii) Frozen pineapple to Japan and the EU.

(iv) Juice, mainly in canned, but also in paper in the USA, the EU, etc.

(v) Other pineapple products such as pineapple, dried and sweetened pineapple, pineapple paste and pineapple jam [4].

2.3.3 Future Markets

Thailand is one of the world's major producers of canned pineapple and pineapple juice. As well as for export, Thailand is the world's largest exporter of the product more than 20 years. From the available evidence, we can predict the future trend of pineapple in Thailand to improve steadily, and it is still too bright.

2.3.4 Economic Environment

Thus, the suitability of the Thai-baht has affected macro-economic of the all including the situations in agricultural sector and agro-industrial sector. Both sector depend not only on imported goods and foreign capital, but also on locally-produced raw materials, land and labor force, and modern facilities for processing pineapples productions. Moreover, it can able to export fresh pineapple and pineapples differently processed products at the same time or other situation better rates, in light of low-prices in US-dollar balanced which established the prices of commodity at lower levels in the world market.

2.3.5 Production and Marketing

The Government, particularly in the event, is to support for farmers on direct and indirect in condition both the upper and lower improvement, an in performing many projects to helping both farmer and factory, in open specialized office to support of pineapple improvement, in attempted to mainly high-quality and low price products, and in monitoring the processed system based on Good Agricultural Practice (GAP) in case to take maximum-quality of pineapple.

Figure 2.7 also illustrate the market for fresh pineapple in domestic country market. Normally, a small farmer sells fresh pineapple to country areas or sub-district farmers. These manufactures domestic market the pineapple to wholesaler in cities such as provincial-capitals. The farmers buy all products, usual activities in country markets. Small-retailers buy pineapples from farmers and sell it totally consumers [4].

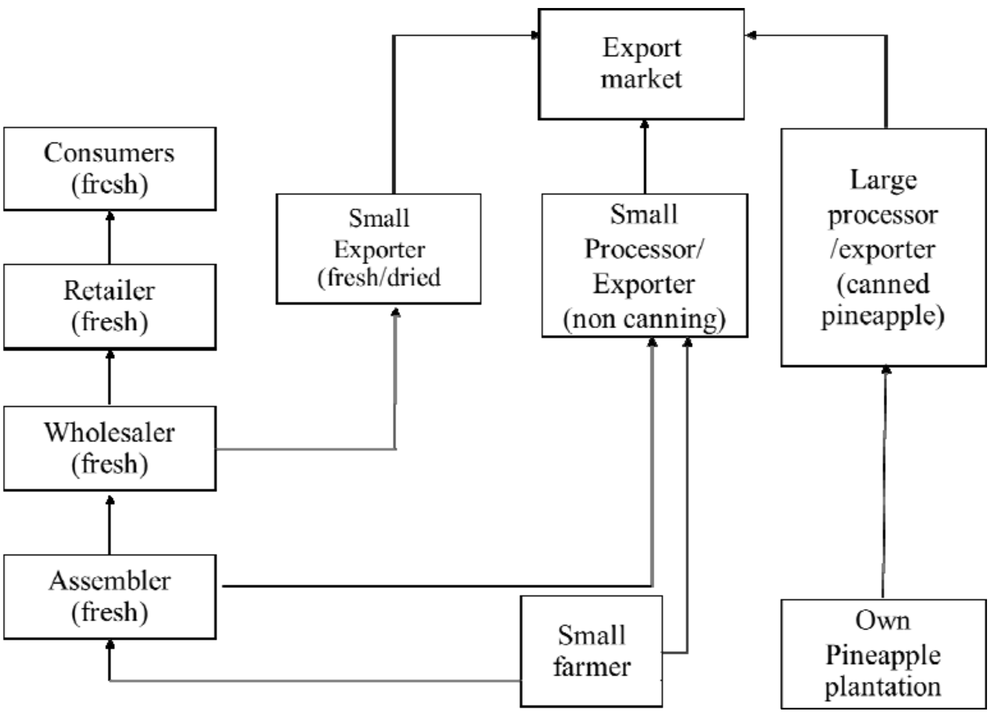

Figure 2.7 Market Channels of Pineapple Products.

2.3.6 Contract Farm of Pineapple

It presents the arrangement on a contract farm which is being performs. It should be advantage for both farmers and the manufactory factories. The farmer will not take a risk for finding domestic markets for their fresh pineapple and price of sell pineapple negotiations. They enable to negotiate the technical-service and credit. They would have the confirmation of supply of raw material with quality control without unpredictable investment on unstable demands land for large cultivated area [4].

2.4 Factor Analysis

The Factor Analysis, called the analysis component. It is a technique which they would be able to group or as well as the variables have the relation to the group or the same factor variables in relation to each other [14]. The relationship, it may be a positive in the direction (in the same way), or negative direction (to the contrary), it is part of a different factor variables. It will not have a relationship with each other or the relation between them.

The analysis component, a technical analysis of the many factors (Multivariate statistical technique), has been used in almost all. The forum is not to be regarded as a leading social sciences such as political science social science demographic anthropology and archeology Social Psychology or in the scientific world as well as in the industry, education, and etc. [7].

Supposes the observable random vector $X_i = x_1,\ x_2,\ \ldots,\ x_n$ is formulated with an unobservable random vector $F_j = F_1,\ F_2, \ldots\ F_m$ given as:

$$X_i = \sum_{j=1}^{m} a_{ij} F_j + C_i \varepsilon_i, \qquad (2.1)$$

$$i = 1,\ldots,n;\ j = 1,\ldots,m \qquad (2.2)$$

Where, $n > m$; a_{ji} is factor loading indicating the correlation coefficient between the i variable and the j factor, that effect the i variables in the efficiency of the j factor; F_j is common factor; C_i, expresses the specific factor loading; and ε_i reflects the specific factor of X_i.

2.4.1 Correlation Analysis

Pearson's correlation coefficient r_{xy} is how to measure the relationship between variables or two sets of variables. It must be in the form of data in section interval or ratio (Interval or Ratio scale) such as the relation between Health Status and Self-Care, and the relation between birth weights of infants and maternal age.

Pearson's correlation coefficient is available to fit the data with a linear relationship. With the average value of $r = 0$, the interpretation is no relationship. May be it is incorrect since it is possible that the information is relevant to the non-linear characteristics (such as curves, etc.). Therefore, it should be noted that the two sets of data is not a linear relationship. It will be clearer.

The Pearson correlation coefficient values can be calculated with the formula:

$$r_{xy} = \frac{n\sum_{i=1}^{n} xy - (\sum_{i=1}^{n} x)(\sum_{i=1}^{n} y)}{\sqrt{[n\sum_{i=1} x^2 - (\sum_{i=1} y^2)][n\sum_{i=1} y^2 - (\sum_{i=1} y^2)]}} \qquad (2.3)$$

When, is the Pearson correlation coefficient; r_{xy};

$\sum X$ is the sum of the measured data from the variable 1 (x);

$\sum Y$ is the sum of the measured data of the variable 2 (y);

$\sum XY$ is a sum of between 1 and 2 variable data;

$\sum X^2$ is the sum of squares of the data measured by the variable 1;

$\sum Y^2$ is the sum of squares of the data measured by the variable 2;

n is a sample sizes.

The value of r_{xy} is between -1 and 1. If r_{xy} > 0, there is an acceptable correlation. If r_{xy} < 0, there is a rejection correlation between the variables.

In addition, with the hypothesis before the factor of a set variable, the effectiveness of correlation and correlation are estimated by the researcher, the matrix of correlation is generated by the data. In normally, if the correlations exceed more 0.30; it indicates that there is sufficient commonality to explain the correlation of factors [8]. If inter-correlations are un-expectedly, the result of low-variance. This is because variable of samples with almost homogenous cannot indicate low-variance. Therefore, the correlation with lower capacity of error to display a factor analysis common correlations is presented.

2.4.2 Evaluation Factor Analysis

- Kaiser-Meyer- Olkin (KMO)

The Kaiser-Meyer-Olkin (KMO) is a measure of the fit of data to be analyzed by the technique Factor Analysis. As shown in Table 2.3, the KMO compares the values of relationship with variables and the partial relationships [9].

The Kaiser-Meyer-Olkin (KMO) measure of sample suitability for variable is given by the formula:

$$KMO_j = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} \mu_{ij}^2} \tag{2.4}$$

Where, the correlation matrix is $r = (r_{ij})$ and the partial covariance matrix is $\mu = (\mu_{ij})$. The overall KMO measurement of sample adequacy is given by the above formula taken over all combinations and $i \neq j$.

Table 2.3 Interpretations of KMO Measurement.

KMO Value	Degree of Common Variance
0.90 to 1.00	Marvelous
0.80 to 0.89	Meritorious
0.70 to 0.79	Middling
0.60 to 0.69	Mediocre
0.50 to 0.59	Miserable
0.00 to 0.49	Don't Factor

- Bartlett's Test of Sphericity

Bartlett's Test is used to test if *n* samples are variables with equal variances, across samples are homogeneous of variances. Some examination tests, assume that the variances are equal across groups or samples [10]. The Bartlett test can verify the assumption. If value is outside the linear objects are often high, some variables are correlated. If these values are close to 0 (*r*), the Principal component analysis is really useless.

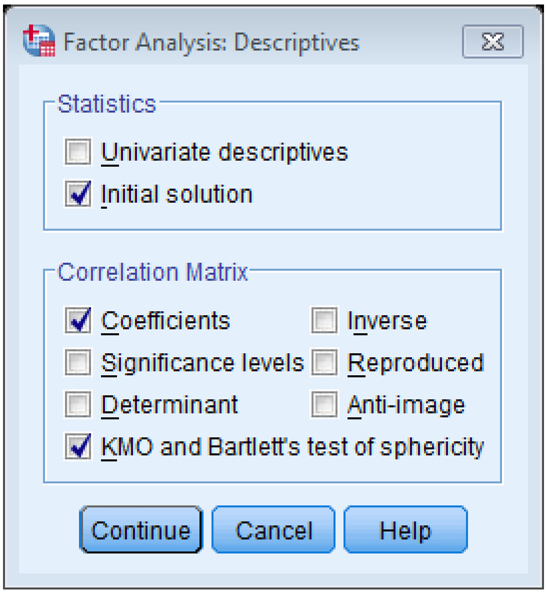

Figure 2.8 Factor Analysis: Descriptives.

2.4.3 Factor Extraction

Factor Extraction factor is to find the number factor variables that can be used for all of them. There are many ways how to extract factors. So we have to decide on how to extract factors. For each method, the result has different by extraction factor is divided into two major ways [11] [12] as follows:

(1) The main components (Principal Component Analysis: PCA) method exploits the relationship between variables based on the linear principal component variables of mixed linear (Linear Combination). The variables explain the variability of the data as possible.

(2) Joint element method (Common Factor Analysis: CFA).

The Eigen Value is a variation of the variables in each element. To analyze the composition Conjoint, Common Factor is the first element that separates the variation of the variables out of the elements as much as possible is the most common variant. The Eigen value ≥ 1, as shown Screen plot in Figure 2.9 [12], which is a plot of Eigenvalue vs factor number.

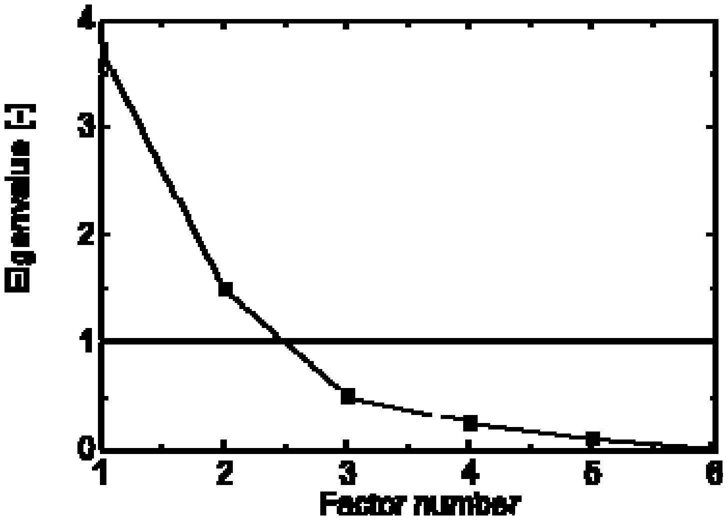

Figure 2.9 Scree Plot of The Example.

2.4.4 Factor Rotation and Interpretation

Factor Rotation is as a step to perform the separation of variables to be obvious variables. The other one should be arranged in groups or any factors because the extraction factor will be several factors. The rotation axis is the way to make each member of the variable factors. The factor rotation can be divided into 2 ways, as follows:

(1) The rotation axis orthogonal (Orthogonal) is the axis of rotation of the rotating elements of the original position perpendicular to the rotation axis of the time called. But, it is not a correlation factor of all. The rotation axis orthogonal to the sub-classified into 3 parts:

a) Varimax.

b) Equamax.

c) Quartimax.

(2) Oblique Rotation is a way of the rotating axis of the factor. The technique, originally conducted in the area of signal processing and neural networks. It extracts from the data matrix an oblique solutions that maximizes statistical independence.

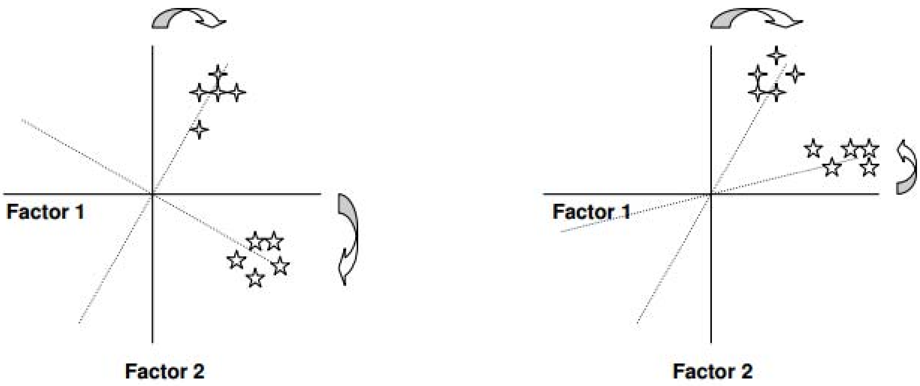

Figure 2.10 Factor Rotation.

Figure 2.10 describes the 2 types of rotation: (1) orthogonal and (2) oblique rotation. Orthogonal rotation, is the rotation that the factors turn from low at the same time. There is a perpendicular axis rotation is called the spin-axis. It is not a relationship factor in each of these factors. On another hand, Oblique rotation, is the rotation axis of the factors. From its original position in a horn and not always perpendicular to the rotation axis, by rotating the rod able to describe the relationship with the factors determining the number of degrees.

2.4.5 Factor Loadings and Factor Scores

The factor loadings are more important for the description of the factors the more high ones, which is the relationship between the elements. Which should be more than 0.4 weights of any variable in any of the components. Variables are the elements that should be in the SPSS weight composition of each element in the table before the rotation axis component matrix elements or from the diagonal of the matrix of the Eigen (Eigen Value), then “advise to explain factored loadings with an absolute value more than 0.4.” The hypothetical in principal component analysis, in the factor analysis the amount of explained variance is calculated in a different way [13]. The recommend should be explain with care.

The result is useful in many ways given as:

1) If their factor enable to find "whether groups or clusters, factor can note that is similarly in scoring on a test, fundamental variables are precipitate to more basic than the original variables, the group of factor scores in the factor space can useful clues" [13].

2) Factor scores can describe a multicollinearity statement of the problem is multiple regression, that the factor scores are no relations.

3) Factor scores can be used in big examining, in more measures indicting the same variables, using the scores on the original variables" [13].

In SPSS program the factor score function can be saved as a variable in the view of the data window. The correlation of the factor score can illustrate in a factor-score matrix, which is shown in the SPSS output.

2.5. NARX Model

The NARX [15] is a recurrent dynamic network with feedback connections. This module is a unique feature using the nonlinear relations between past inputs, outputs and the forecasted process output can be described by the equation as follows:

$$y(t) = f(x(t),...., x(t-a),...., y(t-b), d(t-1),...., d(t-b)) \quad (2.5)$$

Where, d are the subject to the time series that the researcher wants to forecast; y is the past forecast values by the module; *a,b* are the variable input and output; x are the exogenous variables, and f is a nonlinear function.

The NARX model purpose is to be forecast. The next value of the time-series that is effected by owner, but the past values of the series or the past predictions.

In the NARX model, the exogenous variables that have influenced the value of our time-series. When I want to predict. The input showed the number of past exogenous variables that are fed into the system. In generally, the external variables are time series as good, that the variables starting from recent time t until $t-a$, which

a is the input order. The variables in the variable are the input *regression.* y is the past forecasted values, because we want to forecast the variable value at the recent time t, so they can use the values start from $t-1$ to $t-b$. Where b is the variable output. These output variables among with this order are the output *regression* [15].

d represents the real-values of the time-series that for forecasting, which are feeding into the module, the same order as for past forecasting values is used.

NARX model can build on a recurrent neural network, trained by back propagation through time algorithm or simple back propagation.

In Figure 2.11, the NARX model using neural networks is presented.

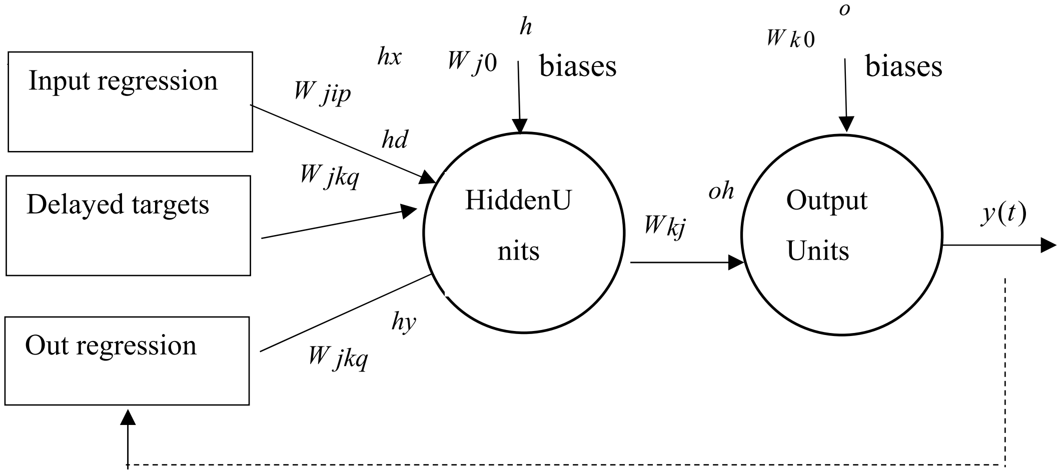

Figure 2.11 NARX with Neural Network Architecture.

Having the specific NARX, one can ask if the vanishing gradient problem still exists, because we have a similar learning algorithm with the Multilayer Perception (MLP), and a very similar network architecture. However, the model behaves much better than the other types, because of the output memories represented jump-ahead connections at the time folded network [16]. This improves the long term dependency detection and somehow softens the vanishing gradient problem that the other types of networks have. Such behavior sees in back propagation.

The NARX model trained by backpropagation algorithms. It described by Jacobean [16]; the past values is higher for NARX network. This algorithms fastdissolve, so the past variable values are basically in to signify that later process of the forecasting.

2.5.1 Training Module

In the NARX model, that we have a feedback loop from the output of the network back to the input. This special connection is part of recurrent neural networks model, and cannot be trained with the simple backpropagation algorithm. The backpropagation through time algorithm needs to be used.

Figure 2.12, the Levenberg-Marquardt algorithm [18] is a repeat locates the least of a multivariate function, which is describe the sum of squares real valued functions. The advantage of this algorithm is guaranteed to converge.

Levenberg-Marquardt algorithm is the linear expression to f when the conductivity function is in the sum of squares, the Hessian matrix is expressed following way as [18]:

$$H = J'J, \tag{2.6}$$

and the gradient is calculated as:

$$g = J'\varepsilon, \tag{2.7}$$

where, J is the Jacobian matrix with obtained of the module network errors with consideration to the weight and biases of errors. The algorithm is adopt the estimation of the Hessian matrix:

$$x_{k+1} = x_k - [J'J + \mu I]^{-1} J'\varepsilon \tag{2.8}$$

If $\mu = 0$ in Eq. (2.8), the module is Newton's method. If not, this module method is a gradient with a small step of sample size. An analysis of the Levenberg-Marquardt algorithm cover's this scope of research [18].

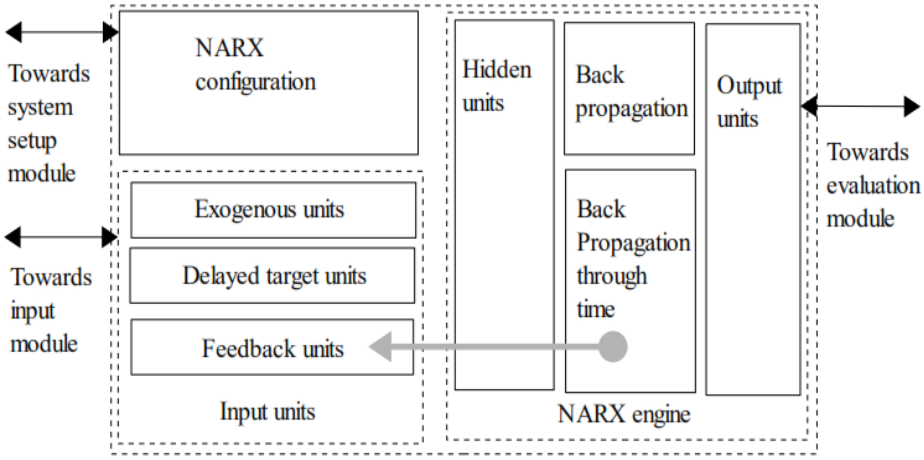

Figure 2.12 Training Module Architecture.

2.5.2 Evaluation Module

The criterions used to evaluate the performance of the neural network prediction model are given as [17]:

1) The Mean Square Error (MSE). The formulation is as follows:

$$MSE = \sum n_i = 1(x_i - y_i)2 / n. \tag{2.9}$$

Mean Square Error must be less than zero for optimum and efficient prediction. And the Correlation Coefficient r is calculated as:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{2.10}$$

Correlation Coefficient r must close to zero for optimum and efficient prediction.

Where, x_i = observed variables, x = mean of x_i, = predicted the volume of canned pineapple exports, y = mean of y_i and n = the number of data set used for evaluation. The best fit between observed and calculated values, which is unlikely to occur, would have MSE = 0 and r =1.

2) Root mean square error (RMSE):

If the measurement value of the actual and the estimated value of the RMSE is less, it is applied the model can be estimated close to the double of actual values.

The Root mean square error of a forecasting model with on estimated variable X_{model} is defined as RMSE [19]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}, \tag{2.11}$$

where, X is observed values and X is model values at time i.

However, the RMSE values can be used to distinguish the model evaluation with that of a validation period as well as to compare the individual model evaluation with other forecasting models.

2.6 NARX-FA Network Algorithm

Combination of NARX-FA with 2 step of the predicted factor analysis data propose is given as: First, the analysis data for determination of the main factor will be considered as a dimensional reduction data of primary. Then, the low-dimensional data is used as an input of neural network to establish the neural network algorithm based on factor analysis solutions. This article takes the most widespread backpropagation neural network for example, which is called NARX-FA. Figure 2.13 shows the flow chart of NARX-FA.

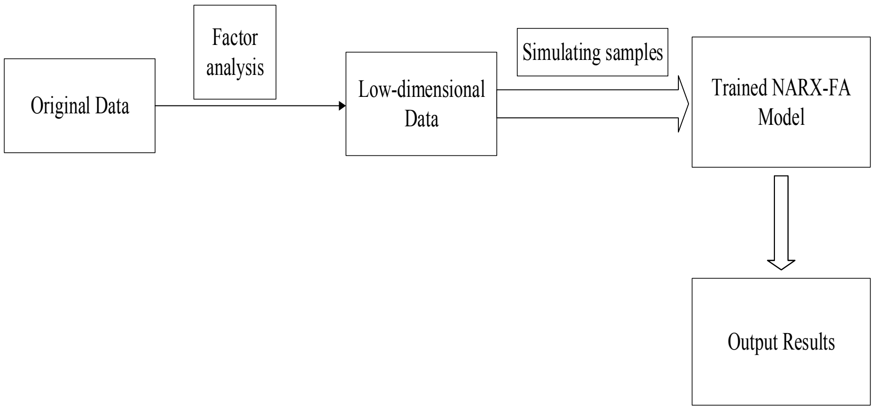

Figure 2.13 The Flow Chart of NARX-FA.

2.7 Related Research

There are several research publications relating to the application of mathematical models to construct forecast models for many kinds of work. The details of techniques using mathematical models to forecast for production plan are as follows:

Shabri, et al. [20] presented forecasting of the Rice Yields Time Series Forecasting using Artificial Neural Network and Statistical Model. In this research, the model combination of the individual forecasts based on an artificial neural network approach for modelling rice yields was investigated. Results were shown that the combination of forecast based on artificial neural network (CANN) model can apply to present forecasting.

Chetouani [25] presented nonlinear modelling of a reactor-exchange by using NARX neural networks. The model training by Multilayer Perceptron based on artificial neural network with input-output data. In this thesis used the validation of the experimental exam for three kinds of statistic; Aikeke's Information Criterion (AIC), Rissanen's Minimum Description Length (MDL) and Bayesian Information Criteria (BIC), which it is successfully for the forecasting model.

Udomsri et al. [22] presented the Design of a Forecasting Support Models on Demand of Durian for Export Markets by Time Series and ANNs. The results represent models that the most performance forecast modules are Deseason alized model which gives the least value of the mean absolute percentage error in 3 kinds of durian and enforcement module by Artificial Neural Networks (ANNs).

Li et al. [23] Studied on Psychological Crisis Evaluation Combining Factor Analysis and Neural Networks. The paper proposed a novel and effective method which is the combination of FA and BPNN to evaluate psychological crisis statue. This combination model has the following advantages

- FA enables to compress the dimension of the evaluation index system and eliminate the correlation between the indices and factors.
- Taking 12 factors as input of the neural networks, this streamlines the structure of neural networks in order to reduces the training costs and improve the output accuracy.
- The FABP neural network model overcomes the subjectivity of traditional psychological crisis evaluation scale, which will give some ideas to psychological crisis evaluation. This has the knowledge and the principles used the medicine or psychotherapy to adjust examinees in this research work.

Ding et al. [24] presented an Improved BP Neural Network Algorithm Based on Factor Analysis. The results represented the error of the forecasting value was reduced by using conduct the new module, that combining multivariate statistical with neural network could improve the best performance of processing with neural network.

CHAPTER 3
RESEARCH METHODOLOGY

This research is to conduct the accurate prediction model of the canned pineapple exports using a Nonlinear Autoregressive model with exogenous input: NARX training with the structural feature of back-propagation and combining based on Factor analysis Solutions: (FA). Figure 3.1 represents the procedure of the research.

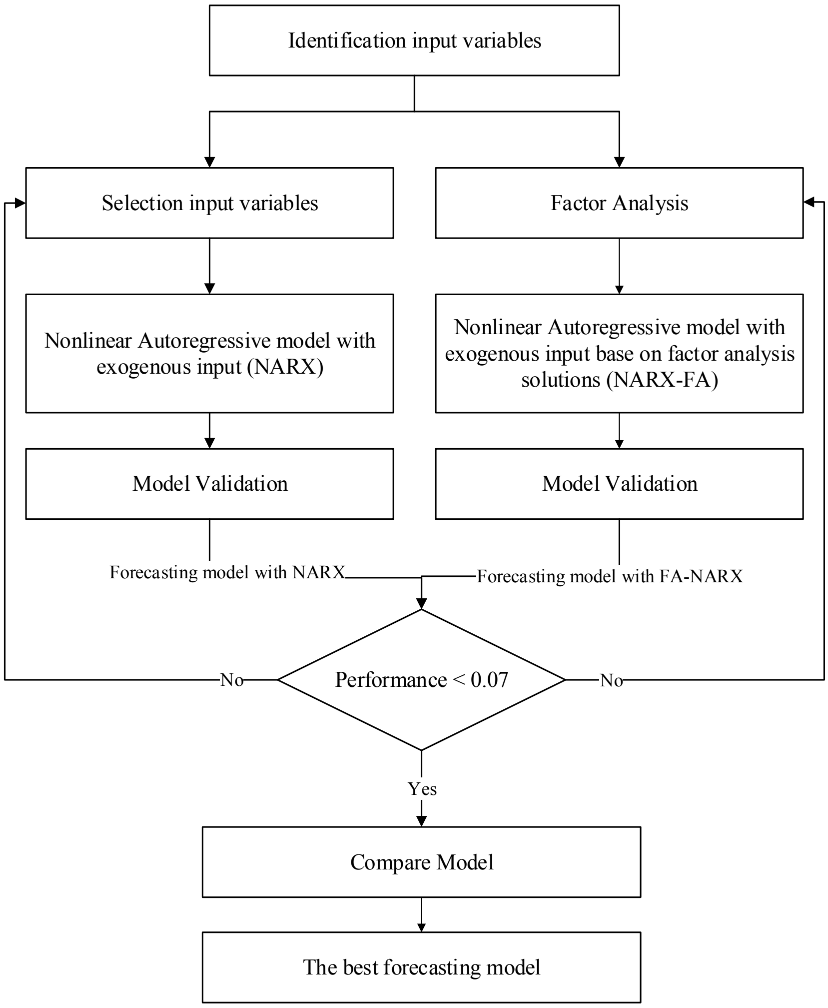

Figure 3.1 The Procedure of the Research.

3.1 The Data Collection

The data of this research is about the fresh pineapple grown in Thailand from 2007 to 2014 provided by the Office of Agricultural Economics, Ministry of Agriculture, and Cooperatives. Figure 3.2 shows quantity of canned pineapple exports in the country with plotted graphs. The data is the movement and the example of the fresh pineapples and canned pineapple in each monthly.

The 11 independent factors are determined as the expected solutions. Those factors will affect the canned pineapple exports, the quantity of canned pineapple export; *(y)* is dependent variables in Table 3.1.

Table 3.1 Symbol and Definition of Variables.

Variables	Meaning	Unit
x1	Pineapple yield	Ton
x2	Volume Production of canned pineapple	Ton
x3	Volume domestic sale of canned pineapple	Ton
x4	Quantity of Fresh Pineapple Exports	Ton
x5	Quantity of juice, pineapple exports	Ton
x6	Agricultural price at farm gate	Thai baht (THB)
x7	Agriculture production price index	Percent
x8	Agriculture price index	Percent
x9	Consumer Price index	Percent
x10	Inflation rate	Percent
x11	Exchange Rate	THB/USD
y12	Quantity canned pineapple export	Ton

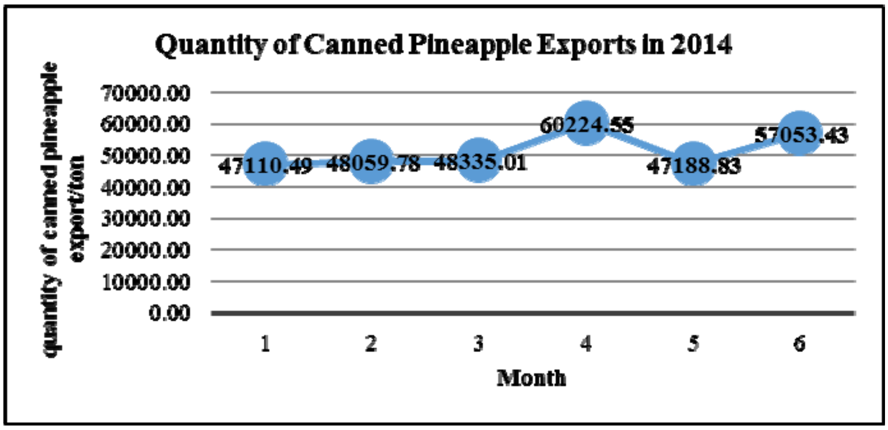

Figure 3.2 Quantity of Canned Pineapple Exports in 2014.

3.2 Manipulating Forecast Model

In the research, the Statistical Program for Social Sciences (SPSS) program's outputs are contained for Factor analysis methodology and the research finding program for the appropriate research is a MATLAB R2014a program, because of availability of use. The widely used forecast model on research on MATLAB program by the function of neural network algorithm toolbox library, a set of tools of MATLAB program create for the research utilization.

3.3 Simulations

3.3.1 Analysis of Correlated Data

The running a factor analysis is to look at the inter-correlation between variables. All of the statistical commands in SPSS are accessed from the analyses menu.

1) Click analyses > Correlate > Bivariate on the menu system as shown below:

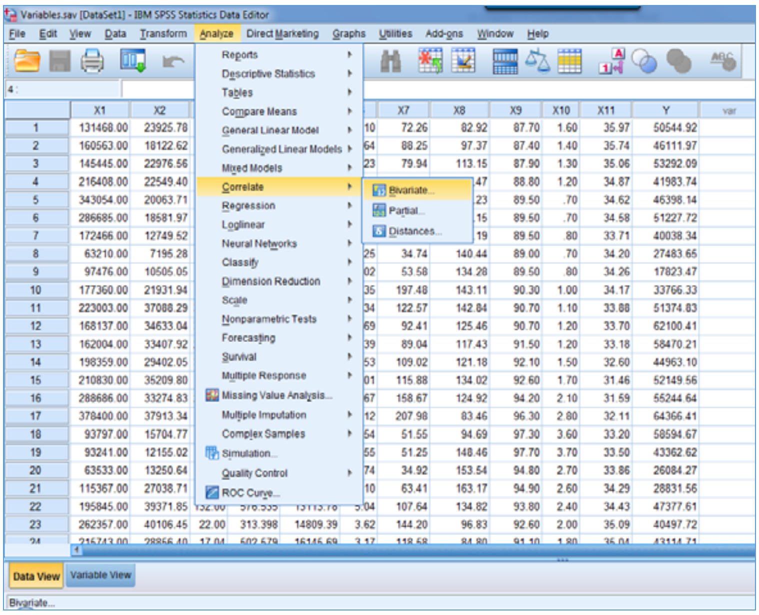

Figure 3.3 The Analyze Menu of SPSS.

2) Transfer the variables into the Variables: box by dragging-and-dropping or by clicking the SPSS Right Arrow Button. The Pearson tick box is checked under the -Correlation Coefficients- area (although it is selected by default in SPSS) Figure 3.4 below:

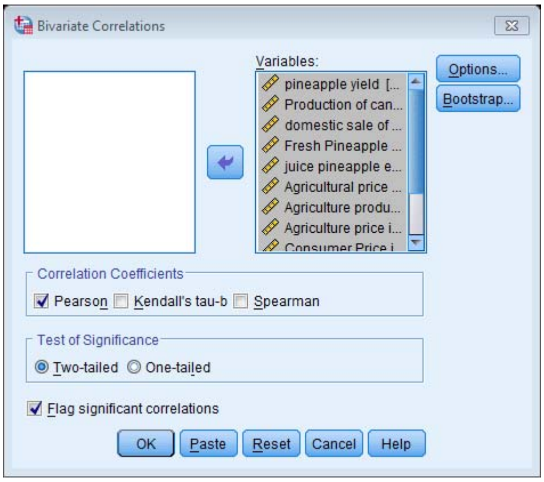

Figure 3.4 Pearson for Correlation Coefficients.

3) Click the SPSS Options Button. If you wish to generate some descriptive, you can do it here by clicking on the relevant tick box under the Statistics area, and click ok. Checking excludes cases pairwise. Clicks continue and ok. The output follows Figure 3.5. And **Error! Reference source not found.**.

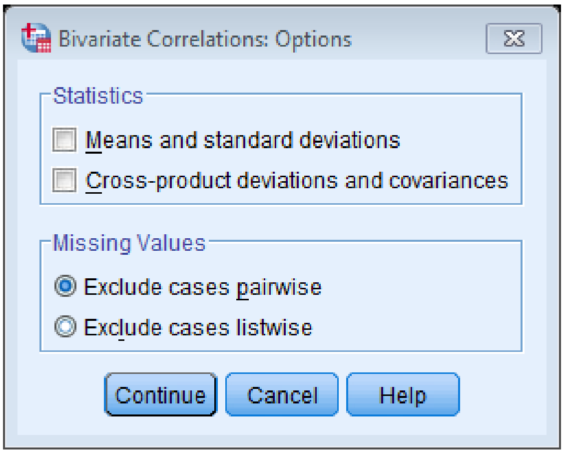

Figure 3.5 Bivariate Correlation Options.

Table 3.2 The Correlation Matrix.

Correlations

		pineapple yield	Production of canned pineapple	domestic sale of canned pineapple	Fresh Pineapple Exports	juice pineapple exports	Agricultural price at farm gate	Agriculture production price index	Agriculture price index	Consumer Price index	inflation rate	Exchange Rate	Quantity canned pineapple export
pineapple yield	Pearson Correlation	1	.640**	-.149	.189	.540**	-.295**	.966**	-.290**	.068	.178	-.190	.552**
	Sig. (2-tailed)		.000	.162	.074	.000	.005	.000	.006	.524	.093	.073	.000
	N	90	90	90	90	90	90	90	90	90	90	90	90
Production of canned pineapple	Pearson Correlation	.640**	1	.002	.100	.425**	-.357**	.618**	-.355**	-.077	.319**	-.094	.423**
	Sig. (2-tailed)	.000		.986	.351	.000	.001	.000	.001	.471	.002	.380	.000
	N	90	90	90	90	90	90	90	90	90	90	90	90
domestic sale of canned pineapple	Pearson Correlation	-.149	.002	1	-.020	.030	-.026	-.116	-.002	.103	-.012	-.128	.186
	Sig. (2-tailed)	.162	.986		.852	.782	.805	.275	.984	.332	.908	.231	.079
	N	90	90	90	90	90	90	90	90	90	90	90	90
Fresh Pineapple Exports	Pearson Correlation	.189	.100	-.020	1	.135	-.169	.175	-.249*	-.279**	.023	.296**	.197
	Sig. (2-tailed)	.074	.351	.852		.205	.112	.099	.018	.008	.828	.005	.062
	N	90	90	90	90	90	90	90	90	90	90	90	90
juice pineapple exports	Pearson Correlation	.540**	.425**	.030	.135	1	-.343**	.500**	-.322**	-.072	-.067	-.023	.562**
	Sig. (2-tailed)	.000	.000	.782	.205		.001	.000	.002	.501	.528	.827	.000
	N	90	90	90	90	90	90	90	90	90	90	90	90
Agricultural price at farm gate	Pearson Correlation	-.295**	-.357**	-.026	-.169	-.343**	1	-.278**	.729**	-.069	-.284**	.131	-.414**
	Sig. (2-tailed)	.005	.001	.805	.112	.001		.008	.000	.518	.007	.217	.000
	N	90	90	90	90	90	90	90	90	90	90	90	90
Agriculture production price index	Pearson Correlation	.966**	.618**	-.116	.175	.500**	-.278**	1	-.267*	.030	.160	-.155	.498**
	Sig. (2-tailed)	.000	.000	.275	.099	.000	.008		.011	.782	.132	.144	.000
	N	90	90	90	90	90	90	90	90	90	90	90	90
Agriculture price index	Pearson Correlation	-.290**	-.355**	-.002	-.249*	-.322**	.729**	-.267*	1	.052	-.328**	.073	-.267*
	Sig. (2-tailed)	.006	.001	.984	.018	.002	.000	.011		.627	.002	.492	.011
	N	90	90	90	90	90	90	90	90	90	90	90	90
Consumer Price index	Pearson Correlation	.068	-.077	.103	-.279**	-.072	-.069	.030	.052	1	.240*	-.716**	.299**
	Sig. (2-tailed)	.524	.471	.332	.008	.501	.518	.782	.627		.023	.000	.004
	N	90	90	90	90	90	90	90	90	90	90	90	90
inflation rate	Pearson Correlation	.178	.319**	-.012	.023	-.067	-.284**	.160	-.328**	.240*	1	-.293**	.309**
	Sig. (2-tailed)	.093	.002	.908	.828	.528	.007	.132	.002	.023		.005	.003
	N	90	90	90	90	90	90	90	90	90	90	90	90
Exchange Rate	Pearson Correlation	-.190	-.094	-.128	.296**	-.023	.131	-.155	.073	-.716**	-.293**	1	-.313**
	Sig. (2-tailed)	.073	.380	.231	.005	.827	.217	.144	.492	.000	.005		.003
	N	90	90	90	90	90	90	90	90	90	90	90	90
Quantity canned pineapple export	Pearson Correlation	.552**	.423**	.186	.197	.562**	-.414**	.498**	-.267*	.299**	.309**	-.313**	1
	Sig. (2-tailed)	.000	.000	.079	.062	.000	.000	.000	.011	.004	.003	.003	
	N	90	90	90	90	90	90	90	90	90	90	90	90

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The results presented in a correlation matrix, as show in Table 3.2 above, the table presents the Pearson correlation coefficient, the significance value, *r*, is 0.80, and that this is significant ($p<0.0005$). For interpreting multiple correlations, then a smaller size ($n > 150$) should be sufficient.

3.3.2 Factor Analysis

Factor analysis solutions, a widely used method of multivariate statistical analysis, can be explained variability among the observed variables and the unobserved variables called factors. If z_i is the standardized variable of x_i, z_i can be expressed as a linear combination of factor variables F_n , error variable μ_i, the weight coefficients of F_n, μ_i, c_{in}, and d_i, respectively, given as:

$$Z_i = \sum_{n=1}^{m} c_{in} F_n + d_i \mu_i \, . \tag{3.1}$$

Where c_{in} is a factor loading expressing the linear correlation between the factor F_n and variable μ_i. Estimating factor loadings are intended to interpret the variation of data as much as possible. The first main factor has the strongest explanatory power for variation, while the second main factor is inferior and so on.

The Step for Factor Analysis in Figure 3.6 provides this refer point in development for decision way. The steps of SPSS explain in many a feature.

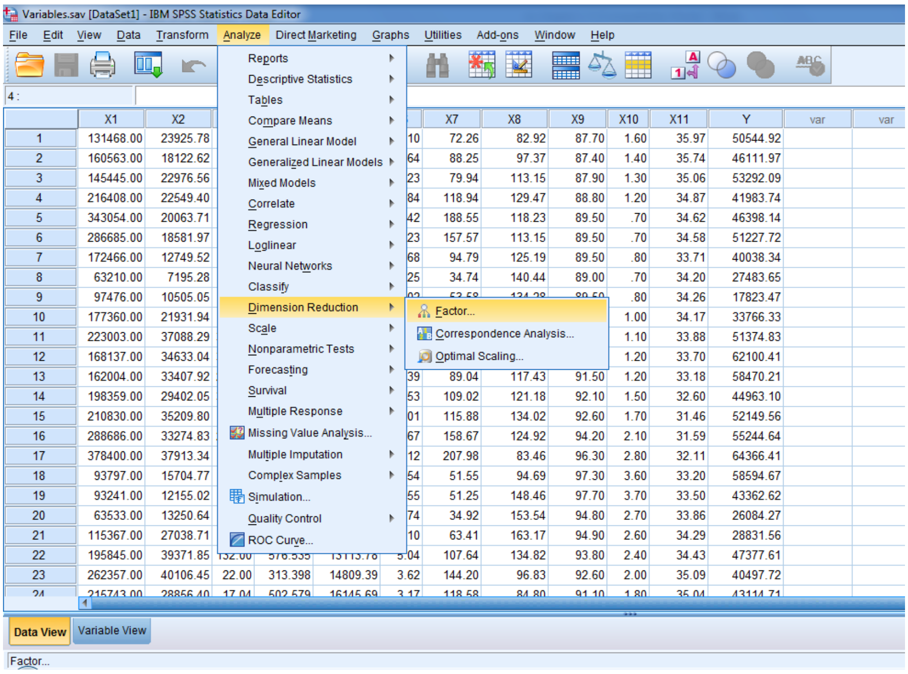

Figure 3.6 Factor Analysis in SPSS.

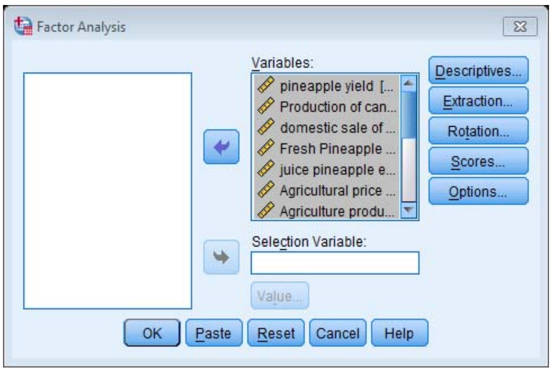

Figure 3.7 The Dialog Box of The Factor Analysis.

In the Figure 3.6 and Figure 3.7 to run a factor analysis, start from the “Analyze” menu, and choose Data Reduction. This process is proposed to reduce the complexity in a data.

3.3.3 Evaluation KMO and Bartlett's Test

To implement the factor analysis, firstly adopts Kaiser-Meyer-Olkin test and Bartlett's test the variable data, whether the values of KMO have between 0.7 and 0.8 are good. The values in range between 0.8 and 0.9 are great, and values with upper 0.9 are superb.

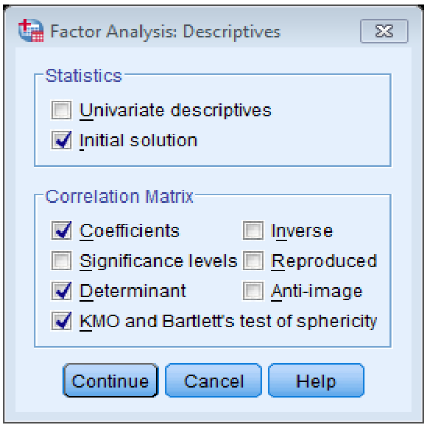

Figure 3.8 The dialog descriptive of Spss.

$$KMO_j = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} \mu_{ij}^2}, \qquad (3.2)$$

where, the correlation matrix is $r = (r_{ij})$ and the partial covariance matrix is $\mu = (\mu_{ij})$. The KMO measure module is given by above formula taken over all combinations and $i \neq j$.

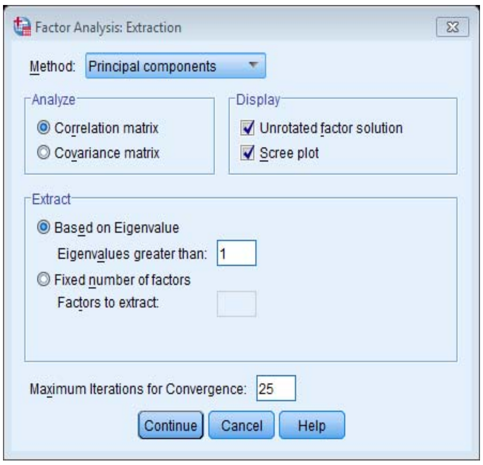

Figure 3.9 The Dialog Box Extraction.

The Bartlett's test measures the relationship-matrix H_0. For a satisfactory factor-analysis to proceed, some relationship with variables is necessary. In other words, if this significant test tells us that the relationship-matrix is not identity-matrix, Bartlett's test is high significantly ($p < 001$). Factor is appropriately represented in Table 3.3.

Table 3.3 KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.674
Bartlett's Test of Sphericity	Approx. Chi-Square	522.090
	df	55
	Sig.	0.000

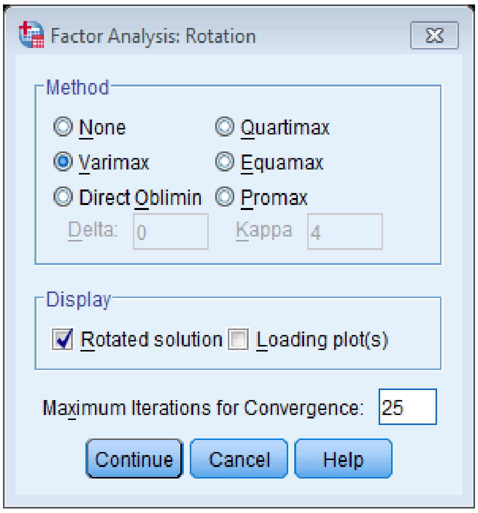

Figure 3.10 The Rotation Method.

Table 3.4 SPSS Output for Communalities.

(Component)	**Initial Eigenvalues**			**Rotation Sums of Squared Loadings**		
	(eigenvalues)	**(% of Variance)**	**(Cumulative % of Variance)**	**(eigenvalues)**	**(% of Variance)**	**(Cumulative % of Variance)**
1	3.548	32.251	32.251	3.548	32.251	32.251
2	2.041	18.552	50.802	2.041	18.552	50.802
3	1.424	12.949	63.752	1.424	12.949	63.752
4	1.048	9.527	73.279	1.048	9.527	73.279

In Figure 3.10 and Table 3.4, the results of the orthogonal rotation, the obliquely rotated solution, is probably more meaningful.

3.3.4 Nonlinear Auto Regressive with Exogenous Inputs Model

Nonlinear Autoregressive with exogenous input model is a type of recurrent neural network defined as following:

$$y(t) = f(x(t),\ldots ., x(t-a),\ldots., y(t-b), d(t-1),\ldots., d(t-b)) \qquad (3.3)$$

The model purposes to not predict only the next value of the time series and into another time series that influence our own, but also the past values of the series or past. This is the predictions.

NARX model can be constructed on a recurrent-neural network, this is trained with backpropagation algorithm or simple backpropagation. In Figure 3.11, the NARX model is built and is presented by MATLAB R2014a.

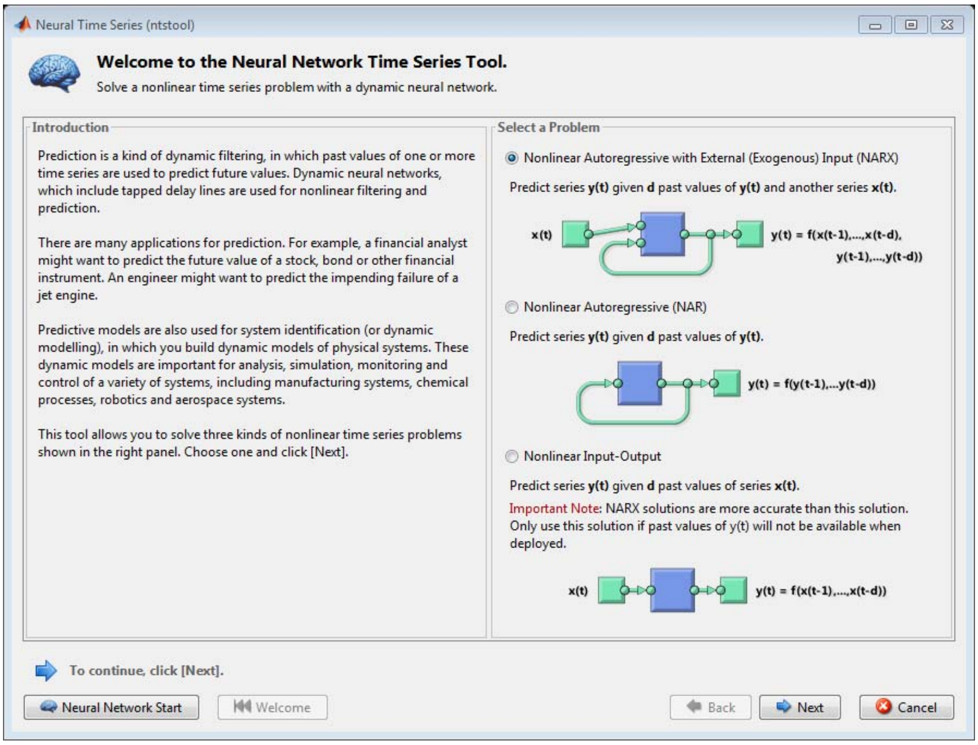

Figure 3.11 NARX Architecture.

3.3.5 Network Training

The Levenberg-Marquardt algorithm is a basic technique indicating the minimum of a multivariate function, explaining the sum of squares of non-linear of real valued functions. The advantage of this algorithm is that it is guaranteed to converge with less sending time.

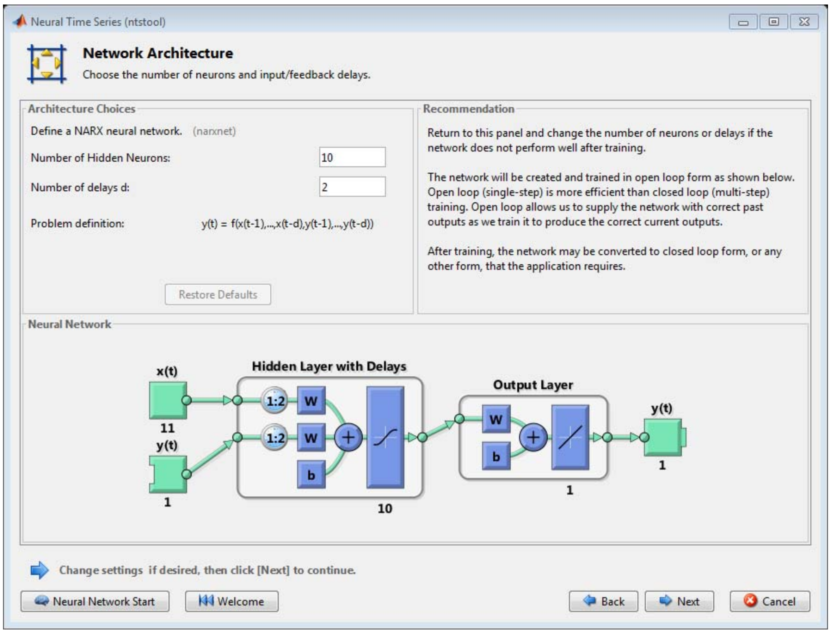

Figure 3.12 NARX Function.

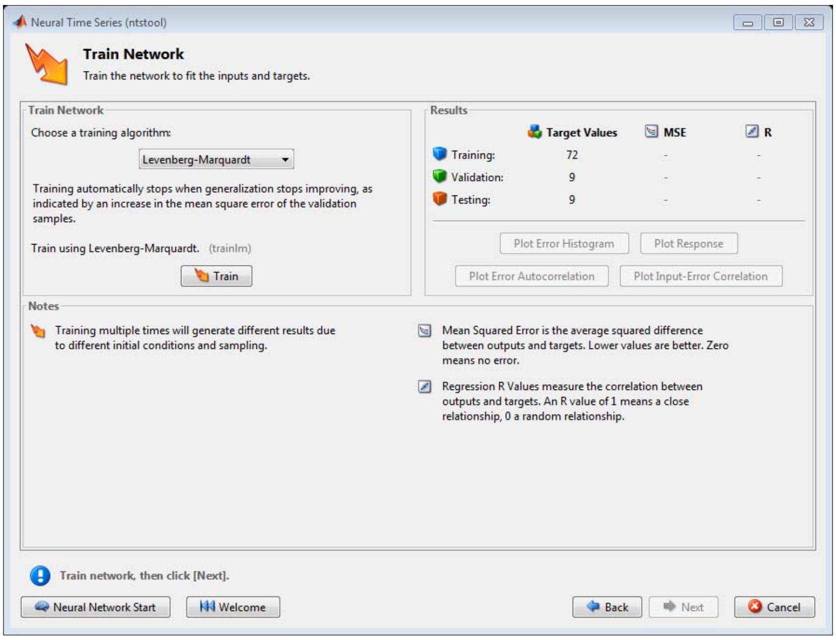

Figure 3.13 The Levenberg-Marquardt Algorithm.

In Figure 3.12 and Figure 3.13, it should be observed a detailed architecture for the specific model. The training module is the most important in the architecture, as it implements all the required learning algorithms: backpropagation and backpropagation through time. It holds the architecture of the entire NARX system.

3.3.6 Evaluation Module

The criteria used to evaluate the performance of the neural network prediction model.

1) The Mean Square Error calculated as:

$$MSE = (\sum (53292.00\text{-}52038.08)^2) /88) \qquad (3.4)$$

Mean Square Error (MSE) must be more less than zero for optimum and efficient prediction. Moreover, the Correlation Coefficient *r* calculated as:

$$r = \frac{\sqrt{(\sum (53292.00 - 52038.08)^2)}}{88} \qquad (3.5)$$

Correlation Coefficient *r* must be nearer to zero for optimum and efficient prediction.

Where, x_i = observed variables; x = mean of x_i, y_i = predicted the volume of canned pineapple exports; y = mean of yi; and n = the number of data set used for evaluation. The best fit between observed and calculated values, which is unlikely to occur, would have MSE= 0 and r = 1.

3.3.7 NARX-FA Neural Network Algorithm

Combination of NARX-FA with 2 step of the predicted factor analysis data propose is given as: First, the analysis data for determination of the main factor will be considered as a dimensional reduction data of primary. Then, the low-dimensional data is used as an input of neural network to establish the neural network algorithm based on factor analysis solutions, which is called NARX-FA. All of description of process is called NARX-FA algorithm.

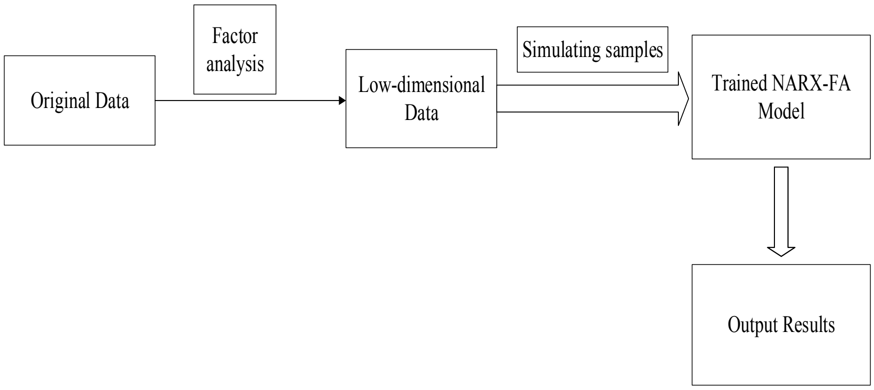

Figure 3.14 Flow Charts of NARX-FA Neural Network Algorithm.

Issues are analyzed by the factor analysis for reducing the sample dimension and the network input, which is more conducive to the design of the network model and simplify the network structure. It will improve the training speed of the network and save network running time. Figure 3.14 shows the flow chart of neural network algorithm based on the Factor Analysis Solutions.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Result of Correlation Test

From the Table 4.1, it is found that correlation of all the independent variables have a value less than 0.80 indicates that the variables are independent each other, or there is no relation to each other Therefore, it could be concluded that it is not a problem of Multicollinearity to all variables.

Table 4.1 Interpretation of The Pearson Correlation Coefficients.

Variables	Pine-apple Yield	Production of Canned Pineapple	Domestic Sale of Canned Pineapple	Fresh Pineapple Exports	Juice Pineapple Exports	Agricultural Price at farm Gate	Agriculture Production Price Index	Agri-culture Price Index	Consumer Price Index	Inflation Rate	Exchange Rate	Quantity Canned Pineapple Export
Pineapple yield	1	0.640**	-0.149	0.189	0.540**	-0.290**	10.000**	-0.290**	0.068	0.178	-0.190	0.552**
Production of canned pineapple		1	0.002	0.100	0.425**	-0.355**	0.640**	-0.355**	-0.077	0.319**	-0.094	0.423**
domestic sale of canned pineapple			1	-0.020	0.030	-0.002	-0.149	-0.002	0.103	-0.012	-0.128	0.186
Fresh Pineapple Exports				1	0.135	-0.249*	0.189	-0.249*	-0.279**	0.023	0.296**	0.197
juice pineapple exports					1	-0.322**	0.540**	-0.322**	-0.072	-0.067	-0.023	0.562**
Agricultural price at farm gate						1	-0.290**	10.000**	0.052	-0.328**	0.073	0.267*
Agriculture production price index							1	-0.290**	0.068	0.178	-0.190	0.552**
Agriculture price index								1	0.052	-0.328**	00.073	-0.267*
Consumer Price index									1	0.240*	-0.716**	0.299**
inflation rate										1	-0.293**	0.309**
Exchange Rate											1	-0.313**
Quantity canned pineapple export												1

**Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

4.2 Result of The Factor Analysis of Exports of Canned Pineapple

4.2.1 Result of Kaiser-Meyer-Olkin

While the canned pineapple exports are a evaluate of the valid method, statistical analysis clearly any type of statistic, preferably with a combined probability density function to build a p value, will be useful to help for decision. That has two statistics are the KMO and The Bartlett's test of measure variables of the sampling accuracy.

In the Table 4.2, test the suitability and sufficiency of the matrix correlation between two variables, considering the test statistic value are the KMO value ranges from 0-1, with 0.50 is acceptable for factor analysis solutions.

Table 4.2 KMO Test of Variables of Exports of Canned Pineapple.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.674
Bartlett's Test of Sphericity	Approx. Chi-Square	522.090
	df	55
	Sig.	0.000

Table 4.2 shows that the KMO value is 0.674, indicating that the eleven variables of the exports of canned pineapple is a reasonable enough is good, because the KMO is greater than 0.05-1, and then Bartlett's test indicated that the Chi-square is equal to 522.090. The Significant of 0.000, which is less than 0.05, so, reject H_0 and accept H_1 and the result means that the correlation matrix of eleven variables of the export canned pineapple is appropriate to analyses the factors as well.

4.2.2 Result of Extracting Principle Component Analysis: PCA

The factor extraction reduces a multi variables of the model into factors to develop variables is simplify the factor. Many factors extraction rules and processed, including that the criteria of Kaiser or Eigen value > 1 rule.

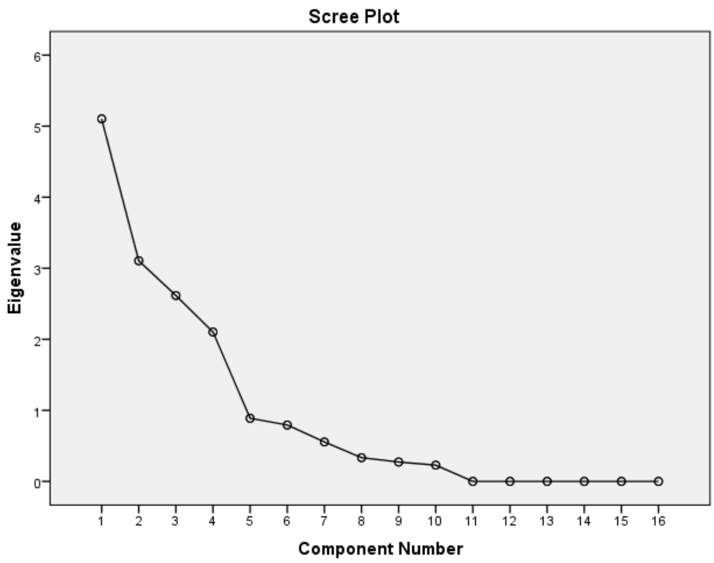

Figure 4.1 Scree Plot of Eigenvalues.

In The Figure 4.1, a Scree Plot is a graph that plots the Eigenvalues of each element by descending. So, there should be a consideration of the elements based on the value of the Eigenvalues is reduced rapidly. In this case, the only element that has a value of 1 or more Eigenvalues has only 4 elements. This analysis shows that it can extract the elements have 4 components factor.

Table 4.3 Total Variance Explained.

(Component)	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	(Eigenvalues)	(% of Variance)	(Cumulative % of Variance)	(Eigenvalues)	(% of Variance)	(Cumulative % of Variance)
1	3.548	32.251	32.251	3.548	32.251	32.251
2	2.041	18.552	50.802	2.041	18.552	50.802
3	1.424	12.949	63.752	1.424	12.949	63.752
4	1.048	9.527	73.279	1.048	9.527	73.279

Table 4.3 shows this indicates how much of the variability in the data has been modelled by the extracted factors, that considering only the export canned pineapple of a variance or the Eigen value) > 1 or the total factor influence on 4 components factor noticed variable from all the factors with it. The percent of the

variance between 9.527 to 32.251 and the cumulative percentage of variance is 73.279 and the total composition of the 11 elements of the variance is equal to 73.279.

4.2.3 Result of Rotation and Factor Loading Techniques

Table 4.3 Rotation Sums of Squared Loadings illustrate when the rotation techniques (Orthogonal rotation) by Max Mainwaring (Varimax method) to variables associated with the elements in a manner that clearly. However, considering that the first element of the selection criteria, the variable whose value factor (factor loading) more 0.50, which found that the export canned pineapple in Thailand consists of 4 factor, the first factor is the maximum Eigen value 3.548 to 32.251 percent of the total variance and other factor have the Eigenvalue and the variance decreased, respectively.

Factors and features that meet the criteria of the variance components 1-4 are all equal to (32.251 + 18.552 + 12.949 + 9.527) = 73.279, which is consistent. With the concept of hard Byng (Habing), factor should explained that the variance of all at least 50 percent is suitable for utility. Therefore, the researchers have changed the new factor name to be described in Table 4.4.

Table 4.4 Factor of Production of The Pineapple/Supply Side.

Factor F1	**Variables**	**Factor Loading**
1	Pineapple yield	0.943
2	Production of canned pineapple	0.711
3	juice pineapple exports	0.711
4	Agriculture production price index	0.931
(eigenvalues)		3.548
(% of Variance)		32.251
(Cumulative % of Variance)		32.251

Table 4.4 shows that the component (Factor F1) conforms to the Eigenvalues greater than 1. The factor loadings ranging between 0.711 and 0.943. The combined effect of 4 factor can explain about 32.251% of variation in pineapple yields. The participants agree that variable pineapple yields the factor almost 0.943. Production variables of canned pineapple and juice pineapple exports are worth their

weight a few elements as well. The character variable is 0.711. Researcher can set up name, given as **"Production of the pineapple."**

Table 4.5 Factor of Economic Stability.

Factor F2	Variables	Factor loading
1	Agricultural price at farm gate	0.820
2	Agriculture price index	0.858
3	inflation rate	-0.617
(eigenvalues)		2.041
(% of Variance)		18.552
(Cumulative % of Variance)		50.802

Table 4.5 shows that the component (Factor F2) conforms to the Eigenvalues with greater than 1. The factor loadings between -0.617 and 0.858. Element consists of 3 variables, with equal to 2.041%. The combined effect of 3 factor can explain about 50.802% of variation in Agriculture price index, that is the most valuable factor 0.858 and variable inflation rate is minimal factor is -0.617. Given the variable nature. Researcher sees fit to name given as "**Economic Stability**."

Table 4.6 Factor of Export Demand.

Factor F3	Variables	Factor Loading
1	Fresh Pineapple Exports	-0.549
2	Consumer Price index	0.872
3	Exchange Rate	-0.875
(eigenvalues)		1.424
(% of Variance)		12.949
(Cumulative % of Variance)		63.752

Table 4.6 shows that the component (Factor F3) conforms to the Eigenvalues with greater than 1 and the factor loadings between -0.875 and 0.872. Element consists of 3 variables, with equal to 1.424%. The combined effect of 3 factor can explain about 63.752% of variation in fresh pineapple exports. The participants agree that the variable factor of Consumer Price index is 0.872, and the variable factor of Exchange Rate is minimal -0.875. Researcher sees fit to name given as **"Export Demand."**

Table 4.7 Factor of Contract Farming.

Factor F4	**Variables**	**Factor Loading**
1	domestic sale of canned pineapple	0.863
(eigenvalues)		1.048
(% of Variance)		9.527
(Cumulative % of Variance)		73.297

Table 4.7 shows that the component (Factor F4) conforms to the Eigenvalues with greater than 1 and the factor loadings between -0.875 and 0.872. Element consists of one variable, with equals to the variance of 1 .0 4 3 %. The combined effect of 1 factor can explain about 73.297% of variation in domestic sale of canned pineapple variable that is the most valuable factor 0.863. Researchers sees fit to name given as **"Contract Farming."**

4.2.4 Factor Score

Factor score values for the four factors which were obtained by means of factor score coefficients given in Table 4.8 is used as independent variables in the regression analysis to determine significant factor. The 4 factors had significant effect the canned pineapple exports.

Table 4.8 Result of Factor Score.

FAC1_1	**FAC2_1**	**FAC3_1**	**FAC4_1**
-0.83812	-1.70865	-2.36151	-0.47138
-0.61363	-0.94921	-1.97526	-0.52668
-0.34302	-0.07397	-0.99748	-0.04353
0.12743	-0.15828	-1.88483	-0.80485
1.51844	0.11142	-1.99383	-0.71408
1.13022	-0.16088	-2.15803	-0.25241
-0.45209	0.00274	-1.34977	-0.41917
-1.74912	0.24595	-1.27515	-0.36782
-1.19144	2.82877	-0.98508	-1.21651

Table 4.8 Result of Factor Score (cont.).

FAC1_1	FAC2_1	FAC3_1	FAC4_1
0.61997	0.79324	-0.75924	0.32443
0.92619	0.3469	-1.01212	2.16198
0.11496	-0.34127	-1.06605	1.95089
0.03171	-0.40492	-0.77093	1.08892
0.21097	-0.21742	-0.20194	1.86745
0.85462	-0.00988	-0.22113	0.87198
1.4451	-0.19486	-0.04685	0.99109
…	…	…	…
…	…	…	…
…	…	…	…
-0.18884	1.73975	0.89967	-0.99421
-0.0261	1.89987	1.37002	-0.99212
0.49699	1.68569	1.21438	-0.80115
0.8359	0.65441	0.8391	-0.55222

Then use the data for analysis the standardized data, leaves 4 main factors. Revolve the factor loading matrix and explain variable with factor, just make it satisfy "the most simple structure criteria." Calculate the scores of factors. All is for achieving the dimensionality reduction. Create the new NARX network with the dimensionality reduction of data as input. Comparing algorithm with NARX algorithm predicted results.

4.3 Result of Nonlinear Autoregressive Model with Exogenous Input

First, to build models of Nonlinear Autoregressive model with Exogenous (External) Inputs (NARX) we use MATLAB (R2014a) platform with required configuration. By using this tool we write scripts to build and perform functions for calculating model performance, error statistics such as R, MSE, and Increase in coefficient of determination and show the improvement in network performance.

For build NARX model architecture, I provide 10 hidden neurons and delay value 2 as inputs. After building NARX model architecture, the researcher trained with 80 % of training data, validated with 10 % of training data, and tested in building phase with 10 % of training data shows in Figure 4.2. - Figure 4.5.

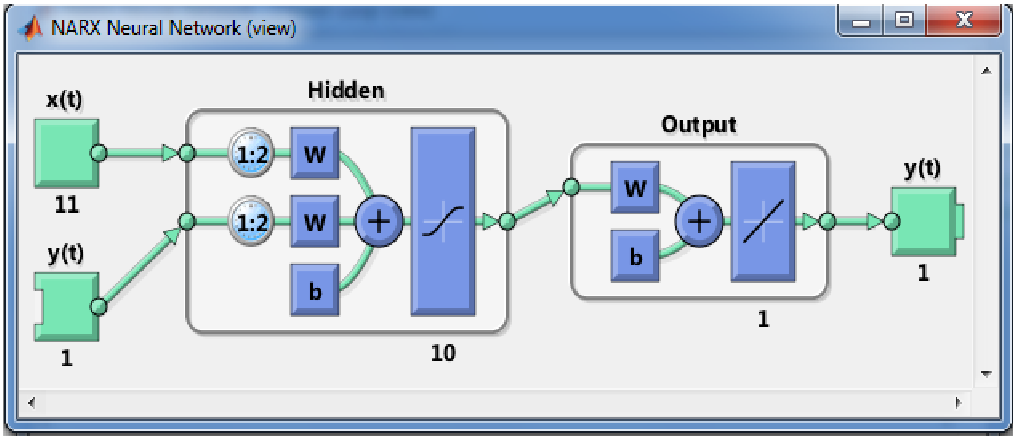

Figure 4.2 NARX Model for The Canned Pineapple Exports.

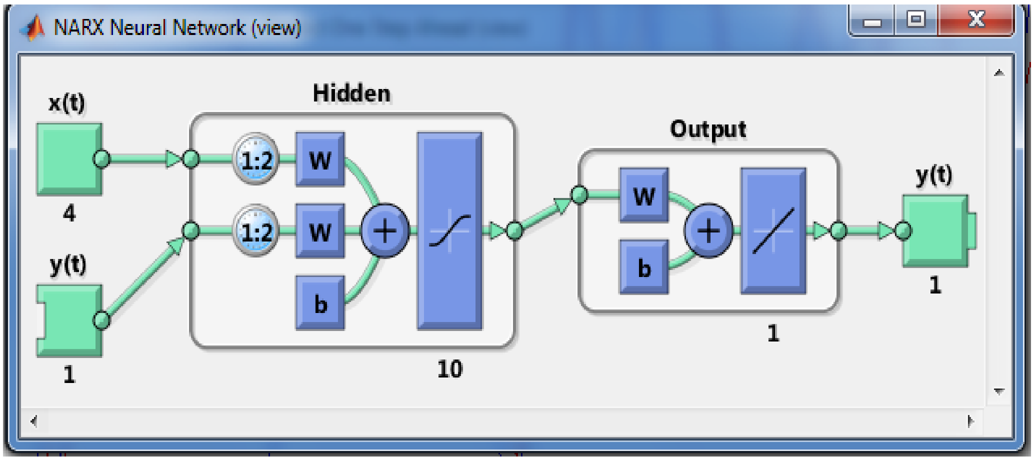

Figure 4.3 NARX based on 4 Factor Analysis Model for The Canned Pineapple Exports.

4.3.1 Result of the Network Training

The network training processed adapts by the neuron weights until no significant to the prediction capability is satisfied. This is trained by back-propagation of performance data a validation process.

Training is continuous satisfied until the best performance is accomplished. Because, the training to achieve for the closest comparison between experiment and model network support force values by minimum the error for the given force disfiguration set. In this Figure 4.4-Figure 4.5 the performance of the network training process measured by MSE has been completed and training time result in 0.468s.

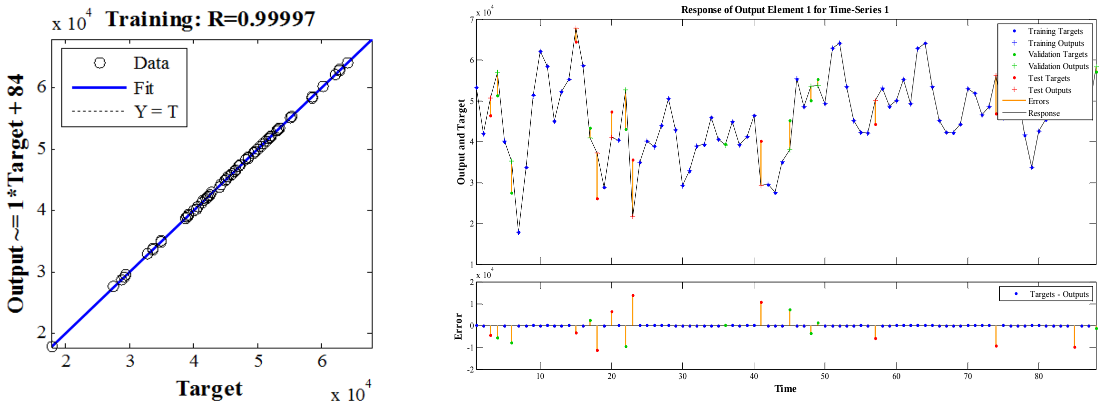

Figure 4.4 Training of NARX Model.

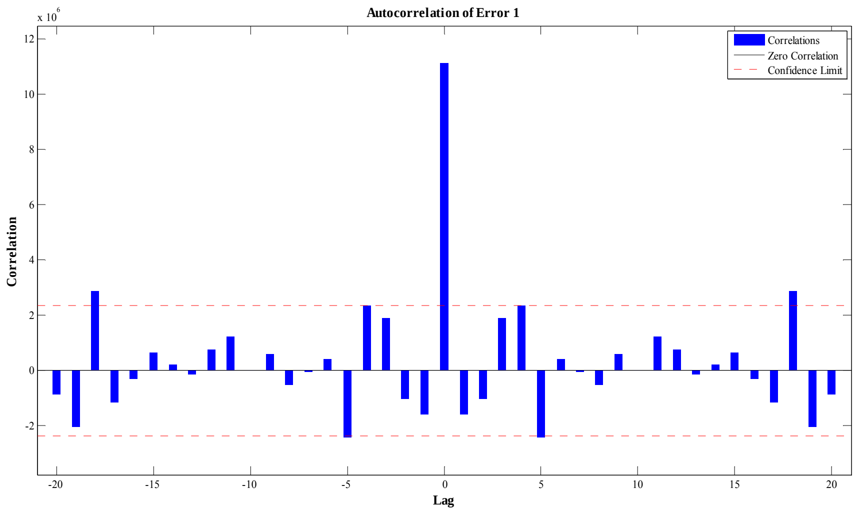

Figure 4.5 Autocorrelation of Error on NARX Model.

4.3.2 Result of Forecast NARX Model

During the forecast for NARX model can show the accuracy of comparing the volume of export canned pineapple forecast with the volume of exports canned pineapple actual.

In this Figure 4.6, from the graph shows a comparison of the forecasting the forecast value of quantity to export canned pineapple compared to the actual the value of exports of canned pineapple that show in Table 4.9.

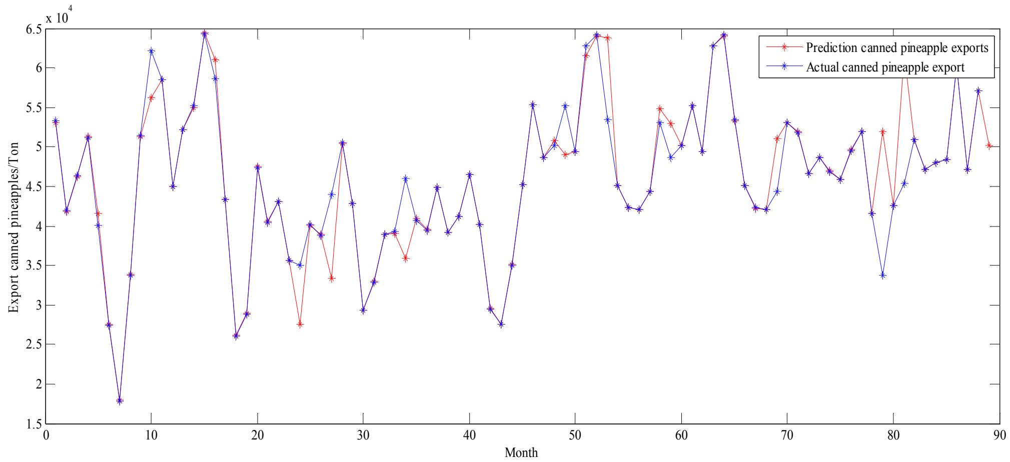

Figure 4.6 Prediction and Actual Data of The Canned Pineapple Exports for NARX Model.

Table 4.9 Comparison between The Volume of Forecast Canned Pineapple Exports and The Volume of Actual Canned Pineapple Exports of NARX Model.

DATE	Actual quantity of export canned pineapple (ton)	Forecast quantity of export canned pineapple (ton)	Residual (e) /Ton	Residual (e) / %
Jan-07	50545.00	-	-	-
Feb-07	46112.00	-	-	-
Mar-07	53292.00	53113.72	178.28	0.00
Apr-07	41984.00	41826.84	157.16	0.00
May-07	46398.00	46237.54	160.46	0.00
Jun-07	51228.00	51308.88	-80.88	0.00
Jul-07	40038.00	41638.91	-1600.91	-0.04
Aug-07	27484.00	27516.07	-32.07	0.00
Sep-07	17823.00	17931.12	-108.12	-0.01
Oct-07	33766.00	33824.78	-58.78	0.00
Nov-07	51375.00	51334.17	40.83	0.00
Dec-07	62100.00	56209.50	5890.50	0.09
Jan-08	58470.00	58467.35	2.65	0.00
Feb-08	44963.00	44977.13	-14.13	0.00
Mar-08	52150.00	52154.33	-4.33	0.00
Apr-08	55245.00	55022.46	222.54	0.00
May-08	------	------	------	------
Jan-09	35625.00	35692.55	-67.55	0.00
Feb-09	34986.00	27599.42	7386.58	0.21
Mar-09	40144.00	40104.71	39.29	0.00

Table 4.9 Comparison between The Volume of Forecast Canned Pineapple Exports and The Volume of Actual Canned Pineapple Exports of NARX Model (cont.).

DATE	Actual quantity of export canned pineapple (ton)	Forecast quantity of export canned pineapple (ton)	Residual (e) /Ton	Residual (e) / %
Apr-09	38862.00	38901.57	-39.57	0.00
May-09	------	------	------	------
Jan-10	40641.00	40909.11	-268.11	-0.01
Feb-10	39461.00	39496.73	-35.73	0.00
Mar-10	44851.00	44871.97	-20.97	0.00
Apr-10	39177.00	39211.30	-34.30	0.00
May-10	41256.00	41261.09	-5.09	0.00
Jun-10	------	------	------	------
Jan-11	48619.00	48645.67	-26.67	0.00
Feb-11	50120.00	50857.65	-737.65	-0.01
Mar-11	55211.00	49085.15	6125.85	0.11
Apr-11	49351.00	49372.66	-21.66	0.00
May-11	------	------	------	------
Jan-12	48619.00	52952.69	-4333.69	-0.09
Feb-12	50120.00	50167.36	-47.36	0.00
Mar-12	55211.00	55177.91	33.09	0.00
Apr-12	49351.00	49459.98	-108.98	0.00
May-12	------	------	------	------
Jan-13	51833.00	51869.99	-36.99	0.00
Feb-13	46567.00	46666.63	-99.63	0.00
Mar-13	48594.00	48621.30	-27.30	0.00
Apr-13	46864.00	46984.42	-120.42	0.00
May-13	45824.00	45916.23	-92.23	0.00
Jun-13	------	------	------	------
Jan-14	47110.00	47128.06	-18.06	0.00
Feb-14	48060.00	48074.76	-14.76	0.00
Mar-14	48335.00	48379.17	-44.17	0.00
Apr-14	60225.00	60244.12	-19.12	0.00
May-14	47189.00	47182.73	6.27	0.00
Jun-14	57053.00	57078.94	-25.94	0.00
Jul-14	-	50157.34	-	-

Table 4.9 The NARX model comparing between the volume of forecast canned pineapple export and the volume of actual canned pineapple export, we can see that the error of prediction is within ± 5% (95% confidence interval) when comparing the volume of actual canned pineapple exports.

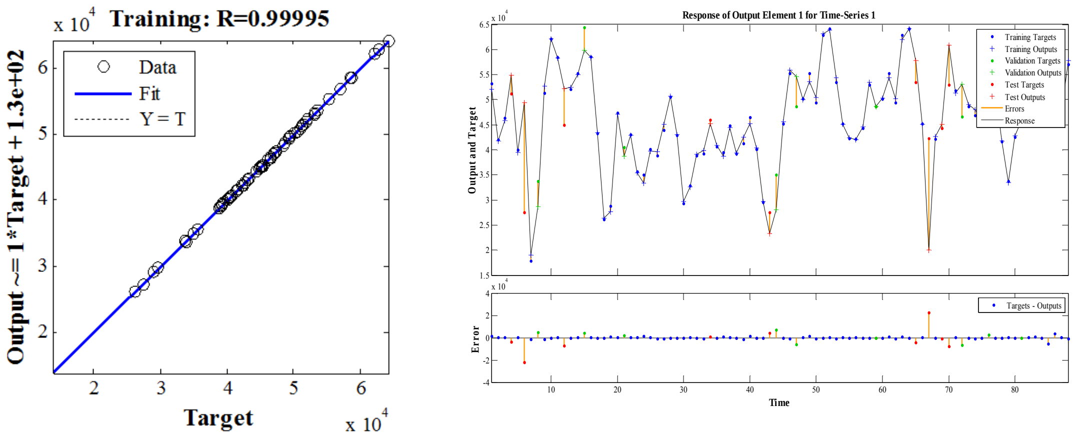

Figure 4.7 Training of NARX-FA Model.

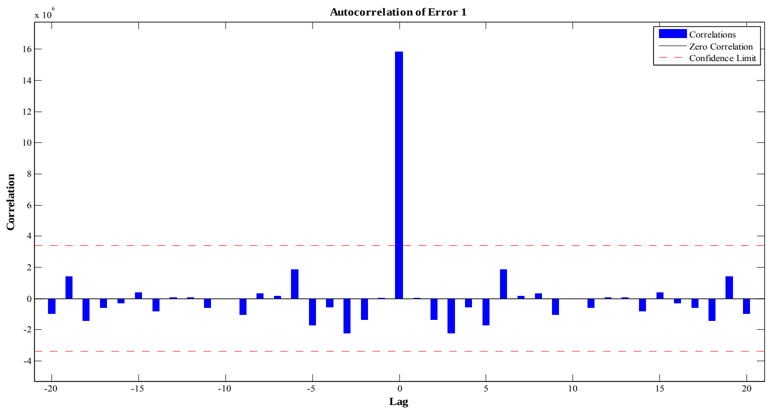

Figure 4.8 Autocorrelation of Error on NARX - FA Model.

After successfully building of NARX model, Figure 4.7-Figure 4.8 then build model base on a Factor Analysis algorithm to predict the canned pineapple export data and use SPSS for analysis the standardized data accord the 4 main factors to design the neural network, determine the number of hidden layer neurons as same as the first model some following to compare networks performance base on MSE, RMSE, and training time result in 0.455s.

4.3.3. Result of Forecast NARX-FA Model

Figure 4.9, during the forecast from NARX-FA model can show the accuracy of comparing between the volume of forecast canned pineapple exports and the volume of actual canned pineapple exports, see in Table 4.10.

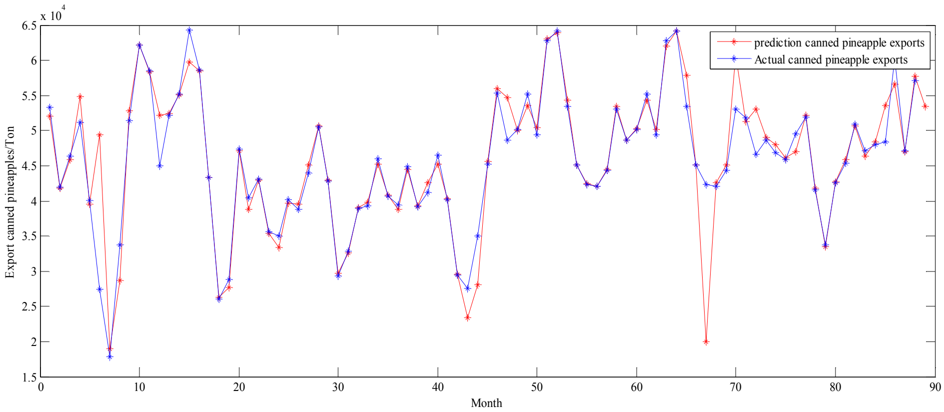

Figure 4.9 Prediction and Actual Data of The Canned Pineapple Exports for NARX-FA Model.

Table 4.10 Comparison between The Volume of Forecast Canned Pineapple Exports and The Volume of Actual Canned Pineapple Exports of NARX-FA Model.

DATE	Actual quantity of export canned pineapple (ton)	Forecast quantity of export canned pineapple (ton)	Residual (e) /Ton	Residual (e) / %
Jan-07	50545.00	-	-	-
Feb-07	46112.00	-	-	-
Mar-07	53292.00	52038.08	1253.92	0.02
Apr-07	41984.00	41779.98	204.02	0.00
May-07	46398.00	45897.61	500.39	0.01
Jun-07	51228.00	54896.48	-3668.48	-0.07
Jul-07	40038.00	39512.16	525.84	0.01
Aug-07	27484.00	49354.31	-21870.31	-0.80
Sep-07	17823.00	19001.97	-1178.97	-0.07
Oct-07	33766.00	28702.10	5063.90	0.15
Nov-07	51375.00	52781.60	-1406.60	-0.03
Dec-07	62100.00	62112.52	-12.52	0.00
Jan-08	58470.00	58309.36	160.64	0.00
Feb-08	44963.00	52227.50	-7264.50	-0.16
Mar-08	52150.00	52431.96	-281.96	-0.01
Apr-08	55245.00	55032.71	212.29	0.00

Table 4.10 Comparison between The Volume of Forecast Canned Pineapple Exports and The Volume of Actual Canned Pineapple Exports of NARX-FA Model (cont.).

DATE	Actual quantity of export canned pineapple (ton)	Forecast quantity of export canned pineapple (ton)	Residual (e) /Ton	Residual (e) / %
May-08	------	------	------	------
Jan-09	35625.00	35382.00	243.00	0.01
Feb-09	34986.00	33366.35	1619.65	0.05
Mar-09	40144.00	39709.81	434.19	0.01
Apr-09	38862.00	39575.39	-713.39	-0.02
May-09	------	------	------	------
Jan-10	40641.00	40853.13	-212.13	-0.01
Feb-10	39461.00	38761.86	699.14	0.02
Mar-10	44851.00	44442.47	408.53	0.01
Apr-10	39177.00	39331.36	-154.36	0.00
Jun-10	------	------	------	------
Jan-11	48619.00	54694.53	-6075.53	-0.12
Feb-11	50120.00	49988.96	131.04	0.00
Mar-11	55211.00	53591.48	1619.52	0.03
Apr-11	49351.00	50381.16	-1030.16	-0.02
May-11	------	------	------	------
Jan-12	48619.00	48711.48	-92.48	0.00
Feb-12	50120.00	50312.65	-192.65	0.00
Mar-12	55211.00	54379.83	831.17	0.02
Apr-12	49351.00	50172.32	-821.32	-0.02
May-12	------	------	------	------
Jan-13	51833.00	51349.57	483.43	0.01
Feb-13	46567.00	53100.07	-6533.07	-0.14
Mar-13	48594.00	49057.03	-463.03	-0.01
Apr-13	46864.00	47965.21	-1101.21	-0.02
May-13	45824.00	46140.77	-316.77	-0.01
Jun-13	------	------	------	------
Jan-14	47110.00	46374.23	735.77	0.02
Feb-14	48060.00	48450.87	-390.87	-0.01
Mar-14	48335.00	53558.89	-5223.89	-0.11
Apr-14	60225.00	56559.12	3665.88	0.06
May-14	47189.00	46982.80	206.20	0.00
Jun-14	57053.00	57779.16	-726.16	-0.01
Jul-14	-	53463.11	-	-

Table 4.10 The NARX-FA model comparing between the volume of forecast canned pineapple export and the volume of actual canned pineapple export we can see that the error of prediction is within ± 5% (95% confidence interval) when comparing the volume of actual canned pineapple exports.

4.3.4 Compare Forecast NARX and NARX-FA Model

Testing results of NARX model and the NARX - FA model is in Table 4.11. The results from the two models are recorded three parameters: MSE, RMSE, and training time. The method which is the combination of nonlinear autoregressive model with exogenous input based on factor analysis is better than the NARX model, the result in Table 4.11.

Table 4.11 The Comparison between NARX and NARX-FA Network Algorithm.

Model	MSE	RMSE	Training Time (s)
NARX Model	1.28×10^{7}	3.58×10^{3}	0.468
NARX-FA Model	1.58×10^{7}	3.98×10^{3}	0.455

Table 4.11, they can see that if the researcher use raw data as input to NARX model. The training for the backpropagation neural network algorithm will take a long time and the test accuracy is not high. When the researcher use factor score which transfer by factor analysis solutions. It has reduced training time more than NARX model.

In conclusion, comparing NARX-FA algorithm with backpropagation neural network algorithm predicted results. The accuracy of prediction is not decreased, but the steps for convergence are reduced and the error sum of squares is also reduce in the predicted results. Through the factor analysis solutions, can obtain the data of dimension reduction, and so make the input of network reduce, network easier be designed, the structure of network be simplified, the speed of network training be improved, and the convergence be more quickly achieved. The NARX-FA neural network algorithm is superior to traditional NARX neural network algorithm, which has stronger application and is worth of more studying and promoting.

CHAPTER 5
CONCLUSION

This the thesis proposes the design and development of two separate forecast models based on independent factor variables impacting the pineapple export, used as the feedback inputs for both forecast system models, given as: Nonlinear Autoregressive Model with Exogenous Inputs (NARX) and an improved NARX based on Factor Analysis Solutions (NARX-FA). This combination model has the following advantages. The result of experiment shows that NARX-FA algorithm has a greater improvement than simple NARX neural network due to an enhanced self-learning, fast convergence, with maintained the solution qualities. This thesis just uses the meteorological factor to predict occurrence.

In the research, researcher discovers that the combination of multivariate statistical analysis and neural network enable to improve the efficiency of neural network processing. For the further study, can get new algorithm with appropriate statistical data and theoretical neural network. It may have new discovery of the combination of neuron network with other intelligence methods.

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APPENDICES

APPENDIX A

EXPERIMENTAL OUTPUT

The coding of NARX model

```
This script assumes these variables are defined:
%
%   xnarx - input time series.
%   ynarx - feedback time series.

X = tonndata(xnarx,false,false);
T = tonndata(ynarx,false,false);

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NTSTOOL falls back to this in low
memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Nonlinear Autoregressive Network with External Input
inputDelays = 1:2;
feedbackDelays = 1:2;
hiddenLayerSize = 10;
net =
narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn);

% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback
output
% For a list of all processing functions type: help nnprocess
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular
network,
% shifting time by the minimum amount to fill input states and layer
states.
% Using PREPARETS allows you to keep your original time series data
unchanged, while
% easily customizing it for networks with differing numbers of
delays, with
% open loop or closed loop feedback modes.
[x,xi,ai,t] = preparets(net,X,{},T);

% Setup Division of Data for Training, Validation, Testing
% The function DIVIDERAND randomly assigns target values to training,
% validation and test sets during training.
```

```
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
% The property DIVIDEMODE set to TIMESTEP means that targets are
divided
% into training, validation and test sets according to timesteps.
% For a list of data division modes type: help
nntype_data_division_mode
net.divideMode = 'value';  % Divide up every value
net.divideParam.trainRatio = 80/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 10/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
% Customize performance parameters at: net.performParam
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
% Customize plot parameters at: net.plotParam
net.plotFcns = {'plotperform','plottrainstate','plotresponse', ...
  'ploterrcorr', 'plotinerrcorr'};

% Train the Network
[net,tr] = train(net,x,t,xi,ai);

% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotregression(t,y)
%figure, plotresponse(t,y)
%figure, ploterrcorr(e)
%figure, plotinerrcorr(x,e)

% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input with a direct
% connection from the outout layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
```

```
view(netc)
[xc,xic,aic,tc] = preparets(netc,X,{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(netc,tc,yc)
% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop form for
as
% long as there is known output data, and then switch to closed-loop
form
% to perform multistep prediction while providing only the external
input.
% Here all but 5 timesteps of the input series and target series are
used to
% simulate the network in open-loop form, taking advantage of the
higher
% accuracy that providing the target series produces:
numTimesteps = size(x,2);
knownOutputTimesteps = 1:(numTimesteps-5);
predictOutputTimesteps = (numTimesteps-4):numTimesteps;
X1 = X(:,knownOutputTimesteps);
T1 = T(:,knownOutputTimesteps);
[x1,xio,aio] = preparets(net,X1,{},T1);
[y1,xfo,afo] = net(x1,xio,aio);
% Next the the network and its final states will be converted to
closed-loop
% form to make five predictions with only the five inputs provided.
x2 = X(1,predictOutputTimesteps);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(x2,xic,aic);
multiStepPerformance = perform(net,T(1,predictOutputTimesteps),y2)
% Alternate predictions can be made for different values of x2, or
further
% predictions can be made by continuing simulation with additional
external
% inputs and the last closed-loop states xfc and afc.
% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a timestep
early.
% The original network returns predicted y(t+1) at the same time it
is given y(t+1).
% For some applications such as decision making, it would help to
have predicted
% y(t+1) once y(t) is available, but before the actual y(t+1) occurs.
% The network can be made to return its output a timestep early by
removing one delay
% so that its minimal tap delay is now 0 instead of 1.  The new
network returns the
% same outputs as the original network, but outputs are shifted left
one timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
view(nets)
[xs,xis,ais,ts] = preparets(nets,X,{},T);
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)
```

```
% Deployment
% Change the (false) values to (true) to enable the following code
blocks.
% See the help for each generation function for more information.
if (false)
  % Generate MATLAB function for neural network for application
deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder tools, or
simply
  % to examine the calculations your trained neural network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x,xi,ai);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  x1 = cell2mat(x(1,:));
  x2 = cell2mat(x(2,:));
  xi1 = cell2mat(xi(1,:));
  xi2 = cell2mat(xi(2,:));
  y = myNeuralNetworkFunction(x1,x2,xi1,xi2);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
plot(cell2mat(ys),'color','r');
hold on
plot(cell2mat(ts));
```

Network Training

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~) takes these arguments:
%
%   X = 2xTS cell, 2 inputs over TS timsteps
%   Each X{1,ts} = 11xQ matrix, input #1 at timestep ts.
%   Each X{2,ts} = 1xQ matrix, input #2 at timestep ts.
%
%   Xi = 2x2 cell 2, initial 2 input delay states.
%   Each Xi{1,ts} = 11xQ matrix, initial states for input #1.
%   Each Xi{2,ts} = 1xQ matrix, initial states for input #2.
%
%   Ai = 2x0 cell 2, initial 2 layer delay states.
%   Each Ai{1,ts} = 10xQ matrix, initial states for layer #1.
%   Each Ai{2,ts} = 1xQ matrix, initial states for layer #2.
%
% and returns:
%   Y = 1xTS cell of 2 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
%   Xf = 2x2 cell 2, final 2 input delay states.
%   Each Xf{1,ts} = 11xQ matrix, final states for input #1.
%   Each Xf{2,ts} = 1xQ matrix, final states for input #2.
```

```
%
%   Af = 2x0 cell 2, final 0 layer delay states.
%   Each Af{1ts} = 10xQ matrix, final states for layer #1.
%   Each Af{2ts} = 1xQ matrix, final states for layer #2.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.

%#ok<*RPMT0>

  % ===== NEURAL NETWORK CONSTANTS =====

  % Input 1
  x1_step1_xoffset =
[43580;3842.7;3;5.9841;5442.868;2.59;23.95;69.2822113241195;87.4;-
1.2;29.08];
  x1_step1_gain = [5.97335881966643e-06;5.51514942607976e-
05;0.00448430493273543;0.0020949320555923 7;0.000154747797842119;0.414
07867494824;0.0108677932945715;0.015479641131815;0.0975609756097561;0
.408163265306122;0.290275761973875];
  x1_step1_ymin = -1;

  % Input 2
  x2_step1_xoffset = 17823.466;
  x2_step1_gain = 4.29710659054543e-05;
  x2_step1_ymin = -1;

  % Layer 1
  b1 = [-1.8778120473708584;-1.3382339809524733;-
0.91957947629172554;0.57662987112452624;0.79391189064807366;0.6095580
189157116;-
1.1608641214362316;1.3802589717577973;0.56489595046833219;-
1.953653034403078];
  IW1_1 = [1.7244590874031231 1.2766868922293584 -0.31011417178986184
0.50580945322884852 -0.072352440417179073 1.2727703171522562
1.5894731936789936 0.60784915654277172 0.71970289037511803 -
0.11713574250685661 -0.37308926703600243 -0.72367519410520786
1.0624314390802947 -1.3571852107285547 -0.29888779057041071 -
0.72880689018848366 -0.3656393805318579 0.16854697906985827
0.021988737027205722 1.1786850494426757 0.92218455783533348 -
0.057972943222524241;-0.076467957007673851 -0.38427850240886446 -
0.37978698869285954 -0.065638352189259674 2.7446615805025978 -
0.53230919736803861 -0.40101982489948146 -1.1830550519795979
0.21683963275639523 0.16143581998386447 -1.6998891595978123
0.65324399358286056 -1.5379350764810824 1.2062867146335958
0.67198788163386625 0.33916120211306844 -0.5076250168851405
0.19773510563849811 -0.36761442441664938 0.9048854069400285
0.46963751584828267 -0.97016297976011767;0.22297229142488148 -
0.29494418857628574 -0.92080858754051342 1.0452024170076635 -
0.75302227049375536 0.84256171035537086 -0.66348542653470288
0.92300517672140292 0.21840426237897034 -0.66635169035235142
0.50122547049296307 -0.88072196209723985 -1.0702403704078118 -
0.76645981572828137 0.31974006896471613 -1.2511777973976217
0.18134303291022502 -1.0023723387539905 0.48093994432287895 -
0.68275663113439078 -0.0094446599528325709
1.4623081765165395;0.22862137747622274 -0.11716226888445687 -
0.40136330375732582 -0.42354579743187126 -0.15904730665361894 -
```

```
0.10409051958272997 0.57605594979825048 0.075069122800047558 -
0.1724524037620887 0.86292350196247236 0.48974296640499299 -
0.19124109541972029 0.65376921043185776 -0.66783206198689027 -
0.19986319452159512 0.76786051496405738 0.068580587185604044
0.054596940260209954 -0.34455968579734741 -0.55851190415178076
0.77016692507461193 -0.031723722240807745;0.98103908300645715
1.7726765151956776 0.98558517021413683 -0.59002418620566677
0.87646363288360496 -0.45851108229934312 0.83081195098060689 -
1.2020119643525624 0.19614506862569708 -0.26420645418789457
0.37213796994805382 0.013459037228243376 0.58046262807502103
0.60413093940024687 -0.22544330804614468 0.98814431627889987
0.6015887143034333 -0.29296471180957728 0.90692544208256265
0.55712006623865706 -0.58039478024320612
0.0089450916922644633;0.033956852525363748 -0.39191085078916832 -
0.32980393965955657 1.9424817109105386 -0.018355963895159737
0.94921379345466084 -0.79485159102342873 0.73709694126950565
0.26489696269823543 -0.086910822801807841 -1.3594921242017737 -
0.49031711124733002 -0.10038129555910758 -0.3448702774053149
2.3282507232557794 -0.61971453618117367 1.0080783566036873 -
1.3094141021806762 0.59435455952178717 1.361022920639795
0.20819771068607057 -0.57919403827963045;-1.0966180807466601
0.15386674927927427 -0.52995688360859194 -0.5636628315213279
1.6178467516297141 -0.63954327561905 -1.1027499636105709 -
0.75363757102176243 -0.92330953512071146 1.0507050923999961 -
0.98110605759063896 -0.65680529534834375 -1.440840599080335 -
0.36514265914107341 -1.4411370359115037 1.5009156051310468
0.050583892750855432 -0.046509448975413162 0.83616999097314748 -
0.47279551565687733 0.61222130444222678 -
0.27192823038677744;1.1712302484972736 0.59381489024492562 -
1.1144836382785952 -1.0228720682610688 0.73732250564824908
0.26829160754457415 1.6860810337873597 -0.46086843315701076 -
0.19185327896932097 0.71423691162876568 -0.26478905328769664 -
1.7803654077096991 -2.0350150261269144 -0.29956032048057235 -
0.18543608383325708 0.80313619166654859 0.57332815357161837 -
2.2854189487926586 0.62837443594679721 0.030861840183933932
0.027073464534502156 0.90906810191265808;0.39698031619319418 -
1.3977147605373619 -0.53131013715696029 -0.93639642937616663 -
0.019347792832421631 -0.92913776966327333 -0.06758459764565064 -
0.10068449559260374 -0.75198254382100638 1.0178594563268286
0.57017935337276549 -0.24244344950047581 -1.4336722163456868 -
0.38251132890375206 1.7257227796411461 -0.30615787014886658 -
0.46663561856540398 -0.24888138576604624 -0.49869164386111076
0.63107109220230095 0.65931133206559844 0.70967784304661186;-
0.081069895026640762 -0.52273768766524564 1.3307747891341077
0.3611628648171607 -0.41777297260729096 -0.64775430147748958 -
0.060928284309372777 -0.77701495293336587 -0.76121478901480399 -
0.2174430779619069 0.32523808511499569 -0.95908076162324818
0.27587443878373563 -0.14019112116501722 0.3886283246444
1.1014564341215656 0.025531255981114772 -1.1112876476659024
0.017177727946824425 -0.32440076630876052 0.36472120805626523
1.0304912730378151];
  IW1_2 = [1.149514065102714 0.43737254225401107;0.10325946818758475
0.7040423169590686;0.063510939142247369 0.49940124682874987;-
0.31375873930340231 -0.11504528628532235;2.1909889203326869 -
1.0584720158906022;-1.3311555626383769 0.66359185139517141;-
0.071208958909034725 0.22320008244915157;1.1798777919446226
1.0144376921977569;1.4658244814266057
0.13768961641545624;0.75001583721010889 -0.19615390713730618];
```

```
  % Layer 2
  b2 = 0.75800214582143843;
  LW2_1 = [0.11845534909871004 0.31783939639363257 -
0.17628628642669547 0.18444908194514958 -0.35499822940094033 -
0.20971749920433569 -0.47948095055246076 0.40720837287746464 -
0.6191240399000616 0.11756717006479775];

  % Output 1
  y1_step1_ymin = -1;
  y1_step1_gain = 4.29710659054543e-05;
  y1_step1_xoffset = 17823.466;

  % ===== SIMULATION ========

  % Format Input Arguments
  isCellX = iscell(X);
  if ~isCellX, X = {X}; end;
  if (nargin < 2), error('Initial input states Xi argument needed.');
end

  % Dimensions
  TS = size(X,2); % timesteps
  if ~isempty(X)
    Q = size(X{1},2); % samples/series
  elseif ~isempty(Xi)
    Q = size(Xi{1},2);
  else
    Q = 0;
  end

  % Input 1 Delay States
  Xd1 = cell(1,3);
  for ts=1:2
    Xd1{ts} =
mapminmax_apply(Xi{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin
);
  end

  % Input 2 Delay States
  Xd2 = cell(1,3);
  for ts=1:2
    Xd2{ts} =
mapminmax_apply(Xi{2,ts},x2_step1_gain,x2_step1_xoffset,x2_step1_ymin
);
  end

  % Allocate Outputs
  Y = cell(1,TS);

  % Time loop
  for ts=1:TS

    % Rotating delay state position
    xdts = mod(ts+1,3)+1;
```

```
    % Input 1
    Xd1{xdts} =
mapminmax_apply(X{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin)
;

    % Input 2
    Xd2{xdts} =
mapminmax_apply(X{2,ts},x2_step1_gain,x2_step1_xoffset,x2_step1_ymin)
;

    % Layer 1
    tapdelay1 = cat(1,Xd1{mod(xdts-[1 2]-1,3)+1});
    tapdelay2 = cat(1,Xd2{mod(xdts-[1 2]-1,3)+1});
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*tapdelay1 +
IW1_2*tapdelay2);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} =
mapminmax_reverse(a2,y1_step1_gain,y1_step1_xoffset,y1_step1_ymin);
  end

  % Final Delay States
  finalxts = TS+(1: 2);
  xits = finalxts(finalxts<=2);
  xts = finalxts(finalxts>2)-2;
  Xf = [Xi(:,xits) X(:,xts)];
  Af = cell(2,0);

  % Format Output Arguments
  if ~isCellX, Y = cell2mat(Y); end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y =
mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
  y = bsxfun(@minus,x,settings_xoffset);
  y = bsxfun(@times,y,settings_gain);
  y = bsxfun(@plus,y,settings_ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n)
  a = 2 ./ (1 + exp(-2*n)) - 1;
end
 % Map Minimum and Maximum Output Reverse-Processing Function
function x =
mapminmax_reverse(y,settings_gain,settings_xoffset,settings_ymin)
  x = bsxfun(@minus,y,settings_ymin);
  x = bsxfun(@rdivide,x,settings_gain);
  x = bsxfun(@plus,x,settings_xoffset);
end
```

Function details for network train

narx (1 call, 1.701 sec)

script in file C:\Users\Administrator\Desktop\matlab\narx model\narx.m
Copy to new window for comparing multiple runs

Refresh

Show parent functions Show busy lines Show child functions
Show Code Analyzer results Show file coverage Show function listing

Parents (calling functions)
No parent

Lines where the most time was spent

Line Number	Code	Calls	Total Time	% Time	Time Plot
67	`[net,tr] = train(net,x,t,xi,ai...`	1	0.609 s	35.8%	
24	`net = narxnet(inputDelays,feed...`	1	0.203 s	11.9%	
40	`[x,xi,ai,t] = preparets(net,X,...`	1	0.109 s	6.4%	
169	`plot(cell2mat(ys),'color','r')...`	1	0.078 s	4.6%	
139	`view(nets)`	1	0.078 s	4.6%	
All other lines			0.624 s	36.7%	
Totals			1.701 s	100%	

Children (called functions)

Function Name	Function Type	Calls	Total Time	% Time	Time Plot
network.train	function	1	0.609 s	35.8%	
preparets	function	4	0.219 s	12.9%	
network.view	function	3	0.218 s	12.8%	
narxnet	function	1	0.203 s	11.9%	
network.subsref	function	7	0.171 s	10.1%	
closeloop	function	2	0.063 s	3.7%	
newplot	function	2	0.062 s	3.6%	
network.subsasgn	function	11	0.047 s	2.8%	
network.perform	function	7	0.032 s	1.9%	
tonndata	function	2	0.031 s	1.8%	
removedelay	function	1	0.015 s	0.9%	
gmultiply	function	3	0.015 s	0.9%	
hold	function	1	0 s	0%	
lineseries	function	2	0 s	0%	
cell2mat	function	2	0 s	0%	
gsubtract	function	1	0 s	0%	
Self time (built-ins, overhead, etc.)			0.016 s	0.9%	
Totals			1.701 s	100%	

The coding of NARX-FA model

```
This script assumes these variables are defined:
%
%   xnarxfa - input time series.
%   ynatxfa - feedback time series.

X = tonndata(xnarxfa,false,false);
T = tonndata(ynatxfa,false,false);

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NTSTOOL falls back to this in low
memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Nonlinear Autoregressive Network with External Input
inputDelays = 1:2;
feedbackDelays = 1:2;
hiddenLayerSize = 10;
net =
narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn);

% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback
output
% For a list of all processing functions type: help nnprocess
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular
network,
% shifting time by the minimum amount to fill input states and layer
states.
% Using PREPARETS allows you to keep your original time series data
unchanged, while
% easily customizing it for networks with differing numbers of
delays, with
% open loop or closed loop feedback modes.
[x,xi,ai,t] = preparets(net,X,{},T);

% Setup Division of Data for Training, Validation, Testing
% The function DIVIDERAND randomly assigns target values to training,
% validation and test sets during training.
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
% The property DIVIDEMODE set to TIMESTEP means that targets are
divided
% into training, validation and test sets according to timesteps.
% For a list of data division modes type: help
nntype_data_division_mode
net.divideMode = 'value';  % Divide up every value
net.divideParam.trainRatio = 80/100;
```

```
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 10/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
% Customize performance parameters at: net.performParam
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
% Customize plot parameters at: net.plotParam
net.plotFcns = {'plotperform','plottrainstate','plotresponse', ...
  'ploterrcorr', 'plotinerrcorr'};

% Train the Network
[net,tr] = train(net,x,t,xi,ai);

% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotregression(t,y)
%figure, plotresponse(t,y)
%figure, ploterrcorr(e)
%figure, plotinerrcorr(x,e)

% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input with a direct
% connection from the outout layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
view(netc)
[xc,xic,aic,tc] = preparets(netc,X,{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(netc,tc,yc)
% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop form for
as
% long as there is known output data, and then switch to closed-loop
form
```

```
% to perform multistep prediction while providing only the external
input.
% Here all but 5 timesteps of the input series and target series are
used to
% simulate the network in open-loop form, taking advantage of the
higher
% accuracy that providing the target series produces:
numTimesteps = size(x,2);
knownOutputTimesteps = 1:(numTimesteps-5);
predictOutputTimesteps = (numTimesteps-4):numTimesteps;
X1 = X(:,knownOutputTimesteps);
T1 = T(:,knownOutputTimesteps);
[x1,xio,aio] = preparets(net,X1,{},T1);
[y1,xfo,afo] = net(x1,xio,aio);
% Next the the network and its final states will be converted to
closed-loop
% form to make five predictions with only the five inputs provided.
x2 = X(1,predictOutputTimesteps);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(x2,xic,aic);
multiStepPerformance = perform(net,T(1,predictOutputTimesteps),y2)
% Alternate predictions can be made for different values of x2, or
further
% predictions can be made by continuing simulation with additional
external
% inputs and the last closed-loop states xfc and afc.


% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a timestep
early.
% The original network returns predicted y(t+1) at the same time it
is given y(t+1).
% For some applications such as decision making, it would help to
have predicted
% y(t+1) once y(t) is available, but before the actual y(t+1) occurs.
% The network can be made to return its output a timestep early by
removing one delay
% so that its minimal tap delay is now 0 instead of 1.  The new
network returns the
% same outputs as the original network, but outputs are shifted left
one timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
view(nets)
[xs,xis,ais,ts] = preparets(nets,X,{},T);
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)

% Deployment
% Change the (false) values to (true) to enable the following code
blocks.
% See the help for each generation function for more information.
if (false)
  % Generate MATLAB function for neural network for application
deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder tools, or
simply
```

```
  % to examine the calculations your trained neural network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x,xi,ai);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  x1 = cell2mat(x(1,:));
  x2 = cell2mat(x(2,:));
  xi1 = cell2mat(xi(1,:));
  xi2 = cell2mat(xi(2,:));
  y = myNeuralNetworkFunction(x1,x2,xi1,xi2);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
plot(cell2mat(ys),'color','r');
hold on
plot(cell2mat(ts));
```

Network Training

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~) takes these arguments:
%
%   X = 2xTS cell, 2 inputs over TS timsteps
%   Each X{1,ts} = 4xQ matrix, input #1 at timestep ts.
%   Each X{2,ts} = 1xQ matrix, input #2 at timestep ts.
%
%   Xi = 2x2 cell 2, initial 2 input delay states.
%   Each Xi{1,ts} = 4xQ matrix, initial states for input #1.
%   Each Xi{2,ts} = 1xQ matrix, initial states for input #2.
%
%   Ai = 2x0 cell 2, initial 2 layer delay states.
%   Each Ai{1,ts} = 10xQ matrix, initial states for layer #1.
%   Each Ai{2,ts} = 1xQ matrix, initial states for layer #2.
%
% and returns:
%   Y = 1xTS cell of 2 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
%   Xf = 2x2 cell 2, final 2 input delay states.
%   Each Xf{1,ts} = 4xQ matrix, final states for input #1.
%   Each Xf{2,ts} = 1xQ matrix, final states for input #2.
%
%   Af = 2x0 cell 2, final 0 layer delay states.
%   Each Af{1ts} = 10xQ matrix, final states for layer #1.
%   Each Af{2ts} = 1xQ matrix, final states for layer #2.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.
```

```
%#ok<*RPMT0>

  % ===== NEURAL NETWORK CONSTANTS =====

  % Input 1
  x1_step1_xoffset = [-2.14082;-2.0682;-2.36151;-1.66686];
  x1_step1_gain =
[0.42272573554278;0.408415816310903;0.528229927923026;0.3786738463227
93];
  x1_step1_ymin = -1;

  % Input 2
  x2_step1_xoffset = 17823.466;
  x2_step1_gain = 4.29710659054543e-05;
  x2_step1_ymin = -1;

  % Layer 1
  b1 = [3.0775725327211942;-3.2434480307354794;-3.1249770057462665;-
2.6600990534330466;0.10577438305239514;1.6628405140119804;0.709980521
12031684;1.7371115964751638;1.5498898374178951;-2.9809794977313215];
  IW1_1 = [-0.7867202199868597 1.347444703377993 -0.41460640549986644
0.84061138189617157 -0.91979013359036088 1.4129289737256783 -
0.88263035862923789 1.2896366237189074;0.24349190678547183 -
1.0051580097636201 1.375284119814028 0.43158224771130665 -
1.2304330674695201 -0.45671343266396752 2.1533419752156231 -
0.96862453643532331;0.65349361836739062 3.5334023901481242
0.047356215895247918 -1.0099167838368213 -0.8748103523236791 -
1.8320965122321666 0.048915033707562158 -0.33484567376652258;-
1.2793550982326805 -2.7624627620720235 0.055959654178677792 -
1.977963713003158 0.97578524453716553 -1.7232244254174747 -
1.0992477305815405 -0.77507715325191517;-0.23087713510420835 -
1.5136962519116888 1.6162818536652959 2.2546551127788499 -
0.45739541950922102 2.3512572417063939 -0.53607868704697614
1.1320355891798579;1.3204454463748856 -1.8026588330619377 -
1.0168226090930985 -0.24597733413284045 1.140747961173374 -
0.68740710795494653 1.8600121260881697 -0.7672752423824678;-
0.078842689074611741 2.3293507390369661 -2.0109479873756202 -
0.86219208641705913 0.51339615480828982 1.4485162305103876 -
0.52433658360327917 -0.62447001002867519;-0.63915570689796375 -
2.2705760207320735 0.69865950364162699 3.0907157982302738 -
0.31940721473329492 2.0271754062982978 -0.88578603828757141
1.7339624953114865;0.3405052821566309 2.1064201887809344
1.7659667155157479 -1.0705757839180698 -1.7789248302192242
1.6249789250085185 1.3882870297069601 2.2343412371862703;-
0.99109163699942648 0.23026108748820251 0.37006481705950695
0.87874269157446983 0.88758510831082349 -0.38919799822704837
1.4576187335455575 -0.48083696464368014];
  IW1_2 = [-0.14536309753292054 1.1030029263741565;-
0.63465568803136818 -0.90065495790012984;-1.220061050818096 -
1.6525387863264811;-1.3179997280216618 -
2.2581226033450519;0.87626852509179942
0.75907052383699947;0.10943673392492101 -
1.7484319358550502;2.50915836727751
0.86757009597484791;2.2513925305711253
0.21494978471497464;0.52108612382853348
2.2360158918439836;0.86994727759146251 -0.085917645438177828];
```

```
  % Layer 2
  b2 = -0.54306071365453623;
  LW2_1 = [-0.73485521480642746 -0.43013218030866857
0.42079853407475637 -0.5189648758552825 0.74429637716885511
0.71246256407352171 -0.1352939813519963 -0.50793442165156499 -
0.15941506273213996 -0.97649393569879173];

  % Output 1
  y1_step1_ymin = -1;
  y1_step1_gain = 4.29710659054543e-05;
  y1_step1_xoffset = 17823.466;

  % ===== SIMULATION ========

  % Format Input Arguments
  isCellX = iscell(X);
  if ~isCellX, X = {X}; end;
  if (nargin < 2), error('Initial input states Xi argument needed.');
end

  % Dimensions
  TS = size(X,2); % timesteps
  if ~isempty(X)
    Q = size(X{1},2); % samples/series
  elseif ~isempty(Xi)
    Q = size(Xi{1},2);
  else
    Q = 0;
  end

  % Input 1 Delay States
  Xd1 = cell(1,3);
  for ts=1:2
    Xd1{ts} =
mapminmax_apply(Xi{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin
);
  end

  % Input 2 Delay States
  Xd2 = cell(1,3);
  for ts=1:2
    Xd2{ts} =
mapminmax_apply(Xi{2,ts},x2_step1_gain,x2_step1_xoffset,x2_step1_ymin
);
  end

  % Allocate Outputs
  Y = cell(1,TS);

  % Time loop
  for ts=1:TS

    % Rotating delay state position
    xdts = mod(ts+1,3)+1;

    % Input 1
```

```
    Xd1{xdts} =
mapminmax_apply(X{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin)
;
    % Input 2
    Xd2{xdts} =
mapminmax_apply(X{2,ts},x2_step1_gain,x2_step1_xoffset,x2_step1_ymin)
;

    % Layer 1
    tapdelay1 = cat(1,Xd1{mod(xdts-[1 2]-1,3)+1});
    tapdelay2 = cat(1,Xd2{mod(xdts-[1 2]-1,3)+1});
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*tapdelay1 +
IW1_2*tapdelay2);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} =
mapminmax_reverse(a2,y1_step1_gain,y1_step1_xoffset,y1_step1_ymin);
  end

  % Final Delay States
  finalxts = TS+(1: 2);
  xits = finalxts(finalxts<=2);
  xts = finalxts(finalxts>2)-2;
  Xf = [Xi(:,xits) X(:,xts)];
  Af = cell(2,0);

  % Format Output Arguments
  if ~isCellX, Y = cell2mat(Y); end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y =
mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
  y = bsxfun(@minus,x,settings_xoffset);
  y = bsxfun(@times,y,settings_gain);
  y = bsxfun(@plus,y,settings_ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n)
  a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x =
mapminmax_reverse(y,settings_gain,settings_xoffset,settings_ymin)
  x = bsxfun(@minus,y,settings_ymin);
  x = bsxfun(@rdivide,x,settings_gain);
  x = bsxfun(@plus,x,settings_xoffset);
end
```

Profiler - Function details for network train

narxfa (1 call, 1.528 sec)

script in file C:\Users\Administrator\Desktop\matlab\narxfa model\narxfa.m
Copy to new window for comparing multiple runs

Refresh

☑ Show parent functions ☑ Show busy lines ☑ Show child functions
☑ Show Code Analyzer results ☑ Show file coverage ☑ Show function listing

Parents (calling functions)
No parent

Lines where the most time was spent

Line Number	Code	Calls	Total Time	% Time	Time Plot
67	`[net,tr] = train(net,x,t,xi,ai...`	1	0.498 s	32.6%	
24	`net = narxnet(inputDelays,feed...`	1	0.203 s	13.3%	
40	`[x,xi,ai,t] = preparets(net,X,...`	1	0.094 s	6.1%	
139	`view(nets)`	1	0.078 s	5.1%	
170	`plot(cell2mat(ys),'color','r')...`	1	0.063 s	4.1%	
All other lines			0.593 s	38.8%	
Totals			1.528 s	100%	

Children (called functions)

Function Name	Function Type	Calls	Total Time	% Time	Time Plot
network.train	function	1	0.498 s	32.6%	
preparets	function	4	0.219 s	14.3%	
narxnet	function	1	0.203 s	13.3%	
network.view	function	3	0.186 s	12.2%	
network.subsref	function	7	0.125 s	8.2%	
newplot	function	2	0.063 s	4.1%	
closeloop	function	2	0.063 s	4.1%	
network.subsasgn	function	11	0.062 s	4.1%	
network.perform	function	7	0.047 s	3.1%	
removedelay	function	1	0.016 s	1.0%	
gsubtract	function	1	0.016 s	1.0%	
tonndata	function	2	0.016 s	1.0%	
gmultiply	function	3	0.015 s	1.0%	
hold	function	1	0 s	0%	
lineseries	function	2	0 s	0%	
cell2mat	function	2	0 s	0%	
Self time (built-ins, overhead, etc.)			0.000 s	0.0%	
Totals			1.528 s	100%	

Factor Analysis Output.

KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.674
Bartlett's Test of Sphericity	Approx. Chi-Square	522.090
	df	55
	Sig.	.000

Communalities.

	Initial	Extraction
pineapple yield	1.000	.932
Production of canned pineapple	1.000	.610
domestic sale of canned pineapple	1.000	.780
Fresh Pineapple Exports	1.000	.416
juice pineapple exports	1.000	.654
Agricultural price at farm gate	1.000	.751
Agriculture production price index	1.000	.896
Agriculture price index	1.000	.804
Consumer Price index	1.000	.766
inflation rate	1.000	.643
Exchange Rate	1.000	.809

Extraction Method: Principal Component Analysis

.

Total Variance Explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.548	32.251	32.251	3.548	32.251	32.251	2.920	26.547	26.547
2	2.041	18.552	50.802	2.041	18.552	50.802	2.048	18.621	45.168
3	1.424	12.949	63.752	1.424	12.949	63.752	2.028	18.438	63.606
4	1.048	9.527	73.279	1.048	9.527	73.279	1.064	9.673	73.279
5	.844	7.672	80.950						
6	.762	6.925	87.875						
7	.438	3.986	91.861						
8	.345	3.135	94.996						
9	.294	2.677	97.672						
10	.226	2.058	99.731						
11	.030	.269	100.000						

Extraction Method: Principal Component Analysis.

Component Matrix (a).

	Component			
	1	**2**	**3**	**4**
pineapple yield	.863			
Production of canned pineapple	.770			
domestic sale of canned pineapple				.826
Fresh Pineapple Exports		.527		
juice pineapple exports	.646			
Agricultural price at farm gate	-.641		.578	
Agriculture production price index	.837			
Agriculture price index	-.638		.628	
Consumer Price index		-.869		
inflation rate				
Exchange Rate		.864		

Extraction Method: Principal Component Analysis.
a 4 components extracted.

Rotated Component Matrix(a).

	Component			
	1	2	3	4
pineapple yield	.943			
Production of canned pineapple	.711			
domestic sale of canned pineapple				.863
Fresh Pineapple Exports			-.549	
juice pineapple exports	.711			
Agricultural price at farm gate		.820		
Agriculture production price index	.931			
Agriculture price index		.858		
Consumer Price index			.872	
inflation rate		-.617		
Exchange Rate			-.875	

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser. Normalization.
a Rotation converged in 5 iterations.

Component Transformation Matrix.

Component	1	2	3	4
1	.838	-.542	.046	-.030
2	.120	.104	-.986	-.048
3	.517	.823	.158	-.175
4	.123	.135	-.018	.983

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

Factor Score from Spss Output.

DATE	fac1_1	fac2_1	fac3_1	fac4_1
Jan-07	-0.83812	-1.70865	-2.36151	-0.47138
Feb-07	-0.61363	-0.94921	-1.97526	-0.52668
Mar-07	-0.34302	-0.07397	-0.99748	-0.04353
Apr-07	0.12743	-0.15828	-1.88483	-0.80485
May-07	1.51844	0.11142	-1.99383	-0.71408
Jun-07	1.13022	-0.16088	-2.15803	-0.25241
Jul-07	-0.45209	0.00274	-1.34977	-0.41917
Aug-07	-1.74912	0.24595	-1.27515	-0.36782
Sep-07	-1.19144	2.82877	-0.98508	-1.21651
Oct-07	0.61997	0.79324	-0.75924	0.32443
Nov-07	0.92619	0.3469	-1.01212	2.16198
Dec-07	0.11496	-0.34127	-1.06605	1.95089
Jan-08	0.03171	-0.40492	-0.77093	1.08892
Feb-08	0.21097	-0.21742	-0.20194	1.86745
Mar-08	0.85462	-0.00988	-0.22113	0.87198
Apr-08	1.4451	-0.19486	-0.04685	0.99109
May-08	2.59038	-1.04955	-0.06476	-0.50947
Jun-08	-1.15907	-1.87768	-0.12567	0.48038
Jul-08	-1.69913	-0.64887	0.12821	-1.54456
Aug-08	-2.09935	-0.37831	-0.39313	-1.33076
Sep-08	-1.1505	-0.00776	-0.48055	-1.66686
Oct-08	0.50508	-0.54114	-1.10065	-0.05192
Nov-08	1.26146	-0.79051	-1.11412	-0.51967
Dec-08	0.61235	-1.28849	-1.72759	-0.1077
Jan-09	-0.47506	-1.09815	-1.23599	-0.39425
Feb-09	-0.10578	-0.492	-1.26862	-0.69181
Mar-09	-0.07769	0.21678	-1.31373	-0.37576
Apr-09	-0.48436	0.78094	-1.07937	0.11964
May-09	1.12637	1.66963	-1.09652	-0.30678
Jun-09	1.25107	1.57886	-1.32957	0.80839
Jul-09	-1.00066	1.45107	-1.22454	0.84149
Aug-09	-2.14082	1.05309	-0.64854	-0.4709
Sep-09	-1.02408	0.98621	-0.73185	0.50588
Oct-09	0.23428	0.95415	-0.7477	0.13315
Nov-09	0.83026	-0.00463	-0.87427	0.71024
Dec-09	0.65772	0.29129	-0.76269	0.96692
Jan-10	0.03653	0.10832	-0.55229	0.26452
Feb-10	0.04277	0.74544	-0.58029	0.04647

DATE	fac1_1	fac2_1	fac3_1	fac4_1
Mar-10	0.90065	0.71726	-0.79786	0.77336
Apr-10	0.43877	1.03674	0.03937	-0.02625
May-10	0.0163	0.6685	-0.05018	-0.33498
Jun-10	-0.57081	0.68921	-0.1352	0.47435
Jul-10	-1.19236	0.90696	0.31327	-0.13216
Aug-10	-1.82514	0.68025	0.37505	-0.51273
Sep-10	-1.30299	0.4251	0.40815	-0.55297
Oct-10	-0.63107	0.71212	0.77205	-0.80537
Nov-10	0.58879	0.71214	0.38529	-0.27914
Dec-10	1.03548	0.97139	0.64038	0.25292
Jan-11	0.03928	0.65283	0.54192	-0.49176
Feb-11	0.08485	0.69339	0.55266	-0.21208
Mar-11	0.95024	1.20134	0.83413	-0.39403
Apr-11	1.74505	0.94228	1.19528	-0.22829
May-11	2.30124	0.47082	1.07264	-0.69131
Jun-11	1.34727	-0.01283	0.86441	-0.51362
Jul-11	-0.82375	-0.41214	1.02697	-0.5686
Aug-11	-1.35056	-0.77772	1.29333	0.16645
Sep-11	-0.97994	-1.14556	0.93825	-1.13267
Oct-11	-0.08787	-0.86166	1.21252	-1.49199
Nov-11	0.92039	-1.52871	0.74647	-0.49123
Dec-11	1.04424	-1.12204	0.89466	-0.11487
Jan-12	-0.21152	-1.56598	0.70451	-0.94384
Feb-12	0.4613	-1.17782	0.96513	-0.47423
Mar-12	0.10347	-1.53718	1.07348	-1.00003
Apr-12	0.63053	-1.38132	0.86551	-0.75868
May-12	1.7121	-1.52659	-0.12768	-0.42231
Jun-12	-0.00472	-2.0682	-0.72912	0.42313
Jul-12	-1.31832	-1.31719	0.09086	0.89188
Aug-12	-1.96014	-0.94831	0.76464	2.58514
Sep-12	-1.48034	-0.75908	0.58758	-0.48243
Oct-12	0.41284	-0.26745	1.0292	-0.12909
Nov-12	0.44535	-1.03304	1.02022	-0.29162
Dec-12	0.50564	-1.30171	0.57816	-0.44501
Jan-13	0.03512	-1.69068	0.43496	-0.35036
Feb-13	-0.12737	-0.91901	1.29975	-0.08501
Mar-13	0.42387	-0.74509	0.84075	0.09001
Apr-13	0.33226	-0.23431	1.42472	0.78225
May-13	0.87117	0.24458	1.29899	1.44377

DATE	fac1_1	fac2_1	fac3_1	fac4_1
Jun-13	0.29392	0.21034	1.00276	2.061
Jul-13	-0.67586	-0.01533	0.98474	3.61473
Aug-13	-1.62387	-0.06128	0.89833	3.52937
Sep-13	-1.38467	0.33394	0.89019	0.04835
Oct-13	-0.02377	0.78478	0.91649	-0.27886
Nov-13	-0.02313	0.85645	1.00738	-0.5583
Dec-13	-0.13143	0.65783	0.82836	1.62424
Jan-14	-0.28887	0.91876	0.60324	-0.72862
Feb-14	-0.26351	1.17512	0.68353	-0.84577
Mar-14	-0.18884	1.73975	0.89967	-0.99421
Apr-14	-0.0261	1.89987	1.37002	-0.99212
May-14	0.49699	1.68569	1.21438	-0.80115
Jun-14	0.8359	0.65441	0.8391	-0.55222

Forecast Output

DATE	pineapple yield /ton	Volume Production of canned pineapple /ton	Volume domestic sale of canned pineapple /ton	quantity of Fresh Pineapple Exports (ton)	quantity of juice pineapple exports(ton)	selling price Agricultural price at farm gate/(Bath)	Agricultural Production Index	Agricultural Price Index	Consumer Price Index	Inflation rate	Exchange Rate(Bath)	Actual quantity of export canned pineapple (ton)	NARX-FA model	NARX model
Jan-07	131468.00	23925.78	12.00	589.87	11240.27	3.10	72.26	82.92	87.70	1.60	35.97	50544.92	-	-
Feb-07	160563.00	18122.62	9.00	427.13	11238.96	3.64	88.25	97.37	87.40	1.40	35.74	46111.97	-	-
Mar-07	145445.00	22976.56	36.00	5.98	13082.09	4.23	79.94	113.15	87.90	1.30	35.06	53292.09	52038.08	53113.72
Apr-07	216408.00	22549.40	18.00	636.35	10413.00	4.84	118.94	129.47	88.80	1.20	34.87	41983.74	41779.98	41826.84
May-07	343054.00	20063.71	10.00	721.89	12344.82	4.42	188.55	118.23	89.50	0.70	34.62	46398.14	45897.61	46237.54
Jun-07	286685.00	18581.97	10.00	742.71	14572.99	4.23	157.57	113.15	89.50	0.70	34.58	51227.72	54896.48	51308.88
Jul-07	172466.00	12749.52	10.00	451.27	10832.97	4.68	94.79	125.19	89.50	0.80	33.71	40038.34	39512.16	41638.91
Aug-07	63210.00	7195.28	4.00	311.63	9366.69	5.25	34.74	140.44	89.00	0.70	34.20	27483.65	49354.31	27516.07
Sep-07	97476.00	10505.05	42.00	336.46	7656.00	5.02	53.58	134.28	89.50	0.80	34.26	17823.47	19001.97	17931.12
Oct-07	177360.00	21931.94	184.00	271.71	9661.69	5.35	97.48	143.11	90.30	1.00	34.17	33766.33	28702.10	33824.78
Nov-07	223003.00	37088.29	365.00	450.62	13334.05	5.34	122.57	142.84	90.70	1.10	33.88	51374.83	52781.60	51334.17
Dec-07	168137.00	34633.04	331.00	458.06	11975.36	4.69	92.41	125.46	90.70	1.20	33.70	62100.41	62112.52	56209.50
Jan-08	162004.00	33407.92	204.00	340.85	12068.07	4.39	89.04	117.43	91.50	1.20	33.18	58470.21	58309.36	58467.35
Feb-08	198359.00	29402.05	338.00	238.19	11603.78	4.53	109.02	121.18	92.10	1.50	32.60	44963.10	52227.50	44977.13
Mar-08	210830.00	35209.80	181.00	376.38	14647.81	5.01	115.88	134.02	92.60	1.70	31.46	52149.56	52431.96	52154.33
Apr-08	288686.00	33274.83	241.00	411.80	14450.54	4.67	158.67	124.92	94.20	2.10	31.59	55244.64	55032.71	55022.46
May-08	378400.00	37913.34	25.00	347.61	18248.21	3.12	207.98	83.46	96.30	2.80	32.11	64366.41	59799.16	64409.30
Jun-08	93797.00	15704.77	136.00	302.75	15540.24	3.54	51.55	94.69	97.30	3.60	33.20	58594.67	58442.42	60986.21
Jul-08	93241.00	12155.02	14.85	319.64	9137.60	5.55	51.25	148.46	97.70	3.70	33.50	43362.62	43380.33	43344.71
Aug-08	63533.00	13250.64	35.00	382.17	6359.47	5.74	34.92	153.54	94.80	2.70	33.86	26084.27	26353.28	26166.30
Sep-08	115367.00	27038.71	15.04	401.20	6668.15	6.10	63.41	163.17	94.90	2.60	34.29	28831.56	27708.14	28952.58
Oct-08	195845.00	39371.85	132.00	576.54	13113.78	5.04	107.64	134.82	93.80	2.40	34.43	47377.61	47173.90	47484.71
Nov-08	262357.00	40106.45	22.00	313.40	14809.39	3.62	144.20	96.83	92.60	2.00	35.09	40497.72	38761.02	40527.47
Dec-08	215743.00	28856.40	17.04	502.58	16145.69	3.17	118.58	84.80	91.10	1.80	35.04	43114.71	42919.79	43133.61

DATE	pineapple yield /ton	Volume Production of canned pineapple /ton	Volume domestic sale of canned pineapple /ton	quantity of Fresh Pineapple Exports (ton)	quantity of juice pineapple exports(ton)	selling price Agricultural price at farm gate/(Bath)	Agricultural Production Index	Agricultural Price Index	Consumer Price Index	Inflation rate	Exchange Rate(Bath)	Actual quantity of export canned pineapple (ton)	NARX-FA model	NARX model
Jan-09	157343.00	23998.61	18.00	281.04	11700.06	3.37	86.48	90.15	91.10	1.60	34.92	35625.16	35382.00	35692.55
Feb-09	174605.00	27750.03	13.00	358.73	12016.26	4.41	95.97	117.97	92.00	1.80	35.33	34986.35	33366.35	27599.42
Mar-09	167507.00	20183.75	14.00	317.68	14010.46	5.09	92.07	136.16	92.40	1.50	35.78	40144.01	39709.81	40104.71
Apr-09	150747.00	14386.16	90.00	303.63	11819.51	5.75	82.86	153.81	93.30	1.00	35.46	38861.84	39575.39	38901.57
May-09	264492.00	24684.04	14.00	340.65	11875.52	5.93	145.37	158.63	93.10	-0.30	34.57	43983.76	45120.99	33344.00
Jun-09	221429.00	22023.71	3.00	327.09	17597.88	5.37	121.70	143.65	93.40	-1.00	34.14	50497.83	50664.20	50476.83
Jul-09	69261.00	7356.98	11.01	270.47	13234.32	5.73	38.07	153.28	93.40	-1.20	34.05	42883.69	43005.19	42851.35
Aug-09	43580.00	7073.78	9.04	189.18	5442.87	5.97	23.95	159.70	93.80	-0.20	34.02	29280.57	29756.30	29292.31
Sep-09	100216.00	18014.85	116.00	283.70	8527.52	5.84	55.08	156.22	94.00	-0.10	33.83	32895.47	32676.28	33013.92
Oct-09	157343.00	27641.20	6.00	252.78	13198.70	5.36	86.48	143.38	94.10	-0.10	33.41	38903.43	39059.53	38942.40
Nov-09	198112.00	26743.78	9.00	243.16	17321.42	3.73	108.89	99.78	94.40	0.10	33.28	39257.17	39844.70	39104.59
Dec-09	190227.00	29978.74	70.01	218.05	14669.83	4.08	104.55	109.14	94.30	-0.30	33.23	45960.07	45228.71	35879.24
Jan-10	158864.00	21526.54	14.00	224.33	14550.43	4.38	87.32	117.16	94.84	0.60	33.04	40640.86	40853.13	40909.11
Feb-10	161676.00	20128.46	4.04	277.60	13484.51	5.23	88.86	139.90	95.37	0.30	33.15	39461.17	38761.86	39496.73
Mar-10	183146.00	26104.72	37.01	449.66	18367.12	5.32	100.66	142.31	95.59	0.40	32.51	44851.44	44442.47	44871.97
Apr-10	195140.00	20929.15	8.00	125.48	13815.98	5.37	107.26	143.65	96.06	0.50	32.29	39176.97	39331.36	39211.30
May-10	190146.00	14367.62	18.00	255.87	12770.01	5.44	104.51	145.52	96.25	1.20	32.39	41255.99	42587.85	41261.09
Jun-10	159002.00	10951.48	151.00	368.72	10545.68	5.84	87.39	156.22	96.50	1.10	32.47	46482.19	45192.37	46495.94
Jul-10	116376.00	9419.46	94.01	166.71	8569.61	6.12	63.96	163.71	96.65	1.20	32.33	40183.38	40325.93	40195.96
Aug-10	71155.00	10858.91	69.02	228.74	6056.87	6.21	39.11	166.12	96.88	1.20	31.74	29514.80	29637.95	29543.11
Sep-10	103635.00	13777.96	36.00	274.73	7495.30	5.69	56.96	152.21	96.81	1.10	30.83	27516.95	23361.30	27621.12
Oct-10	154323.00	16863.18	10.00	206.80	8085.79	5.77	84.82	154.35	96.83	1.10	29.97	35020.84	28069.75	35087.07
Nov-10	225300.00	23865.97	53.12	429.59	11612.97	5.75	123.83	153.81	97.04	1.10	29.89	45210.37	45629.36	45237.57
Dec-10	247380.00	22846.63	99.02	286.69	14522.24	5.85	135.97	156.49	97.19	1.40	30.12	55308.90	55952.21	55336.15

DATE	pineapple yield /ton	Volume Production of canned pineapple /ton	Volume domestic sale of canned pineapple /ton	quantity of Fresh Pineapple Exports (ton)	quantity of juice pineapple exports(ton)	selling price Agricultural price at farm gate/(Bath)	Agricultural Production Index	Agricultural Price Index	Consumer Price Index	Inflation rate	Exchange Rate(Bath)	Actual quantity of export canned pineapple (ton)	NARX-FA model	NARX model
Jan-11	156885.00	27499.13	6.02	247.50	12120.02	5.79	86.23	154.88	97.72	1.32	30.58	48619.13	54694.53	48645.67
Feb-11	176569.00	25810.01	74.00	304.48	11234.83	5.96	97.05	159.43	98.11	1.45	30.72	50119.53	49988.96	50857.65
Mar-11	211546.40	31453.86	25.00	212.57	14557.27	6.39	116.27	170.93	98.59	1.62	30.37	55210.86	53591.48	49085.15
Apr-11	315486.00	28418.22	95.03	203.96	14374.36	5.78	173.40	154.61	99.95	2.07	30.05	49351.21	50381.16	49372.66
May-11	360658.00	28502.02	20.00	222.95	16768.44	5.03	198.23	134.55	100.29	2.48	30.25	62840.00	63102.67	61487.19
Jun-11	267023.00	27602.85	6.00	241.85	17011.35	4.81	146.76	128.67	100.42	2.55	30.52	64140.60	63877.50	64090.87
Jul-11	118388.00	18135.07	24.02	236.28	12109.41	5.05	65.07	135.09	100.60	2.59	30.07	53505.73	54339.27	63822.81
Aug-11	89122.00	22166.32	170.00	226.02	9169.53	4.98	48.98	133.21	101.04	2.85	29.88	45155.89	45074.22	45125.63
Sep-11	142320.00	24256.49	39.00	316.78	7806.19	4.40	78.22	117.70	100.70	2.92	30.42	42321.04	42403.54	42315.93
Oct-11	203326.00	37195.48	25.00	142.47	7334.05	4.34	111.75	116.09	100.89	2.89	30.89	42102.72	42033.38	42140.00
Nov-11	245728.60	39632.08	47.10	262.31	13927.98	3.17	135.06	84.80	101.11	2.90	30.96	44294.17	44544.98	44355.63
Dec-11	306155.00	34019.35	167.00	241.62	10358.00	3.43	168.27	91.75	100.62	2.66	31.22	53035.98	53504.74	54828.04
Jan-12	209536.00	25877.54	30.00	224.92	9752.23	3.16	115.17	84.53	101.02	2.75	31.58	48619.13	48711.48	52952.69
Feb-12	221057.00	29179.76	29.00	168.12	13910.59	3.45	121.50	92.29	101.39	2.72	30.73	50119.53	50312.65	50167.36
Mar-12	235939.00	26909.49	23.02	183.89	9971.42	3.04	129.68	81.32	101.99	2.77	30.70	55210.86	54379.83	55177.91
Apr-12	290183.00	20332.88	9.00	207.88	11360.54	2.59	159.49	69.28	102.42	2.13	30.89	49351.21	50172.32	49459.98
May-12	338906.00	28520.98	14.00	657.04	15165.09	2.71	186.27	72.49	102.82	1.95	31.34	62840.00	61994.62	62835.52
Jun-12	205696.00	21949.61	124.00	960.67	12703.29	3.09	113.06	82.66	102.99	1.92	31.66	64140.60	64230.53	64065.78
Jul-12	87847.00	9825.58	131.00	505.12	13328.27	3.83	48.28	102.45	103.35	1.87	31.65	53505.73	57805.01	53346.91
Aug-12	53524.00	3842.70	364.00	275.32	11484.00	4.19	29.42	112.08	103.76	1.76	31.44	45155.89	45057.90	45082.80
Sep-12	94567.00	11398.32	26.00	424.20	9549.81	4.61	51.98	123.32	104.10	1.89	31.00	42321.04	19989.25	42166.32
Oct-12	208576.00	27973.00	60.00	241.68	12810.70	4.50	114.64	120.37	104.24	1.83	30.69	42102.72	42613.25	42031.09
Nov-12	229218.00	32302.04	55.00	200.69	11159.56	3.34	125.99	89.34	103.87	1.85	30.71	44294.17	45148.97	51031.04
Dec-12	225138.00	31705.76	10.00	416.05	12383.06	3.22	123.74	86.13	104.27	1.78	30.64	53035.98	60808.68	53060.55

DATE	pineapple yield /ton	Volume Production of canned pineapple /ton	Volume domestic sale of canned pineapple /ton	quantity of Fresh Pineapple Exports (ton)	quantity of juice pineapple exports(ton)	selling price Agricultural price at farm gate/(Bath)	Agricultural Production Index	Agricultural Price Index	Consumer Price Index	Inflation rate	Exchange Rate(Bath)	Actual quantity of export canned pineapple (ton)	NARX-FA model	NARX model
Jan-13	199553.00	29552.30	24.00	556.10	10728.45	2.96	109.68	79.18	104.44	1.59	30.07	51833.42	51349.57	51869.99
Feb-13	174531.00	23703.23	18.00	113.46	12433.30	3.35	95.93	89.61	104.66	1.57	29.83	46566.52	53100.07	46666.63
Mar-13	191902.00	27368.61	7.00	364.25	14484.70	3.70	105.48	98.97	104.73	1.23	29.52	48593.98	49057.03	48621.30
Apr-13	230365.00	16901.48	144.00	227.07	12166.51	4.06	126.62	108.60	104.90	1.18	29.08	46863.88	47965.21	46984.42
May-13	256627.00	18499.81	207.00	214.80	14092.74	4.43	141.05	118.50	105.15	0.94	29.78	45824.47	46140.77	45916.23
Jun-13	176186.00	26664.58	276.00	237.74	13847.56	4.84	96.84	129.47	105.31	0.88	30.84	49570.21	46998.61	49602.68
Jul-13	120973.00	11804.11	447.00	225.26	13938.13	4.66	66.49	124.65	105.42	0.85	31.12	51897.48	52122.56	51872.97
Aug-13	51077.00	9770.11	449.00	210.54	11574.21	4.90	28.07	131.07	105.41	0.75	31.60	41593.07	41775.28	41587.53
Sep-13	89954.00	11261.38	46.00	142.77	8927.39	5.07	49.44	135.62	105.58	0.61	31.71	33722.46	33500.61	51870.20
Oct-13	200173.00	15055.72	32.00	262.34	10401.09	5.44	110.02	145.52	105.76	0.71	31.22	42590.19	42735.97	42602.09
Nov-13	194590.00	20170.04	18.00	186.87	9672.11	5.58	106.95	149.26	105.86	0.85	31.63	45344.30	45905.97	61780.26
Dec-13	181976.00	23581.61	314.00	290.62	9445.14	5.68	100.02	151.94	106.01	0.91	32.34	50900.66	50641.56	50933.01
Jan-14	166382.00	20085.62	5.00	275.94	9932.36	6.01	91.45	160.77	106.46	1.04	32.94	47110.49	46374.23	47128.06
Feb-14	171550.00	17011.37	3.00	323.25	10184.99	6.50	94.29	173.87	106.71	1.22	32.65	48059.78	48450.87	48074.76
Mar-14	180098.00	15909.53	14.00	320.91	9593.75	7.34	98.99	196.34	106.94	1.31	32.39	48335.01	53558.89	48379.17
Apr-14	197591.00	16531.81	36.00	152.55	9655.64	7.42	108.60	198.48	107.47	1.66	32.32	60224.55	56559.12	60244.12
May-14	217469.00	22408.18	35.00	193.67	11884.20	7.10	119.53	189.92	107.90	1.75	32.53	47188.83	46982.80	47182.73
Jun-14	238341.00	26593.09	22.00	289.59	13608.99	5.62	131.00	150.33	107.79	1.71	32.51	57053.43	57779.16	57078.94
Jul-14	-	-	-	-	-	-	-	-	-	-	-	-	**53463.11**	**50157.34**

APPENDIX B
FORECASTING OF NONLINEAR AUTO-REGRESSIVE WITH EXOGENOUS INPUT (NARX) IN THE CANNED PINEAPPLE EXPORTS

Management and Innovation Technology International Conference (MITiCON2014)
Pattaya, Thailand, December 17-19, 2014

FORECASTING OF NONLINEAR AUTO - REGRESSIVE WITH EXOGENOUS INPUT (NARX) IN THE CANNED PINEAPPLE EXPORTS

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***Abstract*— Thailand is one of the world's first exporting countries of fresh and processed pineapples. Each year in the pineapple season, there are excess or lower supplies of fresh pineapple which directly cause a decrease in pineapple price. The farmers sell their pineapple at a price which is actually lower than the production cost. This problem recurs every year. The purpose of this research is to design and develop the models which can effectively forecast the quantity of canned pineapple production. The aim of this paper is to introduce a methodology that uses Nonlinear AutoRegressive with eXogenous inputs network with Levenberg-Marquardt learning algorithm to improve the prediction model to find an accurate forecasting model that can effectively forecast the quantity of canned pineapples export. The NARX artificial neural network model is built with 50 hidden neurons and 2 delay into the Matlab. The performance of the NARX model is equal to the least value of Mean Absolute Percentage Error (MAPE). It is in the good level of forecasting, and can be applied to forecast the canned pineapple quantity effectively. The data of fresh and processed pineapple planning can be helpful to the farmer, as they can then make the maximum profit from selling their pineapples.**

Keywords: forecasting pineapple; NARX model,

I. INTRODUCTION

Thailand is the second largest economy in Southeast Asia, with gross domestic product (GDP) of $ 366 billion. Exports now account for over 62 percent of GDP Furthermore, Thailand remains a strong agricultural competitor as it is the world's leading exporter of natural rubber, frozen shrimp, canned tuna, canned pineapples, cooked poultry, and cassava. It is also a major exporter of sugar and rice. In 2013, Thailand's economy is estimated to grow by 3 percent compared to 6.5 percent in 2012 due to slowing exports, weakness in domestic demand, delays in government spending on infrastructure projects, and political challenges. However, The largest export market for U.S. agricultural products [12]. In 2012, Thailand imported $401 million in consumer oriented foods from the United States while U.S. imports from Thailand were nearly $1.2 billion

The canned pineapple processing industry is one of the highest potentiality industries in Thailand. It is ranked as top five of the world in exporting consumable products. Thailand pineapple were divided into 2 categories: domestic and international consumers. This statistic shown as Figure 1 the leading countries in pineapple production worldwide in 2012. In that year, Thailand was the biggest producer of pineapples; producing approximately 2,650 thousand metric tonnes. It's exports to USA, Germany, Japan, France, etc., [1] Meanwhile, Philippines is found to be the top of the countries exporting pineapple juice as well as Indonesia is secondly ranked for exporting fresh pineapple and pineapple juice shown as Figure 1.

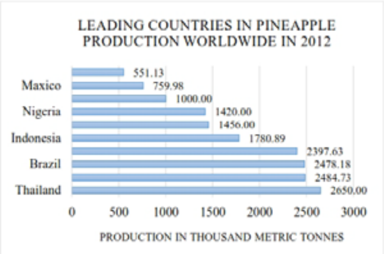

Fig. 1. Global pineapple production 2012

However, Increased canned pineapple imports in the United States during the first 5 months of 2013 reflect larger volumes received from Thailand and the

Philippines—the country's top two sources for the canned product (Table 1). Thailand supplied more than half of the total import volume to date and posted a 23-percent gain over last year.

Table 1. Imports of canned pineapples, by country

				Jan-May	Jan-May	change
Country	2010	2011	2012	2012	2013	2012-13
	...1,000...					Percent
Thailand	309,359	333,593	354,108	136,703	168,383	23
Philippines	216,908	210,219	209,660	74,057	77,467	5
Indonesia	110,395	131885	128,025	47,374	46,794	-1
Chaina	52,744	40,577	26,153	9,624	14,822	54
Malaysia	9,071	6,067	5,473	2,696	2,370	-12
Vietnam	1,333	5,350	3,738	2,650	411	-84
Other countries	3,068	2,575	3,194	1,609	1,062	-34
World	702,879	730,351	730,351	273,105	311,310	14

There are problems to consider in pineapple production. First, the pineapple is a seasonal fruit whose harvest period, in both central and southern regions, is from April to June and December and January. The second problem is flooding which spoils the harvest and consequently forces a decrease in the sale price of pineapple.

The problem of declining fresh pineapple price depends on production quantity as mentioned above. The main reason is that pineapple farms in each cultivated area did not have enough data to form production plans. These production plans will make use of customers' demand to tell us how many fresh pineapple and processed pineapple products should be manufactured each year. Then, to solve these long term problems, the researcher conducted this study to create a forecasting model in order to predict canned pineapple production quantity for Thailand. The forecasting model must be accurate enough to give precise data to plan the production quantity of fresh pineapple and processed pineapple products. The model, on the other hand, has to be appropriate for each pineapple cultivating area in Thailand. The forecast results are going to be used for planning and determining the appropriate fresh pineapple production and processed pineapple production over a long-term period. This developed model is to set solutions to the problems of superabundant pineapple production and low pineapple price

This study aims to construct forecasted models by applying accurate mathematical models to forecast canned pineapple production quantity.

II. THEORIES RELATED

There are several research publications relating to the application of mathematical models to construct forecast models for many kinds of work. The details of techniques using mathematical models to forecast and plan for production are as follows:

Co and Boosarawongse [3] forecast Thai rice export by comparing the Exponential Smoothing model and the Autoregressive Integrated Moving Average (ARIMA) model with Artificial Neural Networks (ANNs) model. The result is shown as follows. Mean Absolute Percentage Error (MAPE) of the Back- propagation Neural Networks (BNP) model is less than MAPE of Holts-Winters and Box-Jenkins model.

Prybutok et al. [9] study how to forecast the highest ozone quantity each day by comparing 2 Time Series models which are Regression and Box-Jenkins ARIMA with Artificial Neural Networks (ANNs) model. The result shows that the Artificial Neural Networks (ANNs) model is the most accurate forecast model.

Arash Negahdari KIA et al. [14] practices KNN (K-nearest neighbors) and DTW (dynamic time warping) technique with USD/JPY (United States Dollar/Japanese Yen) exchange rate time series which is collected from 1971 to 2012 and are separated into 30 element segments regarding the monthly cyclic behavior of time series data.

After that two different set of these 30 element segments are divided into 7:3 ratio and KNN is executed to discover out the 3 nearest neighbors using DTW as resemblance function. In this paper directional status of last component is predicted by an elected function introduction and experimental result compared with results of past executed models.

Xian Hua et al. [19] study and perform a performance comparative study for functional link artificial neural network based on Kernel Regression (FLANN-KR) with functional link artificial neural network [13] based on Adaptive Exponential Smoothing method (FLANN- AES) and FLANN without KR using JAPANESE YEN (JPY), BRITISH POUND and INDIAN RUPEE (INR) to US DOLLAR (USD) currency pairs for predicting range exchange rates.

In FLANN-KR model, KR used to level noise in exchange rate datasets and resulting datasets expanded using sine and cosine expansions after that datasets provide to FLANN model. According experimental results of this paper, FLANN-KR outperforms FLANN-AES and FLANN without KR models. Hongxing LI et al. [6] practices RLS-TS model with GBP/USD currency pair. RLS-TS model implements better than random gait, linear regression; auto regression integrated moving average and artificial neural network model in forecasting GBP/USD currency exchange rates. To indicate the prime parameters used grid search.

From all these studies the researcher can determine that Neural Network Nonlinear Autoregressive with External (Exogenous) Input (NARX) shown to be a promising model for the canned pineapple export quantity prediction

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even with limited amount of data. The significant parameters also advantageous for forecasting.

III. METHODOLOGY

In this model, the researcher to be considering Nonlinear AutoRegressive with eXogenous inputs (NARX) model with Levenberg-marquardt training algorithm.

A. Nonlinear Autoregressive with Exogenous.

Input (NARX)

Nonlinear Autoregressive with Exogenous (External) Inputs (NARX) [16-18] model is kind of recurrent neural network defined by the following:

$$yt = f(x(t),\ldots,x(t-a),y(t-1),\ldots,y(t-b), d(t-1),\ldots d(t-b)) \quad (1)$$

where d are the targets for the time series datasets that we want to predict, y are the past predicted values by the model, a, b are the input and output order, x are the exogenous variables and f is a nonlinear function.

The NARX model determination is to predict the next values of time series datasets taking into account other time series datasets that influence our own, but also past values of time series datasets or past predictions.

For NARX model we can detect the exogenous variables: variables that influence the value of our time series, the one we want to predict. The input order offers the number of past exogenous variables that are fed into the system. In following Figure.2, one can observe the complete architecture.

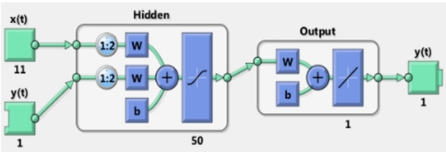

Fig. 2. NARX Architecture

NARX model can then be built on a recurrent neural network, trained by BPTT (back propagation through time) algorithm or simple BP (back propagation).

B. Levenberg-Marquardt Training Algorithm.

The Levenberg-marquardt algorithm is a modification of the classic Newton algorithm for discovery an optimum solution to a minimization problem. The update rule of the Gauss-Newton algorithm is presented as [7-8].

$$xk+1 = xk - [fTf]-1fTe \quad (2)$$

In order to make sure that the approximated hessian matrix fTj is invertible, Levenberg-marquardt algorithm introduces another approximation to Hession matrix:

$$H = fTf + \mu I \quad (3)$$

Then, the Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update.

$$Xk+1 = xk - [fTf + \mu I]-1fTe \quad (4)$$

where x the weights of neural network, J the Jacobian matrix of the performance criteria to be minimized, μ a scalar that controls the learning process and e the residual error vector. When the scalar μ is zero, Eq. (2) is just the Newton's method [15], using the approximate Hessian matrix. When μ is large, Eq. (2) becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible.

Levenberg-Marquardt has great computational and memory requirements and thus it can only be used in small networks. The Levenberg-Marquardt [4] algorithm is often characterized as more stable and efficient.

C. Evaluation

There are two way used to evaluate the performance of the neural network prediction model.

The Mean Square Error calculated as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=0}^{N} (y_i - \hat{y}_i)^2 \quad (5)$$

Mean Square Error must be more less than zero for optimum and efficient prediction. And the Correlation Coefficient R calculated as:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (6)$$

Correlation Coefficient R must be more near to zero for optimum and efficient prediction.

Where, xi = observed the canned pineapple export quantity,

x = mean of xi

yi = predicted the canned pineapple export quantity,

y = mean of yi.

n = the number of data set used for evaluation.

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The best fit between observed and calculated values, which is unlikely to occur, would have MSE= 0 and R =1.

First step, the data is applied with the Artificial Neural Networks (ANNs) model [10-11]. There are many variables that affect the canned pineapple exports; the variable inputs of this research are provided by the Office of Agriculture Economics and Department of Agriculture, Ministry of Agriculture [1] and Cooperatives. Input variables of this research start from 11 input variables as follows:

(1) pineapple yield
(2) Volume Production of canned pineapple
(3) Volume domestic sale of canned pineapple.
(4) Quantity of fresh pineapple exports.
(5) Quantity of juice pineapple exports.
(6) Selling price Agricultural price at farm gate.
(7) Agricultural Production Index.
(8) Agricultural Price Index.
(9) Commodity Agricultural Raw Materials Index
(10) Inflation rate.
(11) Exchange rate.

Data from the years 2007-2014 has been used for the calculation. Second step or data preprocessing step of data mining which makes data less noisy and transform whole data in one common format. By using this tool the researcher write scripts to build and perform function for calculating model performance error statistics such as R and MSE. For build NARX model architecture. This is provide 50 hidden neurons and delay value 2 as inputs. After building NARX model architecture, the researcher trained with 70 % of training data, validated with 15 % of training data and tested in building phase with 15 % of training data. After successfully building of NARX model.

The forecast model efficiency compares the forecast errors by comparing MSE, RMSE and MAPE resulting from forecast models some following shown in Table 2.

Table 2. Error comparison of forecasting

Error of forecasting	MSE	RMSE	MAPE
Back-propagation Neural Networks	1.29×10^7	3.59×10^3	4.17

In general, the selected models are not very accurate in most of the measuring dimensions. The classified forecasts with MAPE values are less than 10% as highly accurate forecasting, between 10% and 20% as good forecasting, between 20% and 50% as reasonable, and forecasting, larger than 50% as inaccurate forecasting from Frechtling. [5]

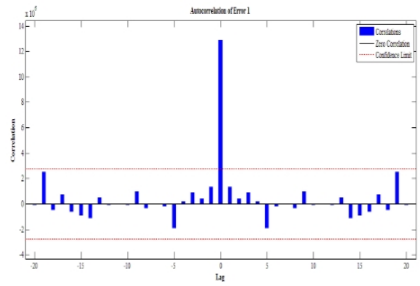

Fig. 3. NARX Testing Error Autocorrelation

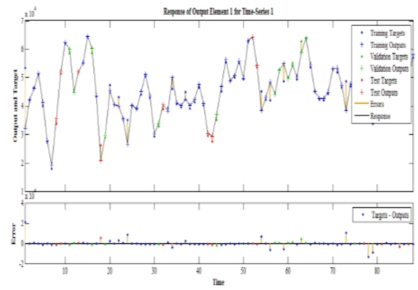

Fig. 4. NARX Testing Time-Series Response

IV. RESULT

The model of Back-propagation Neural Networks are to forecast the canned pineapple production quantity. The error of the forecasting of every aspect with the structure of 1:2:50. It can be seen that the result of the forecasting is accurate at the good forecasting level by MAPE [20]. The comparison error of the forecasting and the comparable graph in Figures.5

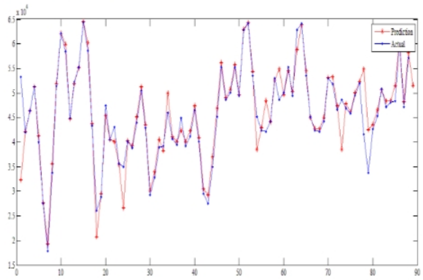

Fig. 5. NARX Prediction and Actual Data

The Back-propagation Neural Networks (BPN) model gets the effectively good level forecasting.

V. CONCLUSION

The study results are found in the Back-propagation Neural Networks (BPN) model that has the most accurate forecast with the least errors, i.e. MAPE is equal to 4.17 %, which are in the range of good forecasting. Because fresh pineapple and other fruits production yields depend on several unpredictable factors. The result is that some years more or less have the same pineapple production quantity.

Therefore, the Back-propagation Neural Networks (BPN) model has the abilities of generalization and adaptability, which could take data of input variables to make a forecast accurate. The result of this calculation can be used as information to make a suitable plan of fresh pineapple production for farmers from each cultivated area in Thailand and to appropriately plan advanced processed pineapple production quantity, e.g. canned pineapple, pineapple chips, and pineapple juices which can solve problems of excessive or lacking canned pineapples and the pineapple price decline. These are active solutions for farmers in the long term and thus sustainable.

The result from the forecasting model can be applied to other fruits in Thailand in the same aspect.

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Certificate of Presentation

"Forecasting of nonlinear auto-regressive with exogenous input(NARX) in the canned pineapple exports"

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