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Forecasting Rubber Production using Intelligent Time Series Analysis to Support Decision Makers

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1. Introduction

Decision support system (DSS) have become a significant factor for many organisations as assistive tools for managers to deal with problems (Nakmuang, 2004). Although DSS are used globally in the agricultural, public, government and especially in business sectors, they have not been effectively utilised within the public agricultural rubber industry in Thailand. They assist decision makers to complete decision procedure activities, obtain data, documents, knowledge or models, increase the number of alternatives examined, achieve better understanding of the business, provide fast responses to unexpected situations, offer capability to carry out *ad hoc* analysis, obtain new insights and learning, facilitate improved communication, achieve cost savings, achieve better decisions, facilitate more effective teamwork, achieve time savings and better use of data resources (Keen, 1981; Olson & Courtney, 1992; Power, 2004; Royal Thai Army, 2007). DSS also present graphical information and may be integrated with expert systems (ES) and artificial intelligence (AI) and support both individual and group decision makers (Power, 2004, 2007). Intelligent DSS demonstrate a range of capabilities and have the capacity to deal with complex data or problems. Hence, the evolution of intelligent DSS has demonstrated increasing functionality, including data mining, geographical information systems (GIS), business intelligence (BI), group DSS (GDSS) and hybrid DSS (Intelligent Science Research Group, 2002; Power, 2007). These functionalities are applied in intelligent DSS in a wide range of sectors, especially tourism, agriculture, industry and commerce (Intelligent Science Research Group, 2002; Power, 2007).

Forecasting, as a significant capability of decision support systems, provides useful information and supports organizations by facilitating enhanced and desired performance or management in decision making. Moreover, forecasting is critical within industry because it enables prediction of future events and conditions by statistically analyzing and using data or information from the past (Markland & Sweigart, 1987; Tomita, 2007). Results from forecasting directly affect organizations in the areas of management, planning, production, sales and prices (Geurts, Lawrence, & Guerard, 1994; Markland & Sweigart, 1987; Olson & Courtney, 1992). Therefore forecasting requires a trustworthy tool to enhance accuracy before management decisions may be made.

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This chapter examines the use of non-neural network training and neural network training in rubber production forecasting to create a feasible forecasting model for the Thai rubber industry. This chapter is organized as follows: the Thai rubber industry situation is described in Section 2. Section 3 presents the methods which will be used in this study. An experiment is developed by employing non-neural network training and neural network training Techniques in Section 4. Section 5 concludes the paper.

2. The public agricultural rubber industry in Thailand

The agricultural sector has been selected as it is a significant growth sector in Thailand; forecasting may assist in advancing this sector and thereby contribute to Thailand's economic development. Thailand is the world's largest rubber exporter to Japan, China and the United States of America with a 39% share of the world market (Office of Industrial Economics & Economic Research and Training Center, 1998; Rubber Research Institute of Thailand, 2007a; Subsorn, 2008). Thailand exports rubber sheet, rubber block, rubber latex and other primary rubber products, whereas only a small fraction of rubber production is reserved for manufacturing within Thailand (Office of Industrial Economics & Economic Research and Training Center, 1998; Rubber Research Institute of Thailand, 2007a; Subsorn, 2008).

Production in the public agricultural rubber industry in Thailand is increasing in order to satisfy market demand (Department of Agriculture, 2004). There are several factors related to production, namely seasonal changes, government policy and fluctuations in the global market (Tanguthai & Silpanuruk, 1995). Annual seasonal shifts directly affect rubber production nationally. Between February and September, rubber production decreases because of low levels of rubber latex during the rainy season. However, rubber production increases between October and January because of suitable climatic conditions such as cool climate and no rain (Tanguthai & Silpanuruk, 1995).

Government policy is another factor influencing rubber production in Thailand; this relates to supporting agriculturists to produce rubber in order to respond to market demand. The *National Economic and Social Development Plan (Issue 10)* for Thailand was developed to support agriculturists to respond to market demand, reduce costs and risks in production, gain more income and improve agricultural products and resource management (Office of the National Economic and Social Development Board, 2007).

Economic fluctuations directly relate to the global demand for rubber, the market trends and foreign currency exchange (Rubber Research Institute of Thailand, 2007b; Tanguthai & Silpanuruk, 1995). The global demand for rubber is increasing every year, which is the most important factor related to rubber production (Rubber Research Institute of Thailand, 2007b). This global market trend influences forward selling which is important for the marketing and sales of rubber in Thailand (Rubber Research Institute of Thailand, 2007b; Tanguthai & Silpanuruk, 1995). Hence, it is necessary to forecast rubber production in order to know the marketing future so that the industry can respond to the increased demand effectively. Foreign currency exchange directly affects rubber sales (Tanguthai & Silpanuruk, 1995). It influences profit and loss in rubber sales because products in the global market are traded in US dollars. Hence, fluctuations in the US dollar value will also directly affect the Thai Baht value which may positively or negatively affect the Thai economy.

In recent years, little attention has been paid to improving production forecasting models or enhancing accuracy in forecasts even though several studies in the Thai rubber industry have focused on management, control and forecasting and have illustrated the need for planned development (Leechawengwong, Prathummintra, & Thamsiri, 2002; Subsorn, 2008). However, a focus on improving forecasting is exceptional as this sector has been using the similar models for a long period of time. The existing models apply traditional statistical techniques and may not conduct sufficient tests of validity and reliability of forecasting results. Applying a modern forecasting technique may enhance forecasting results. Thus this chapter attempts to derive a feasible forecasting model for national rubber production in the Thai rubber industry by applying non-neural network training and neural network training techniques. The survival of the current models has created an excellent environment for this study, which aims to create a feasible forecasting model which may provide beneficial additional information for the Thai rubber industry. Results of this chapter may support policy makers in forecasting through its potential to enhance the accuracy of rubber production trends in a competitive environment and reduce losses and risks in development and policy plans.

3. Method

Many existing forecasting methods are differentiated by objectives and/or problems within organizations. Basically, they focus on improvement to gain better performance or to deal with current and future problems. However, some forecasting techniques may not manage particular situations or problems efficiently as they may not be entirely accurate. Hence, this study attempts to gain a feasible forecasting model based on a comparative method and to select a forecasting model which supplies less forecasting errors for this selected sector. In order to provide a better understanding, the following subsections provide a description of non-neural network and neural network Techniques, three main components and data analysis procedures for a feasible new forecasting model for the public agricultural rubber industry in Thailand.

3.1 Non-neural network training and neural network training techniques

i. Non-neural network training technique

Time series analysis is often applied in prediction for the component analysis of historical data sets to determine a forecasting model used to predict the future (Sangpong & Chaveesuk, 2007). There are several well-known time series forecasting techniques such as simple moving average (SMA), weight moving average (WMA), exponential smoothing (ES), seasonal autoregressive integrated moving average (SARIMA). This study deployed ES and SARIMA techniques for rubber production forecasting. The ES technique has the capability and efficiency to create trend and seasonal analysis for time series forecasting. The formula of the ES technique, particularly the simple seasonal exponential smoothing is as shown below.

$$\begin{aligned} L(t) &= \alpha(Y(t) - S(t-s)) + (1-\alpha)L(t-1) \\ S(t) &= \delta(Y(t)) + (1-\delta)S(t-s) \\ \hat{Y}_t(k) &= L(t) + S(t+k-s) \end{aligned} \tag{1}$$

where $\hat{Y}_t(k)$ is the model-estimated k-step ahead forecasting at time t for series Y, t is the trend, S is the seasonal length, α is the level smoothing weight and δ is the season smoothing weight (Statistical Package for the Social Sciences (SPSS), 2009c).

The SARIMA technique has the capability and efficiency to create seasonal time series forecasting based on a moving average (MA). Time series data from several consecutive periods of time are added and divided to obtain mean values to create the prediction (Sangpong & Chaveesuk, 2007). The formula of the SARIMA technique or equivalent to autoregressive integrated moving average (ARIMA) (0, 1, (1, s, +1)) (0, 1, 0) with restrictions among MA parameters is as follows:

$$\Phi(B)[\Delta y - \mu] = \Theta(B)a_t \qquad t = 1,\ldots,N \tag{2}$$

where

$$\begin{aligned} \Phi(B) &= \varphi_p(B)\Phi_P(B) \\ \Theta(B) &= \theta_q(B)\Theta_Q(B) \end{aligned} \tag{3}$$

where N is the total number of observations, $a_t(t = 1,2,\ldots,N)$ is the white noise series normally distributed with mean zero and variance σ_a^2, p is the order of the non-seasonal autoregressive part of the model, q is the order of the non-seasonal moving average part of the model, d is the order of the non-seasonal differencing, P is the order of the seasonal autoregressive part of the model, Q is the order of the seasonal moving average part of the model, s it the seasonality or period of the model, $\varphi_p(B)$ is the autoregressive (AR) polynomial of B of order p, $\theta_q(B)$ is the MA polynomial of B of order q, $\Phi_P(B)$ is the seasonal AR polynomial of BS of order P, $\Theta_Q(B)$ is the seasonal MA polynomial of BS of order Q, Δ is the differencing operator, B is the backward shift operator and μ is the optional model constant or the stationary series mean. Independent variables $x_1, x_2,\ldots, x_m$ may be included in the model as the formula is shown below.

$$\Phi(B)\left[\Delta\left(y_t - \sum_{i=1}^{m} c_i x_{it}\right) - \mu\right] = \Theta(B)a_t \tag{4}$$

where c_i, $i = 1,2,\ldots, m$ is the regression coefficients for the independent variables.

ii. Neural network (NN) training technique

NN is a well-known predictive technique which claims to provide more reliable results than other forecasting techniques (Sangpong & Chaveesuk, 2007; Statistical Package for the Social Sciences (SPSS), 2009a, 2009b). This technique creates the relationship between dependent and independent variables from several training data sets during the learning process. The results from this learning process are called neurons. Neurons arrange themselves in a level form and have connection lines to transfer or process data from input, hidden and output layers. Each connection line presents weights between each layer connection. Moreover, neurons adjust their weights via an activation function, which is the processing function to create the results, to calculate the desirable results (Fausett, 1994; Sangpong & Chaveesuk, 2007). The activation function deployed in this study is the sigmoid function, which is a non-linear function. Its formula is as shown below.

$$\gamma(c) = \frac{1}{1 + \exp(-c)} \tag{5}$$

Furthermore, this study employed a supervised learning technique and a feed-forward backpropagation neural network (BPN). Feed-forward BPN were considered to be suitable learning techniques for national rubber production forecasting because of their reliability and accuracy. The supervised learning technique is used to adjust weights for producing forecasting with fewer errors between an output from NN and a desirable output. A feed-forward architecture is the one way connection from input and hidden layers to output layers within the network in the model (Statistical Package for the Social Sciences (SPSS), 2009a). The input layer consists of independent variables or predictors. The hidden layer, consisting of unobservable nodes or units, presents a function to be utilized for independent variables or predictors. The output layer consists of dependent variable(s). Additionally, BPN has the capability to simulate the complicated relationship of the function correctly, which is called an universal approximator, without having knowledge previously of the function relationships (Funahashi, 1989; Hornik, Stinchcombe, & White, 1989; Sangpong & Chaveesuk, 2007).

However, overtraining of data sets may cause low efficiency of non-training data sets in the forecasting model. Thus data separation is introduced to solve this problem by dividing the same data set into two groups, namely a training data set and a test data set (Sangpong & Chaveesuk, 2007; Twomey & Smith, 1996). This study partitioned the data set at 70% for the training data set and 30 % for the testing data set.

The multilayer perceptron (MLP) was used in this study to facilitate the use of a supervised learning network and a feed-forward BPN. The MLP network is a function of one or many independent variables or predictors in the input layer which may reduce forecasting errors of one or many dependent variables in the output layer (Statistical Package for the Social Sciences (SPSS), 2009b). The MLP formulae are shown below.

Input layer: $J_0 = P$ units, $a_{0:1},\ldots, a_{0:J_0}$ with $a_{0:j} = x_j$

Hidden layer: J_i units, $a_{i:1},\ldots, a_{i:J_i}$ with $a_{i:k} = \gamma_j(c_{i:k})$ and

$$c_{i:k} = \sum_{j=0}^{J_{i-1}} w_{i:j,k} a_{i-1:j} \quad \text{where} \quad a_{i-1:0} = 1$$

Output layer: $J_I = R$ units, $a_{I:1},\ldots, a_{I:J_I}$ with $a_{I:k} = \gamma_I(c_{I:k})$ and

$$c_{I:k} = \sum_{j=0}^{J_1} w_{I:j,k} a_{i-1:j} \quad \text{where} \quad a_{i-1:0} = 1$$

Additionally, an error measurement in the forecasting model used in this study is the root mean square error (RMSE). The formula of this error measurement is shown below.

$$RMSE = \sqrt{\frac{\sum (Y(t) - \hat{Y}(t))^2}{n-k}} \tag{6}$$

where $RMSE$ is the root mean square error values of the forecasting model, Y is the original series of time (t), t is the time series, n is the number of non-missing residuals and k is the number of parameters in the model.

3.2 Components of the newly refined production forecasting model

This section presents a description of the three main components in the newly refined forecasting model for national rubber production in the public agricultural rubber industry in Thailand.

The input component consists of two main subcomponents, namely individual or group policy makers and input data for forecasting. Policy makers may retrieve or modify forecasting results via the existing database. Also, they may input new rubber data sets to create forecasts.

The processing component consists of three main subcomponents, namely time-series forecasting, artificial intelligence (AI) and error measurement. This study analyses rubber data sets into two main categories, namely non-neural network training and neural network training. Then each data set is separately processed using the Statistical Package for the Social Sciences (SPSS) to create forecasts. Lastly, forecasting errors for accuracy and reliability purposes are measured with each data set.

The output component consists of two main subcomponents, namely the forecasting results and the database. The results are produced during the processing component (above). Both forecasting data sets (non-neural network training and neural network training) are then compared to the actual corresonding data set. The forecast data is stored in the database for retrieval and modification for policy makers to make decisions.

3.3 Data analysis process

This chapter used a rubber production data set from the website of the Office of Agricultural Economics (OAE) in Thailand to examine a newly refined production forecasting model. The data set was collected on a monthly and yearly basis from the period January 2005 to December 2008. This chapter focused on national rubber production forecasting. The data analysis process involved six procedures, as shown in Fig. 1 and described below.

i. Data preparation
   Time series data from January 2005 to December 2008 was used to prepare a data set for four months, six months and one year for 2007 and 2008 forecasting. The reason for selecting forecasting for three different time periods is to enhance validity and reliability of the newly refined forecasting model.
ii. Sequence chart creation
   A sequence chart to consider national rubber production trends from January 2005 to December 2008 was plotted before the forecasts were created. This chart displayed national rubber production trends to examine a seasonality factor within the trends, so that suitable forecasting techniques were selected and utilized.
iii. Data processing
   Non-neural network training and neural network training were used with forecasting techniques provided in SPSS, namely ES and SARIMA. Analysis involved the use of these two time-series forecasting techniques for non-neural network training and neural network training.
iv. Error measurement
   Errors in the forecasts were examined while SPSS created the forecasts for non-neural network training and neural network training. Forecasting accuracy was thereby strengthened.

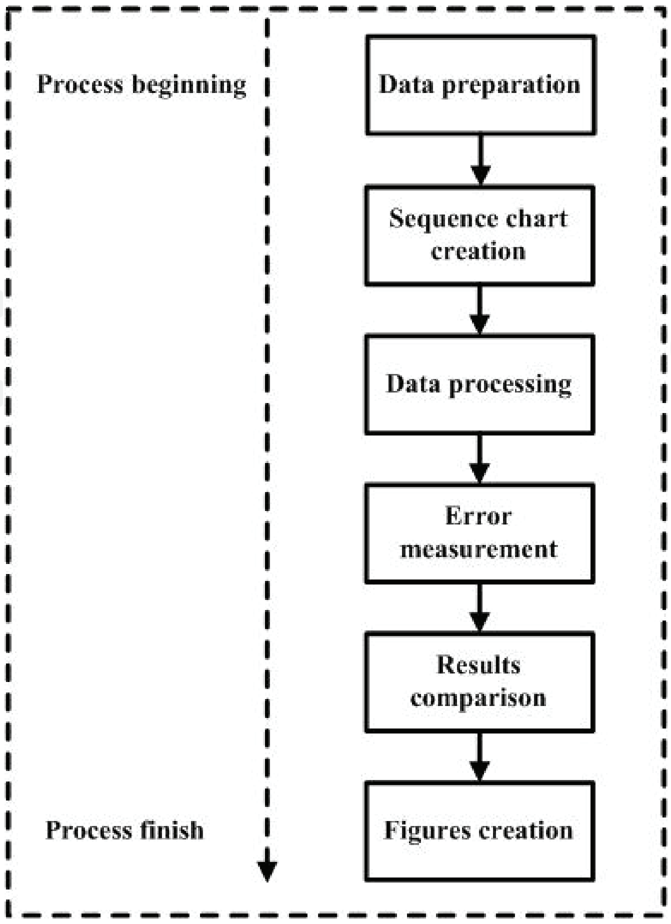

Fig. 1. Data analysis process

v. Comparison of results
Forecasting results from non-neural network training and neural network training were compared with the actual prodcution data set for national rubber production to determine the possibility of using this newly refined forecasting model for the public agricultural rubber industry in Thailand.

vi. Creation of figures
Figures were created to present forecasting results, comparisons and errors to policy makers and/or decision makers, so that they may have a better understanding or vision before planning and/or making decisions.

The following section presents experimental results, which were compared between non-neural network training and neural network training. Then, the results were classified and presented in four months, six months and one year subsets respectively.

4. Experimental results

This section presents rubber production trends and forecasting results. The trends are presented from January 2005 to December 2008 for rubber production. The forecasting results are presented for four months, six months and one year for 2007 and 2008. Fig. 2 illustrates rubber production trends from national rubber production. These show that rubber production usually decreases in the middle of the year. Rubber production increases at the end of the year. The rainy season usually occurs during June to October and the winter or mild season usually occurs during November to February. Hence, these results confirm that rubber production are related to time-series and seasonality factors.

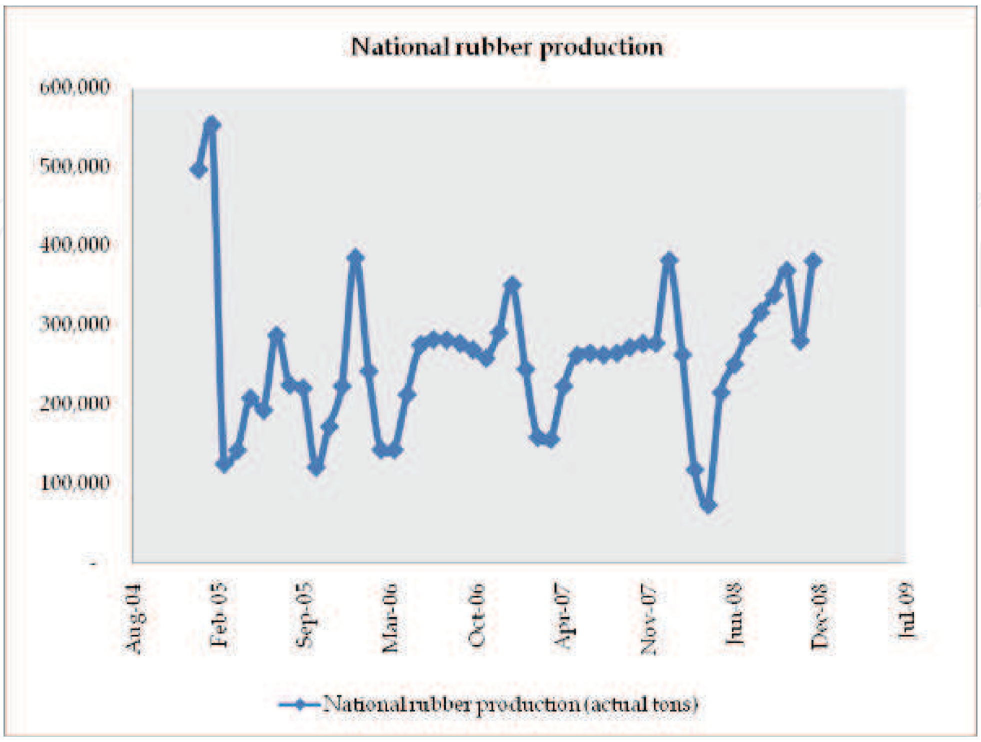

Fig. 2. National rubber production trend

Fig. 3 and Fig. 4 presents the comparison between the actual national rubber production with non-neural network training and neural network training to identify the best-fitting model in forecasting. Rubber production forecasting results were used with a hold-out sample method to deliver forecasting results validation and evaluation of forecasting accuracy. Rubber production data collected was based upon a hold-out sample method in this section.

The following subsections present forecasting results for national rubber production. They were divided into two main subsections as presented below.

4.1 National rubber production forecasts for 2007

The actual rubber production forecasts for 2007 are displayed in Fig. 3 and Tables 1-3, which compare non-neural network training and neural network training with the actual rubber production. It demonstrates that the one year prediction is more successful, for both non-neural network and neural network training techniques, than the four months and the six months predictions. The one year prediction has a root mean square error (RMSE) of 54591.4 for non-neural training and 54261.8 for neural network training. Moreover, the six months prediction is more accurate than the four months prediction. The six months prediction has a RMSE of 56657.4 for non-neural network training and 56141.8 for neural network training. The four months prediction has a RMSE of 57415.8 for non-neural network training and 56847.5 for neural network training.

Comparing the RMSE of each model, it is seen that the one year prediction provides the best-fitting forecasting model. Based on this analysis of national rubber production, this demonstrates that the use of neural network training, particularly for three different periods of time, was better than non-neural network training. Non-neural networks are used more appropriately when there is data fluctuation which may cause forecasting noise or errors. Moreover, it does not require independent variables in forecasts, unlike neural network forecasting. However, both non-neural network training and neural network training showed similar trends as displayed in the following Fig. 3.

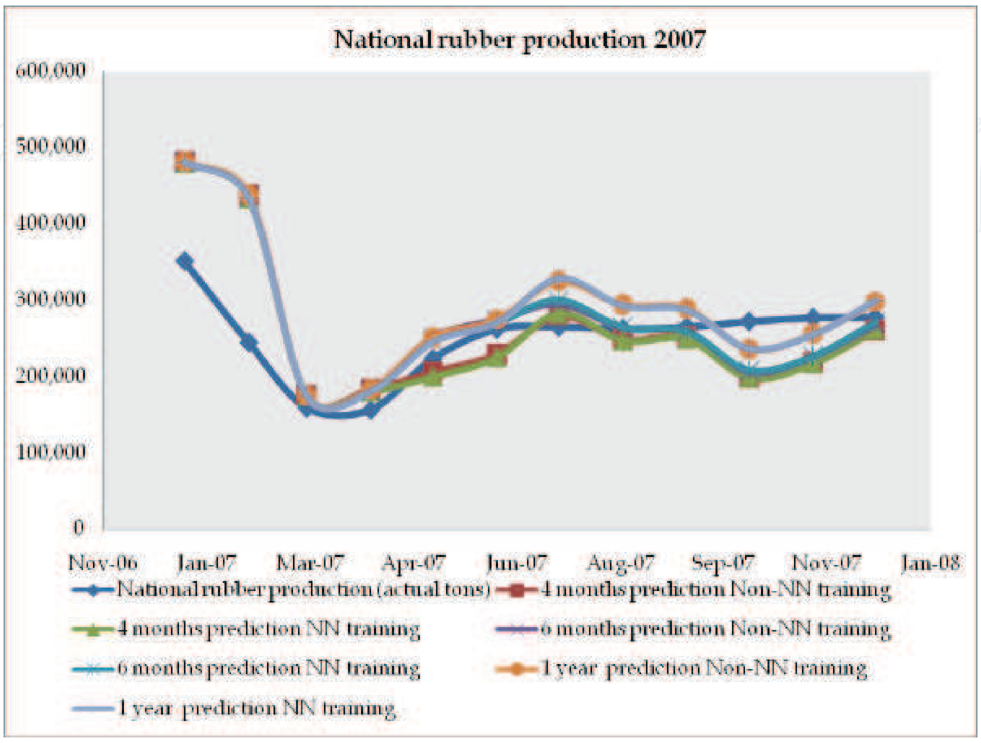

Fig. 3. National rubber production forecasts for 2007

Because it is difficult to show data clearly using graphs, actual figures have been included below in Tables 1-3. The tables include the actual production data and the corresponding predictions using non-neural network training and neural network training predictions respectively.

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-07	351,663	481,562	480,852
Feb-07	245,387	437,861	434,469
Mar-07	159,733	174,706	175,371
Apr-07	157,011	183,331	181,373
May-07	224,145	250,985	246,082
Jun-07	262,923	274,522	271,340
Jul-07	265,593	325,202	328,781
Aug-07	263,391	293,836	293,179
Sep-07	265,564	289,302	287,606
Oct-07	272,872	235,638	237,084
Nov-07	277,741	255,913	255,620
Dec-07	278,184	297,640	299,691

Table 1. One year national rubber prediction

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-07	351,663	481,562	480,852
Feb-07	245,387	437,861	434,469
Mar-07	159,733	174,706	175,371
Apr-07	157,011	183,331	181,373
May-07	224,145	250,985	246,082
Jun-07	262,923	274,522	271,340
Jul-07	265,593	295,649	300,577
Aug-07	263,391	264,282	264,975
Sep-07	265,564	259,748	259,402
Oct-07	272,872	206,085	208,880
Nov-07	277,741	226,360	227,416
Dec-07	278,184	268,088	271,488

Table 2. Six months national rubber prediction

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-07	351,663	481,562	480,852
Feb-07	245,387	437,861	434,469
Mar-07	159,733	174,706	175,371
Apr-07	157,011	183,331	181,373
May-07	224,145	205,852	200,660
Jun-07	262,923	229,389	225,918
Jul-07	265,593	280,069	283,359
Aug-07	263,391	248,703	247,758
Sep-07	265,564	251,902	249,828
Oct-07	272,872	198,238	199,306
Nov-07	277,741	218,513	217,842
Dec-07	278,184	260,240	261,913

Table 3. Four months national rubber prediction

4.2 National rubber production forecasts for 2008

The actual rubber production forecasts for 2007 are displayed in Fig. 4 and Tables 4-6, which compare non-neural network training and neural network training with the actual rubber production. It demonstrates that the four months prediction is more successful than the six months and the one year predictions. The four months prediction has a RMSE of 52807.5 for non-neural network training and 52020.3 for neural network training. Moreover, the six months prediction is more accurate than the one year prediction.The six months prediction has a root mean square error (RMSE) of 53031.7 for non-neural training and 52254.4 for neural network training. The one year prediction has a RMSE of 53936.8 for non-neural network training and 53398.2 for neural network training.
Comparing the RMSE of each model, it is seen that the four months prediction provides the best-fitting forecasting model. Based on this analysis of national rubber production, this

demonstrates that the use of neural network training, particularly for three different periods of time, was better than non-neural network training. Non-neural networks are used more appropriately when there is data fluctuation which may cause forecasting noise or errors. Moreover, it does not require independent variables in forecasts, unlike neural network forecasting. However, both non-neural network training and neural network training showed similar trends as displayed in the following Fig. 4.

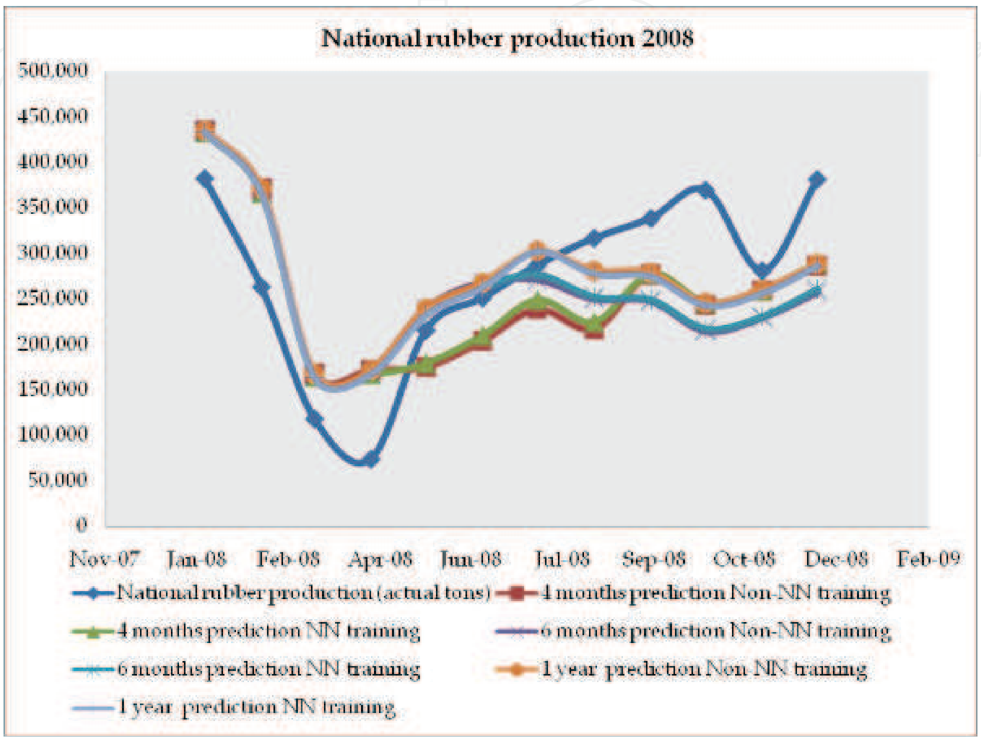

Fig. 4. National rubber production forecasts for 2008

Because it is difficult to show data clearly using graphs, actual figures have been included below in Tables 4-6.

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-08	382,784	436,014	433,865
Feb-08	263,678	371,455	366,969
Mar-08	118,678	167,467	164,537
Apr-08	74,203	172,310	167,664
May-08	215,961	239,791	232,806
Jun-08	251,524	268,409	263,379
Jul-08	287,558	303,085	302,535
Aug-08	317,122	281,440	278,140
Sep-08	338,903	279,142	275,063
Oct-08	369,928	245,802	243,100
Nov-08	281,325	260,942	256,651
Dec-08	381,908	288,908	286,743

Table 4. One year national rubber prediction

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-08	382,784	436,014	433,865
Feb-08	263,678	371,455	366,969
Mar-08	118,678	167,467	164,537
Apr-08	74,203	172,310	167,664
May-08	215,961	239,791	232,806
Jun-08	251,524	268,409	263,379
Jul-08	287,558	271,688	277,156
Aug-08	317,122	250,043	252,761
Sep-08	338,903	247,745	249,684
Oct-08	369,928	214,405	217,720
Nov-08	281,325	229,545	231,272
Dec-08	381,908	257,510	261,364

Table 5. Six months national rubber prediction

Date	National rubber production (actual tons)	Non-NN training prediction	NN training prediction
Jan-08	382,784	436,014	433,865
Feb-08	263,678	371,455	366,969
Mar-08	118,678	167,467	164,537
Apr-08	74,203	172,310	167,664
May-08	215,961	175,572	179,783
Jun-08	251,524	204,190	210,357
Jul-08	287,558	238,867	249,512
Aug-08	317,122	217,223	225,117
Sep-08	338,903	277,217	278,401
Oct-08	369,928	243,877	246,438
Nov-08	281,325	259,017	259,989
Dec-08	381,908	286,983	290,081

Table 6. Four months national rubber prediction

5. Conclusion

This chapter has investigated the best-fitting forecasting model for national rubber production forecasting for 2007 and 2008. The methods used in this study were based on non-neural network training and neural network training techniques to compare with the actual rubber production data for the best-fitting forecasting model. Hence, neural network training was presented to obtain more accurate forecasts for 2007 and 2008. To our knowledge, this is the preliminary study that brings a new perspective to policy makers in the public agricultural rubber industry in Thailand in creating forecasts with AI techniques. This proposed methodology may be considered as a successful decision support tool in national rubber production forecasting in Thailand. It appears that the prediction based on annual production figures is the most likely to be successfully implemented. However, further research over a longer period of time is need to judge more clearly how effectively this forecasting model may be applied to the public agricultural rubber industry in Thailand.

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This book by In-Tech publishing helps the reader understand the power of informed decision making by covering a broad range of DSS (Decision Support Systems) applications in the fields of medical, environmental, transport and business. The expertise of the chapter writers spans an equally extensive spectrum of researchers from around the globe including universities in Canada, Mexico, Brazil and the United States, to institutes and universities in Italy, Germany, Poland, France, United Kingdom, Romania, Turkey and Ireland to as far east as Malaysia and Singapore and as far north as Finland. Decision Support Systems are not a new technology but they have evolved and developed with the ever demanding necessity to analyse a large number of options for decision makers (DM) for specific situations, where there is an increasing level of uncertainty about the problem at hand and where there is a high impact relative to the correct decisions to be made. DSS's offer decision makers a more stable solution to solving the semi-structured and unstructured problem. This is exactly what the reader will see in this book.

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