Chapter 10
A New Latex Price Forecasting Model to Reduce the Risk of Rubber Overproduction in Thailand

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Abstract. One of the key areas in risk management in the public rubber industry in Thailand (PARIT) is to accurately forecast rubber latex prices thus to adjust rubber production in a timely manner. Accurately forecasting rubber latex price may not only reduce risks of overproduction and costs of over stocking, but also respond promptly and directly to global market thus improve in gaining higher sales in the competitive rubber marketing environment. This chapter presents a rubber latex price forecasting model, with three variations, i.e., one-year prediction, 6-month prediction and 4-month prediction, each embedding with either non-neural or neural network training techniques. The model is validated using actual rubber latex prices trend data, which in turn compared with experimental forecasting results to determine forecasting accuracy and the best-fitting model for policy makers in PARIT.

Keywords: Risk management, latex price, forecast, neural network training techniques.

1 Introduction

The last several years have witnessed a tremendous increase and volatility in commodity prices, such as natural rubber prices. The most recent episode with such an increase in commodity prices is the period from 2002 and 2008, which has been labeled a "supercycle" by many observers. After a sharp sell-off during the 2001 recession, the rubber prices rose to unprecedented levels between 2006 and 2008 only to collapse in late 2008 due to the global economic downturn [10]. At the initial stage of the supercycle, the demand ran ahead of available supply, reducing inventories. The supply-side of market then began to respond by raising prices. Higher prices then affected demand, with resultant slowing down of consumption growth. At the same time, investments were made, which, after a period of time, began to yield higher production. With production growth first catching and then surpassing consumption growth, market began to shift from deficit to equilibrium, and then to surplus. The

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transformation in markets was completed by 2008, although prices kept escalating for a period of time before it dived sharply. Even so, the behavior of markets during the last 5 years was normal in the broadest sense [10].

In addition to raising commodity prices, the last few years also saw a very high level of volatility in commodity prices [10]. The various players in the rubber supply chain have evolved different responses to the volatility [6]. The increased volatility has raised the need for reliable and timely market intelligence. While buyers and purchasing agents need to have a good feel of where prices are heading before entering a new contract and negotiation, suppliers and production planners also need a concise yet efficient way to forecast the market demand and price movement.

Southeast Asia (Thailand, Indonesia and Malaysia) produced over 70 percent of global natural rubber, with Thailand being the largest of the three producers [17, 10]. Thailand, as the world's largest rubber exporter, sells rubber and raw rubber products to countries around the world, and possesses about 39 percent share of the world market [24, 15, 18]. Their exported rubber products include rubber latex, rubber sheet, rubber block and other primary rubber products which contribute to production of tyres, gloves and shoes, etc. To monitor global rubber production and market trends, Thai Rubber Association offers world's natural rubber production data on its website. Although the data is more than 4 months old, it does give an accurate breakdown of production data by the major natural rubber producing countries.

Rubber latex prices in the public agricultural rubber industry in Thailand (PARIT) are affected by many factors, such as global rubber demand, changes in supply, input costs, government policies, economic and political factors in local and global markets, etc. A small change in these factors may cause large rubber price fluctuations and cause difficulties for policy development and planning. It is also traditionally accepted that it is more difficult to pinpoint an exact cause for upward or downward pricing pressure on rubber prices at any point in time because the markets are globally more competitive and rubber production costs typically do not influence rubber market prices. In addition, exchange rates and interest costs influence prices of all commodities.

According to Dana and Gilbert [6], price management techniques have the potential to improve the functioning of the rubber supply chain in developing economies. They pointed out that many developing countries still lack expertise on market-based approach to managing risk, a problem which is exacerbated by cumbersome decision-making processes that permit insufficient delegations for quick response to market signals. Dana and Gilbert suggested some important steps to the agricultural commodity risk management for the developing countries, including those of applying modern financial techniques for identifying and quantifying risk, and monitoring price exposure throughout the course of the season, and establishing the type of risk management monitoring and reporting functions, and so on.

Risk management is an important step to sustain the natural rubber industry in Thailand. One of the key areas in risk management in PARIT is to accurately forecast rubber latex prices thus to adjust rubber production accordingly and in a timely manner. Accuracy in forecasting rubber latex price not only reduces risks of overproduction and costs of over stocking, but also allows for a prompt and direct response to the global market, ultimately improves in gaining higher sales in the competitive rubber marketing environment. Results from forecasting directly affect PARIT in the areas of risk management, planning, production, sales and prices. Taking rubber plant planning as an example, too much planting may result in rubber overproduction which increases rubber inventory, leading to rubber latex price cut; while too little planting may lead to losing opportunity for higher economic income from the rubber exports in the Thai rubber industry sector.

Forecasting, as a significant capability of decision support systems, provides useful information in supporting organizations' decision making processes. It is one of the critical steps in facilitating desired management and improving various performances of organizations because it enables prediction of future events and conditions by statistically analyzing and utilizing data or information from the past [12, 25]. While the forecasting results may directly affect many areas such as planning, production, sales and prices [9, 16] in PARIT, the success of performing forecasting activities depends on a trustworthy tool to enhance accuracy of the forecasting results.

This chapter investigates a possible rubber latex price forecasting model, with three variations, i.e., one-year prediction, 6-month prediction and 4-month prediction, each embedding with either non-neural or neural network training techniques. The model is validated using actual rubber latex prices trend data, and its outcomes are compared with experimental forecasting results to determine forecasting accuracy and the best-fitting model for policy makers in PARIT.

The rest of the chapter is organized as follows: Section 2 briefly introduces the rubber industry in Thailand. Section 3 presents the methods used in this study. Experiments are developed by employing non-neural network training and neural network training techniques in Section 4. Section 5 concludes the chapter.

2 The Public Agricultural Rubber Industry in Thailand

Thailand is the world's largest rubber exporter. It exports rubber or raw rubber products to many countries over the world, such as Japan, China and the United States of America, etc., with a 39 percent share of the world market [15, 18]. The exported products include rubber sheet, rubber block, rubber latex and other primary rubber products, whereas only a small fraction of rubber products is reserved for manufacturing within Thailand [24, 15, 18].

The agricultural sector is one of the significant growth sectors in Thailand. This sector is responsible for rubber production planning and selling price policy development. However, little attention has been paid to enhancing price forecasting models or improving the accuracy in forecasts in this sector even though several studies in PARIT have focused on management, control and forecasting in the recent years [24, 11]. A focus on improving forecasting is exceptional as the agricultural sector has been using similar models for a long period of time. Their existing models apply traditional statistical techniques only.

The Office of Agricultural Economics (OAE) in Thailand makes its rubber latex price trend data available in its website, which are utilized as information references for non-government agencies to create their own production planning. The data also assists Thai agriculturists to decide upon quantities of rubber to produce for the next period of time. In addition, the data is also employed to conduct research for a rubber latex price index every month to provide information about the current situation and assist planning of emergency policy for the future [1, 2].

We attempt to derive a feasible forecasting model for rubber latex prices in PARIT using artificial intelligence (AI) techniques, such as non-neural and neural network training techniques. We use the monthly rubber price data from PARIT's websites to create an experimental environment for testing the model and verifying the proposed techniques in this study. The outcomes of this study may be used to assist policy makers in the agricultural sector in forecasting future rubber price trends in a competitive environment through policy development and implementation. This may assist in advancing the agricultural sector's forecasting practice and thereby contribute to Thailand's economic development.

3 The Rubber Price Forecasting Model and Analysis Procedure

There has been a dramatic development in combining traditional forecasting techniques, such as the statistics-based forecasting techniques, to IT-related forecasting techniques, especially AI-based techniques. Examples of such techniques include fuzzy logic, neural network, genetic algorithms and hybrid ones [14]. While these modern forecasting techniques have been widely used around the world, especially in developed countries, it is not the case in some traditional areas and sections in Thailand, such as in PARIT. The traditional statistics-based forecasting models, and similar ones, have been used by PARIT for a long period of time [24, 11]. The adoption of modern forecasting techniques may not only improve the accuracy in forecasting results, but also enhance forecasting process and risk management practices in PARIT.

There have been some works on utilizing AI techniques for forecasting purposes in the past few years. For example, Co's work [4] compared the performance of artificial neural networks with exponential smoothing and ARIMA models in forecasting rice exports from Thailand. However, our work differs from his work in a few ways. First, our model is for forecasting rubber latex prices, while his work is for forecasting rice exports. Secondly, while we focus on creating forecast models using neural network and non-neural networking training techniques, his work compared the performance of artificial neural networks with traditional forecasting models.

Existing forecasting methods differ in objectives and application problems within the organizations. Basically, one forecasting technique may be efficient for particular application scenarios but it may be unsuitable or inaccurate for other situations. This study, based on a comparative method, attempts to gain a feasible forecasting model that supplies less forecasting errors for the Thai rubber industry. We first provide a description of non-neural and neural network tech-niques in the next subsection, and then present the main components and data analysis procedures of the new forecasting model.

3.1 The Training Techniques

Two types of training techniques, i.e., *neural network (NN)* training technique and *non- neural network (non-NN)* training one, are used in our latex price forecasting model. A brief description of each will be given in this subsection.

3.1.1 Non-NN 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 [19].

There are several well-known time series forecasting techniques such as simple moving average (SMA), weight moving average (WMA), exponential smoothing (ES) and seasonal autoregressive integrated moving average (SARIMA) [12, 19]. Among these techniques, ES has the capability to create trend and seasonal analysis efficiently for time series forecasting, while SARIMA has the capability and efficiency of creating seasonal time series forecasting based on a moving average (MA). This study deployed ES and SARIMA as base techniques for rubber latex price forecasting.

The formula for the ES technique, particularly simple seasonal exponential smoothing, is shown below:

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

where $\hat{Y}_t(k)$ is the model-estimated *k*-step ahead forecasting at time *t* for series *Y*, *t* the trend, *L* the length of time, *S* the seasonal length, α the level smoothing weight and δ is the season smoothing weight [21].

Time series data from several consecutive periods of time are added and divided to obtain mean values to create the prediction [19]. 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:

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

where

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

and *N* is the total number of observations, a_t $(t = 1, 2, \ldots, N)$ is the white noise series which normally distributed with mean zero and variance σ_a^2, *p* is the order of the non-seasonal autoregressive element, *q* is the order of the non-seasonal moving average element, *P* is the order of the seasonal autoregressive element, *Q* is the order of the seasonal moving average element, *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.

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

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

3.1.2 NN Training Technique

Neural network is a well-known predictive technique that claims to provide more reliable results than other forecasting techniques [19, 22, 23]. This technique creates a 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 the input, hidden to 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 results that are used to calculate the desirable results [19, 7]. The activation function deployed in this study is the sigmoid function, which is a non-linear function. Its formula is

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

To improve the reliability and accuracy of the forecasting results, we employed a supervised learning technique, i.e., feed-forward back propagation neural network (BPN), which was considered to be a suitable learning technique for rubber latex price forecasting. 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 a one way connection from the input, hidden to output layers within the network in the model [22]. The input layer consists of independent variables or predictors. The hidden layer consists of unobservable nodes or units, presenting a function to be utilized for independent variables or predictors. The output layer consists of dependent variable(s). Additionally, a feed-forward BPN has the capability to simulate the complicated relationship of the function correctly, which is called a universal approximator, without having previous knowledge of the function relationships [19, 22, 8].

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 [19, 8]. Based on the Crowther and Cox's principle [5, 20], this study partitioned the data set at 70 percent for the training data set and 30 percent 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 [26]. 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 $a_{i:k} = \gamma(c_{i:k})$ and $c_{i:k} = \sum_{j=0}^{J_{i-1}} w_{i:j,k} a_{i-1:j}$

where $a_{i-1:0} = 1$

Output layer: $J_I = R$ units, $a_{I:1},\ldots,a_{I:J_I}$ with $a_{I:k} = \gamma(c_{I:k})$ and $c_{I:k} = \sum_{j=0}^{J_1} w_{I:j,k} a_{i-1:j}$

where $a_{i-1:0} = 1$

Additionally, error measurements in the forecasting model used in this study are the root mean square error (RMSE) and mean absolute percentage error (MAPE). The formula of this error measurement is

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

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

MAPE is an average of the differences between the actual and forecasted data of the absolute percentage [3]. It is one of the commonly used measurements for assessing accuracy in quantitative forecasting because it is easy to compute and understand as it reported the results in typical percentage format [13].

The formula of this error measurement is represented as

$$\sum |PE|/N$$

where PE is the absolute value of the percent error and N the number of periods for the percent error [13], or

[(∑ | Actual data – forecasted data | /Actual data) x 100 / N]

3.2 Components of the Forecasting Model

The new forecasting model for latex prices in PARIT has three main components: input, processing and output components. The input component consists of two main subcomponents, one for individual and the other for group policy makers to input data for forecasting. Policy makers may input new rubber data sets to create forecasts, or retrieve data from the existing rubber price database (and/or forecasting results database) to form dataset/s for forecasting.

The processing component consists of three main subcomponents, namely time-series forecasting, AI and error measurement. This study analyzes rubber data sets into non-neural and neural network training date sets. Each data set is separately processed using the Statistical Package for the Social Sciences (SPSS) to create forecasts. Forecasting errors for accuracy and reliability purposes can be measured with each data set.

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

3.3 Data Analysis Procedures

This study deployed rubber latex price data sets from the website of OAE in Thailand to examine a newly refined price forecasting model. These data sets were collected on a monthly and yearly basis from the period January 2004 to April 2009. We focus on rubber latex prices in three provinces: Rayong, Nakornsrithammarat and Pattani, Thailand. The data analysis process involved six procedures, as described below.

Data Preparation: Time series data from January 2004 to April 2009 are used to prepare data sets for four months, six months and one year for January to December 2007 and January to April 2009 forecasting. The reason for selecting forecasting for three different time periods is to enhance validity and reliability of the newly refined forecasting model.

Sequence Chart Creation: A sequence chart to consider rubber price trends from January 2004 to April 2009 is plotted before the forecasts are created. This chart displays rubber latex price trends to examine a seasonality factor within the trends, so that suitable forecasting techniques could be selected and utilized.

Data processing: Non-neural and neural network training are used for analysis with application of forecasting techniques provided in SPSS, namely ES and SARIMA.

Error Measurement: Errors in the forecasts are examined while the SPSS application created the forecasts for non-neural and neural network training. Forecasting accuracy is thereby strengthened.

Results comparison: Forecasting results from non-neural and neural network training are compared with the actual price data sets for these provinces to determine the possibility of using this new forecasting model in this industry.

Figures Creation: Figures are created to present forecasting results, comparisons and errors to policy makers and/or decision makers, so that they may have a better understanding or visual summary when planning and/or making decisions.

The following section presents experimental results based on the data from the three selected provinces where the market prices for rubber latex in Thailand are most significant. The results are compared between non-neural and neural network training. The results are then classified and presented in four months, six months and one year subsets, respectively.

4 Experimental Results

This section presents the rubber latex price trends and forecasting results. The trends data from three selected provinces, Rayong, Nakornsrithammarat and Pattani in Thailand are used as testing data sets. The data span from January 2004 to April 2009, as shown in Fig. 1. It can be seen that the rubber latex price data from the abovementioned three provinces have similar trends. Generally, the rubber latex prices increase in the middle of the year as demand for rubber rises while there is less rubber production. Prices decrease at the end of the year as there is high rubber production and normal rubber demand. In Thailand, the rainy season starts from June and ends in October, and the winter or mild season starts from November and ends in February the next year. It is apparent that rubber latex prices are time series data (with seasonality factors).

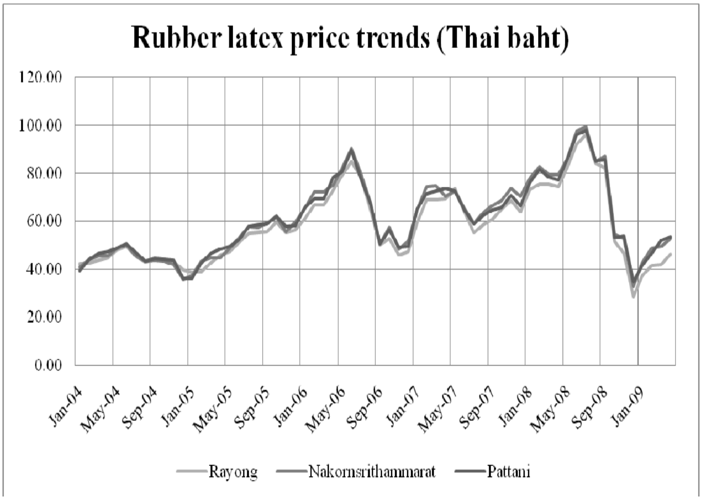

Fig. 1. Summary of rubber latex price trends

Rubber latex price forecasting results are used with a hold-out sample method to perform forecasting result validation and evaluation of forecasting accuracy. Rubber latex prices data collected are based upon a hold-out sample method in this section. A hold-out sample method was also utilized to prevent data overtraining. As mentioned early, the data set was separated into two groups, called training and testing data sets at the rates of 70 and 30 percent, respectively. The confidence interval was set to 95 and 99 percent for RMSE and MAPE in the SPSS software for each experiment.

While we have conducted a range of forecasting trends, we show only a part of the experimental results to demonstrate the feasibility of our method. For example, we present the forecasting results in four months trends, six months trends and one year trends, respectively. We selected the experimental results for Rayong province as a representative exemplar to present the forecasting results as those from other provinces also have the similar forecasting results.

4.1 One Year Rubber Latex Price Forecasts

Fig. 2 shows the actual Rayong price forecasts for January to December 2007. Two types of forecasts, using either non-neural or neural network training approach, are shown in the figure. For the 4-month prediction, three sets of forecasting results (i.e., January-to-April curve, May-to-August curve, and September-to-December curve) are concatenated to form a single one-year forecast curve. Similarly, the 6-month prediction concatenated two half-year predictions in the figure. As a comparison, the actual rubber latex prices curve is also shown in the figure. It demonstrates that the one year prediction is the most accurate one among the three predictions. Actually, the one year prediction has RMSE and MAPE values which were 3.6328 or 5.13 percent for non-neural training and 4.3943 for neural network training, respectively. In contrast, the RMSE and MAPE values for the four month prediction and the six month prediction are much higher. In addition, the 6-month prediction is more accurate than the

4-month prediction. This is because that the 6-month prediction has a RMSE and MAPE of 3.9404 or 5.52 percent for non-neural network training and 4.5526 for neural network training, and the 4-month prediction has a RMSE and MAPE of 4.0245 or 5.65 percent for non-neural network training and 4.5796 for neural network training.

The 2007 forecast by the NN training technique for Rayong province was shown in Fig. 3. Similar to the forecasting results displayed in Fig. 2, the one year forecast created lower RMSE and MAPE values, which were 3.8957 or 5.41 percent, than the other two forecasts. The RMSE and MAPE values were 4.0053 or 5.58 percent for the six month forecast and 4.0951 or 5.71 percent for the four month forecast, both of which were much higher than the one year forecast. It can be summarized that the one year forecast performed better than the four month and the six month forecasts.

Comparing the actual rubber latex price curve with the forecasting curves demonstrated that the one-step ahead forecast, January to December, was the most accurate one among the three periods of forecasts for both non-NN and NN training techniques. Based on the forecasting results, RMSE and MAPE values, the one year forecast provided the best-fitting forecasting model for adoption in PARIT, followed by the six month and the four month forecasts. Furthermore, the forecasting results with the use of the non-NN training technique, particularly the ES technique for three different time intervals, were better than the NN training technique. Therefore, it can be summarized that the one year forecast with the non-NN training technique provided a better performance than the other 2007 forecasts for Rayong province. Both the non-NN and NN training techniques created similar forecasts and none was found to be close to the actual data. This occurred because of a short-term fluctuation in the input data. Additionally, the major reason that the one year forecast performed better than the four month and the six month forecasts is the seasonality which can generate fluctuations in data. This suggests that further research is needed to follow in this direction in the future.

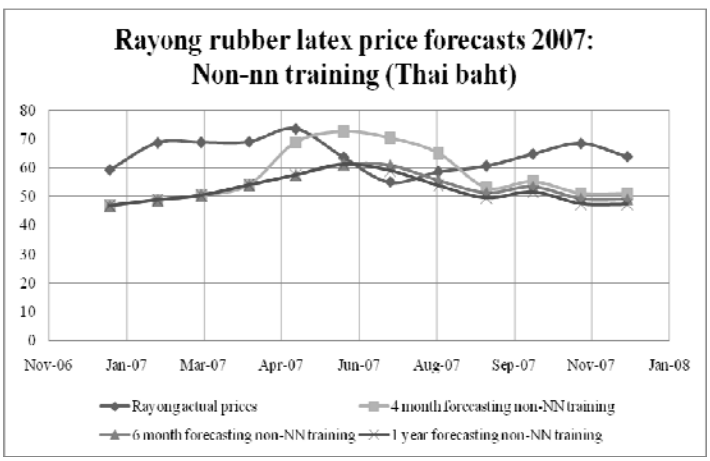

Fig. 2. Summary of Rayong rubber latex price forecasts by the non-NN training for January to December 2007

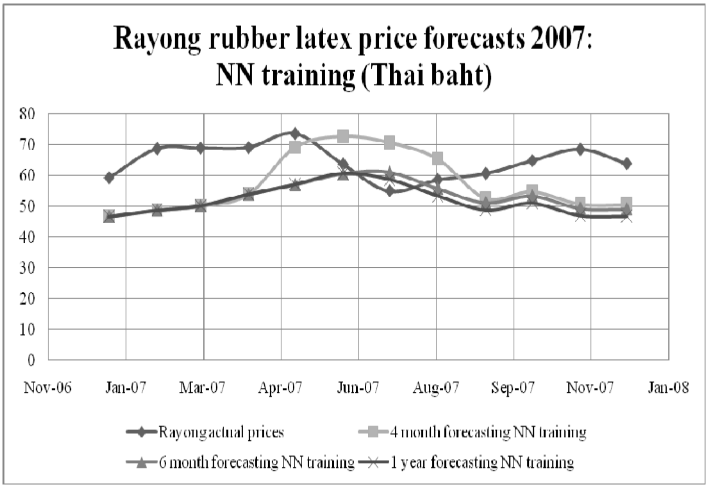

Fig. 3. Summary of Rayong rubber latex price forecasts by the NN training for January to December 2007

4.2 Four Month Rubber Latex Price Forecasts

Apart from Rayong rubber latex price forecasts for January to December 2007, another experiment for January to April 2009 was conducted in order to examine the proposed forecasting model further. Non-NN and NN training forecasting results were, once again, compared with actual rubber latex prices for January to April 2009, and are shown in Figure 4. It demonstrated that the results produced using the NN technique was marginally better than those of the non-NN training technique. The RMSE and MAPE values were 6.2279 or 7.70 percent for the non-NN training and 6.2211 or 7.53 percent for the neural network training.

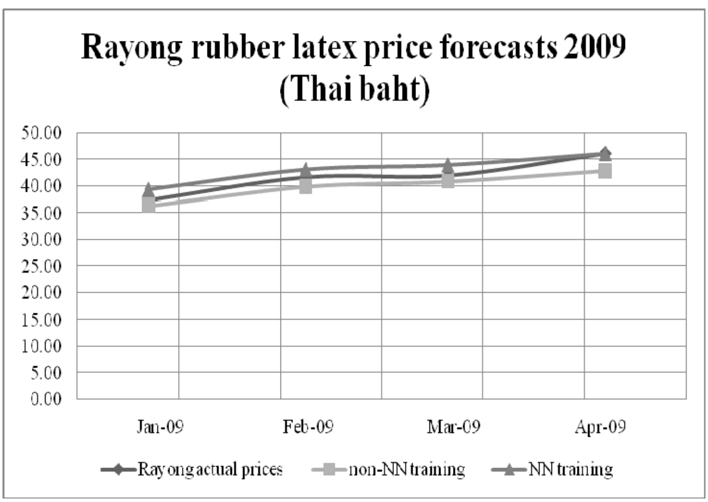

Fig. 4. Summary of Rayong rubber latex price forecasts for January to April 2009

For the four month prediction, the RMSE and MAPE values suggest that the model that includes neural network training prediction provides the best-fitting forecasting model. Based on this analysis, these results demonstrate that the neural network training method generated more accurate forecast results than that of the non-neural network training method. Our experiments also showed that the forecasting with neural network training support is more useful when there is not much data fluctuation to cause forecasting noise or errors. Similar to the case of one year forecasting, it does require independent variables in forecasts, unlike non-neural network training. Again, both non-neural network training and neural network training showed similar trends, as displayed in the Fig. 4.

5 Conclusions

This chapter described a new latex price forecasting model for PARIT, in the aim of improving the accuracy of the latex price forecasting thus to reduce the risk of rubber overproduction in PARIT.

We investigated the best-fitting forecasting model for rubber latex prices forecasting. The method was based on non-neural and neural network training techniques. We compared the forecasting results with the actual rubber latex price data to determine the best-fitting forecasting model. Experiments have shown that the model with non-neural network training generates more accurate forecasts for one year prediction, and the model with neural network training generates more accurate forecasting result for the four month prediction.

To our knowledge, this preliminarily study brings a new perspective to policy makers in PARIT in creating forecasting with AI techniques. This method may be considered as a possible decision support tool in rubber latex price forecasting in Thailand. Further research on longer time-span rubber price forecasting is needed to judge more clearly how effective this forecasting model may be applied to rubber price forecasting in PARIT.

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