Research Article

An Application of Forecasting Models for the Supply and Demand Management of Cassava Products

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Abstract
The objectives of this research are to generate models that can effectively forecast the supply and demand of four cassava products. The appropriate forecasting models for cassava production volume is Back Propagation Neural Network (BPN) 4-14-1, cassava starch is BPN 7-12-1, cassava chip is BPN 7-14-1, cassava pellets is Multiple Linear Regression (MLP), and sago is BPN 7-13-1. Then, Linear Programming is used to calculate the optimization of cassava products to obtain the maximum profit and for cassava plant areas to obtain the maximum yield per area. The benefits of this research can support management planning for farmers and manufacturers.

Keywords: Cassava, Forecasting models, Back Propagation Neural Network (BPN), Multiple Linear Regression (MLR), Linear Programming (LP)

1 Introduction

Among many important exported tropical food commodities, cassava root is regarded as the third largest source of carbohydrate food in tropical countries, next to rice and maize consecutively [1]. In Thailand cassava is cultivated in 50 provinces. In 2014, cassava cultivation was carried out all years on 3,548,755 acres with a yield of 30,022,052 tons. Exported cassava products in 2014 were at 29,161,067 tons (fresh root) and imported cassava products were at 1,618,304 tons (fresh root) [2]. Therefore, the supply of cassava for the domestic market in Thailand is 2,684,780 tons (fresh root) or approximately 8% of the total cassava shipments (fresh root) in Thailand.

The main products of cassava root are dried cassava (chips and pellets) and cassava starch. Thailand is regarded as the largest exporting country of cassava products. In 2011, the exported volume of dried cassava was 3.74 million tons (56% of the world market), which is equivalent to 978.59 million USD, and the volume of cassava starch exported was 1.86 million tons (90.65% of world export) with a value of 922.29 million USD [3]. China is the largest imported market from Thailand cassava products.

Based on information prior to 2009, the world market demand for cassava products changes swiftly. During that time, Thailand exported cassava pellets to Europe as an ingredient to feed various productions. However, the changes in the Common Agricultural Policy (CAP) in the EU with a substitution of cassava with locally-produced barley caused cassava products

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to become less competitive. Hence, exported quantities of cassava pellets declined rapidly, from 9.1 million tons in 1989 to less than 400,000 tons in 2009 [4]. These data reflecting a near-collapse of the export market in Europe was partially offset by the accelerating growth of the production of starch and starch derivatives, as well as the increasing demand for cassava chips in China. However, in 2012, China reduced the import of cassava products, thus leading to a lower price for cassava.

As stated previously, therefore, Thailand, the world largest cassava product exporter, is facing tremendous variations in the global cassava product demand, which directly affects local and export products management as well. These problems have found the significant demand variability and brought an imbalance in the demand for and supply of cassava products that has finally caused a price reduction. In order to address this problems, this research aims to: 1) generate models that can effectively forecast the volume of cassava production and the demand for four cassava products, including: cassava starch, cassava chips, cassava pellets, and sago; 2) calculate the production volume of each cassava product suitable for local markets and world export demands, where the objective is to maximize profit; and 3) calculate the cassava planting area in order to minimize the area (acre).

The benefit of this research is that the results can be employed to accurately forecast the amount of both cassava production and the export demand, to optimize the cassava processing method for maximum profit, and to develop cassava planting area that generates the optimal benefit of area for cultivating. These results are anticipated to be able to support the manufacturing sector in planning and optimizing the manufacturing processes for the beneficial of farmers, manufacturers and stakeholders involved.

2 Literature Review

There are several research publications related to the application of forecasting models to construct the forecasting demand and supply of agricultural products, such as a report by Khamis *et al*. [5], who investigated the development of a forecasting model for oil palm yield via the neural network approach versus the multiple linear regression approach. They found that the modeling accuracy using the neural network was much greater than the multiple linear regression approach. The neural network model proved to be an efficient and reliable tool.

Co and Boosarawongse [6] forecast Thailand's rice exports using statistical techniques compared with Artificial Neural Network model (ANN). They found that the ANN was more accurate than the time series model and the Auto Regressive Integrated Moving Average model (ARIMA). Shabri *et al*. [7] examined the forecasting performance of combining forecasting based on the artificial neural network model compared it with other statistical models (ARIMA and exponential smoothing model) and the ANN model in forecasting rice yields in Malaysia. The results suggested that the ANN forecasting models were considerably more accurate than the traditional ARIMA and exponential smoothing models used as benchmarks.

Furthermore, Pokterng and Kengpol [8], who studied the forecasting of durian production quantity for consumption in domestic and international markets, found that the Back Propagation Neural Network (BPN) model with a 4-8-1 structure had the least value of Mean Absolute Percentage Error (MAPE), which indicated that the model can be applied to effectively forecast fresh durian yields. Hence, the Linear Programming (LP) was used to estimate the value of fresh durian suitable for each region in the subsequent year. The data on fresh and processed durian planning can be helpful for farmers in terms of making a maximum profit from selling their durian.

In addition, Udomsri *et al*. [9] studied demand forecasting for four kinds of durian (fresh durian, frozen durian, durian paste, and durian chips) in the following year. First, the time series models (moving average, deseasonalised, exponential smoothing and double exponential smoothing) were applied as output models. Second, the regression model and ANN were applied as input models. The results for the output models revealed that the most accurate forecast model was the deseasonalised model, which yielded the least value for MAPE regarding three kinds of durian: durian paste, frozen durian, and fresh durian. Moreover, the input models demonstrated that the most accurate forecasting model was an ANN model which gave the least value for the MAPE for durian chips. After that the LP was applied to assess the value of the appropriate quantity for the domestic and export markets of four kinds of durian for maximum profit in the following year. The maximum profit quantities of particular durian products can help durian growers to process durian and plan their sales in ways where the highest profit was achieved.

Most of the previous research using mathematical models to forecast agricultural products such as palm oil, rice, and durian applied the ANN and traditional regression such as time series models, MLR, and ARIMA. Two previous studies related to cassava yield forecasting have been carried out. The first report made by Choosuk and Kengpol [10] investigated cassava yield forecasting via 4 time series models (moving average, weighted moving average, single exponential smoothing, Holt's linear exponential smoothing) and BPN. The forecasting results for the individual patterns were compared in terms of the MAPE and the results demonstrated that the BPN delivered the least errors. The second research was connected to models of Thailand export requirements of 4 cassava products (cassava starch, cassava chips, cassava pellets, and sago) using 4 time series models (moving average, weighted moving average, single exponential smoothing, Holt's linear exponential smoothing) and BPN. The results showed that the BPN gave the least MAPE for 4 cassava products. Therefore, based on both researches, it was clearly revealed that the forecasting model of the BPN can give more accurate results than the time series models [11].

Based on the review of the related literature, we were interested in studying the models that can effectively forecast the supply and demand of cassava products by using MLR and the BPN. The output of the forecasting models has been subsequently used as an input data for planning purposes using LP techniques to find out the volume of cassava products that mostly met the demands of the domestic and export markets and to investigate the appropriate cassava plantation that gave the minimum planting area in each region.

3 Research Methodology

This research is composed of 4 parts as shown in Figures 1–4.

In part I, information related to cassava yield have been collected in order to design an accurate forecasting model to predict the cassava production volume (supply) in advance by applying 2 basic forecasting models: MLR and the BPN as can be seen in Figure 1.

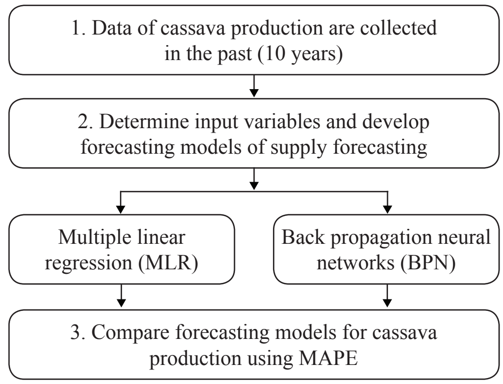

Figure 1: Research steps, part I.

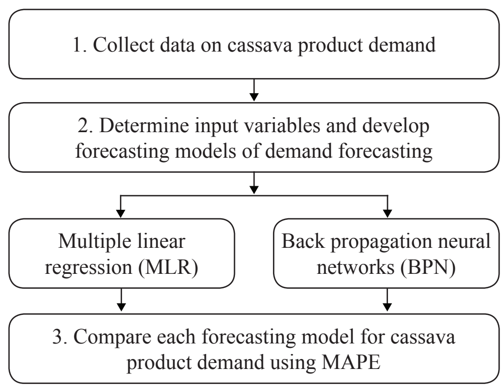

Figure 2: Research steps part II.

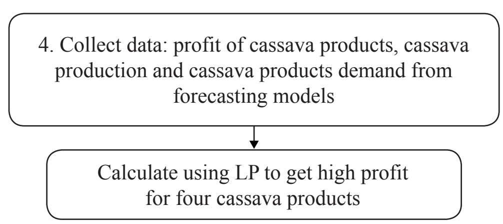

Figure 3: Research steps part III.

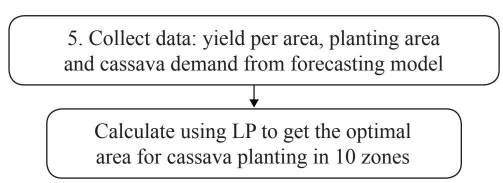

Figure 4: Research steps part IV.

In part II, information are collected on four exported cassava products consisting of cassava starch, cassava chips, cassava pellets, and sago in order to design accurate forecasting models to predict the export demand for these products in advance by applying 2 basic forecasting models: MLR and the BPN as shown in Figure 2. This part, the exported cassava products are forecasted by models. For the domestic market are calculated from proportion of 8% of the total cassava shipments (fresh root) in Thailand (data in 2014) [2].

Part III forecasts the data by means of the models developed in part I and part II and collects the profit data for 4 cassava products in order to calculate the amount of each cassava product suitable for the local and export markets demand, and to maximize the profit using LP as seen in Figure 3.

Part IV forecasts the data by means of the models developed in part I and part II and collects the yield per area each zone, planting area and cassava demand from forecasting model in order to calculate the cassava planting area suitable for demand in 10 zone areas and to minimize the planting area using LP follow as shown in Figure 4.

The steps of this research are conducted as follows:

1. Collect the information on cassava production and exported cassava products of Thailand from 2006 to 2015 from the Office of Agricultural Economics, Department of Agricultural Extension, Department of Agriculture, Royal Irrigation Department (Ministry of Agriculture and Cooperatives), Food National Bureau of Agricultural Commodity and Food Standards, Department of International Trade Promotion (Ministry of Commerce), and Agriculture Organization of the United Nations.

2. Determine the input variables for the forecasting models. The input variables are related to the cassava production volume (supply) and four cassava products for export (demand) by asking three experts on cassava and cassava products consisting of one staff member from Agricultural Economics Research and two senior professionals in Agricultural Extensionist from Chachoengsao and Nakhonratchasima provinces. The four input variables related to cassava production volume (supply) are 1) planting area of cassava (12 months before harvest), 2) yield per area of last crop year, 3) precipitation during six months of cassava planting, and 4) cassava price in the month before the cassava planting. For the four cassava products, seven input variables are: 1) consumer price index of the previous year, 2) gross domestic product of the previous year, 3) gross national product of the previous year, 4) oil price of the previous year, 5) exchange rate (THB/USD), 6) previous year farm price, and 7) free on board price of the previous year. Then, forecasting models of supply and demand forecasting in advance 1 year and demand (cassava products) forecasts are created. The models are the BPN (nonlinear model) and MLR (linear model).

3. The forecasting models are obtained by comparing the forecast error in terms of MAPE resulting from forecasting models [12]. In the presented work, the accuracy of the BPN and MLR models is evaluated using MAPE, which can be calculated by means of the following equation (1).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \tag{1}$$

A_t = actual value of the variable of interest in period t
F_t = forecast for period t
t = period at consideration
n = total number of periods

MAPE is classified into 4 levels. The values below 10% are considered as highly accurate forecasting. The values between 10% and 20% are considered to be good forecasting, and the values between 20% and 50% are considered reasonable good forecasting. Any values over 50% are considered inaccurate forecasting [13]. The forecasting models of BPN and MLR are compared in order to achieve forecasts that give the lowest MAPE regarded as the most accurate.

4. Calculate the processing of cassava products that suit the cassava demand on the domestic and export markets, and then export to maximize profit using LP. The input data for the LP is provided by the forecasting models, both for the supply and demand of the cassava products and the profit of each product, are used for the calculation.

5. Calculate cassava planting area in 10 zones suitable for meeting the cassava demand on the domestic and export markets in order to minimize the planting area using LP. The LP data consists of the planting area of each zone, and the maximum percent yield per area of 10 zones in the past are used for the calculation.

4 Mathematical Models

4.1 *Artificial neural networks model*

Artificial neural networks model (ANNs) are constructed and established from the characteristics of the human brain. [13]. ANNs are a computer construction that models the human brain's working, thinking and remembering [14]. The structure of ANNs consists of input layer, hidden layer and output layer (see Figure 5).

Back propagation neural network (BPN) is the model that represents ANNs. The training procedure of networks is the adjustment and finding the appropriate weight to forecast the least error and accuracy results [12]. The gradient descent method is used to calculate the weight of the network and to adjust the weight of the interconnection between input neuron, hidden neuron and output neuron in order to minimize the output error [15]. The efficiency of the BPN model depends on the selection of relationship with network structure, consisting of numbers of hidden layers, hidden units, and parameters of learning [16].

The X_i and F_y represent the input and output variables respectively. Each input variable is represented by each neuron of the input layer. The neurons of the input layer are connected to each hidden neuron and each hidden neuron is connected to the output neuron. Connections between neurons have numerical weights (w_{ji}), which are adjusted in the training process. Each neuron has two main functions: the first function is the summation function. The second function is the activation function. The value for a neuron in the hidden or output layers is typically the sum of each incoming activation function times its respective connection weight.

In Figure 5, each neuron in the hidden layer calculates the summation function (y_j), where j is the index of the given neuron in the hidden layer and n is the number of input data, as shown in equation (2).

$$y_i = \sum_{i=1}^{n} x_i w_{ij} \tag{2}$$

The result of the summation is modified using an activation function which becomes an output of the given neuron. This in turn becomes input for one or more neurons in the subsequent layer. An activation function is a tan sigmoid function (y) which transforms

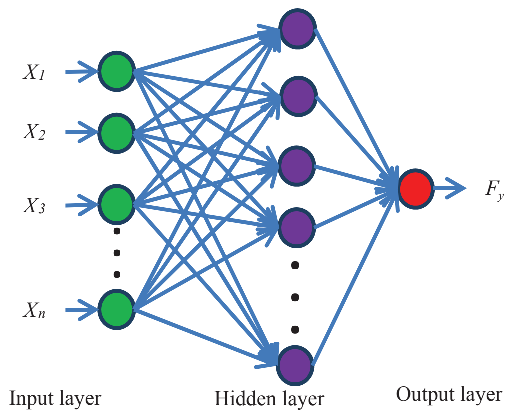

Figure 5: Structure of Artificial Neural Networks.

the input signals into output signals. It is represented by equation (3).

$$y = \frac{1}{1+e^{-y_i}} \tag{3}$$

The output variable is obtained by equation (4).

$$F_y = \sum_{i=1}^{m} y_i w_i \tag{4}$$

The main function of the ANN training process is the ability to recognize, recall, capture, and create the pattern of multi-dimensional input-output and non- linear functions. This research applies the Alyuda NeuroIntelligence 2.2 (577) [17] program to analyse the BPN.

4.2 *Multiple linear regression*

Multiple linear regression (MLR) attempts to present the relationship between a dependent (output) variables and independent (input) variables using a multivariate mathematical function [18], [19]. The equation for the linear regression is shown in equation (5).

$$F_y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{5}$$

Where:

F_y = forecasted value
β_0 = a constant term
$\beta_1 \ldots \beta_n$ = parameters representing the contributions of the independent variables
$X_1 \ldots X_n$ = input variables.

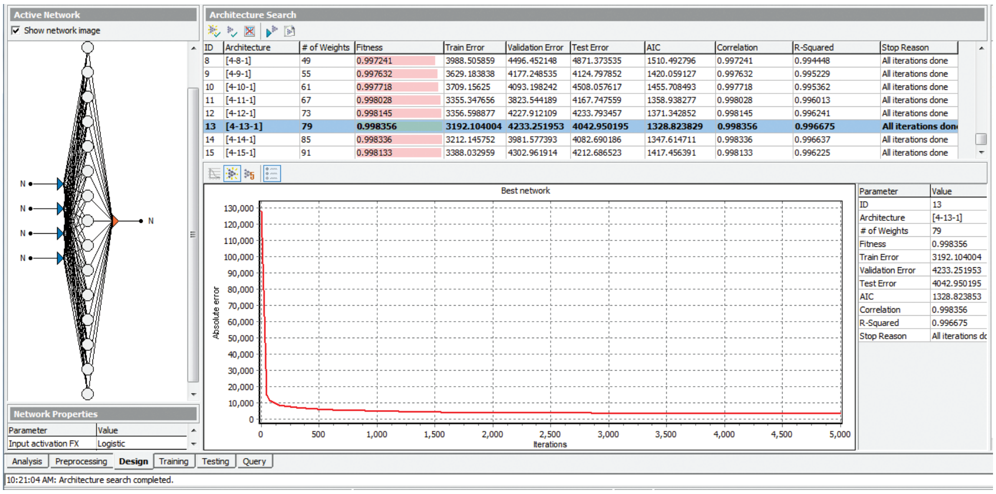

Figure 6: The best network suggested by Alyuda NeuroIntelligence 2.2 (577).

4.3 *Linear programming*

Linear programming (LP) or linear optimization is a mathematical technique to achieve the best outcome (such as maximum profit or lowest cost), which is called the objective function of LP problems. The elements of LP have four parts [20].

1. Objective function to be maximized or minimized $f(X_1, X_2, \ldots, X_n)$ [21].

$$Max\ Z = a_1X_1 + a_2X_2 + \ldots + a_nX_n \quad (6)$$

Where: X_n = decision variables
a_n = coefficient of variable in the objective.

2. The constrain function is constraint condition of an optimization problem.

3. The decision variables in the objective and constrain equation of the linear program. These are written by $X_1, X_2, \ldots, X_n$.

4. The decision variables are more than or at least zero value.

5 Results

5.1 *Forecasting of cassava production volume (supply): Part I*

The input variables related to cassava yield have four variables as follows:
X_{s1} = plant area (12 months before harvest)
X_{s2} = yield per area (previous planting)
X_{s3} = precipitation (6 months after planting)
X_{s4} = price of cassava (previous year planting)
The output variable is:
F_s = cassava production volume (supply) at the time t

5.1.1 Forecasting of cassava production volume (supply) using the BPN model

According to the cassava yield data for each province and each month from 2006 to 2015 for training, there are 4630 data records, which can be divided into three partitions including 68% for the training set, 16% for the validation set, and the others 16% for the testing set using the program Alyuda NeuroIntelligence 2.2 (577) [17]. The parameters of learning consist of 4 input variables, 1 output layer, and 12–14 hidden nodes, of which the highest R-squared (R^2=0.9967) are selected (Figure 6), that the best network suggest is equalled to 13 hidden nodes, additional ±1 hidden nodes are added for sensitivity analysis. The results are shown in Table 1.

5.1.2 Forecasting of cassava production volume (supply) using the MLR model

According to the cassava production data, which are collected monthly from 2006 to 2015, the following MLR equation is created with a confidence coefficient of 98.6% (R^2=0.986, p-value = 0.000) by using the

Minitab program version 13.

$$F_s = -9980 + 3.19X_{s1} + 9221X_{s2} - 0.99X_{s3} - 13.3X_{s4} \quad (7)$$

The forecasting results regarding the cassava production volume (supply) obtained from the BPN and MLR models are compared using MAPE. It is found that the best model is BPN 4-14-1 with a learning rate of 0.6 because it has the least MAPE of 6.89% when it is compared with BPN 4-12-1 (learning rate 0.6), BPN 4-13-1 (learning rate 0.7) and MLR model that, MAPE of 10.04%, 10.16% and 17.82% respectively (Table 1).

Table 1: MAPE of cassava production volume

MAPE of BPN Model				MAPE of MLR Model
Learning Rate	BPN 4-12-1	BPN 4-13-1	BPN 4-14-1	
0.1	19.59	21.25	16.86	17.82
0.2	15.38	13.74	16.47	
0.3	16.05	16.39	11.88	
0.4	14.41	21.82	11.62	
0.5	12.82	17.19	13.35	
0.6	**10.04**	18.49	**6.89**	
0.7	14.51	**10.16**	10.91	
0.8	19.03	17.84	13.41	
0.9	17.82	13.72	10.79	
1.0	11.88	19.92	18.92	

5.2 *Forecasting of cassava product demands for export: Part II*

There are seven inputs of cassava products (cassava starch, cassava chips, cassava pellets, and sago) as seen below.

X_{d1} = consumer price index (previous planting)
X_{d2} = gross domestic product (previous planting)
X_{d3} = gross national product (previous planting)
X_{d4} = oil price (previous planting)
X_{d5} = exchange rate (THB/USD, previous planting)
X_{d6} = farm price (previous planting)
X_{d7} = free on board price (previous planting)

One hundred twenty data sets concerning the demand for 4 cassava products (cassava starch, cassava chips, cassava pellets, and sago), which are collected monthly from 2006 to 2015, are applied to forecasting the demand for cassava products in 2016 using the BPN and MLR models.

For the BPN, the parameters of learning consist of 7 input variables, 1 output layer, and changing 12–14 hidden nodes (selected from the highest R-square same as previous). The MLR equations for each cassava product demand are shown in Table 2.

Table 2: The MLR equations for cassava product demand

Product	MLR	*p*-value
Cassava starch	$-2.12*10^9 + 30447496\ X_{d1} - 464\ X_{d2} + 517\ X_{d3} - 16228006\ X_{d4} + 8869395\ X_{d5} + 2.12*10^8\ X_{d6} - 38227\ X_{d7}$ (8)	0.000 (R^2=0.878)
Cassava chip	$-6.84*10^9 + 66403089\ X_{d1} - 837\ X_{d2} + 1190\ X_{d3} - 36086029\ X_{d4} + 57440225 X_{d5} + 4.61*108\ X_{d6} - 94780\ X_{d7}$ (9)	0.000 (R^2=0.759)
Cassava pellet	$-18537480 + 1811755\ X_{d1} - 90.5\ X_{d2} + 16.9\ X_{d3} + 3733001\ X_{d4} - 387253\ X_{d5} + 7437457\ X_{d6} - 4721\ X_{d7}$ (10)	0.000 (R^2=0.749)
Sago	$-26032034 + 141448\ X_{d1} + 7.93\ X_{d2} - 7.12\ X_{d3} + 111527\ X_{d4} + 402784\ X_{d5} - 3904648\ X_{d6} + 732\ X_{d7}$ (11)	0.000 (R^2=0.792)

According to Table 3, the best model for forecasting the demand for cassava starch is BPN 7-12-1, with a learning rate of 0.6 because it has the lowest MAPE of 4.49% when it is compared with BPN 7-14-1 (learning rate 0.6), BPN 7-13-1 (learning rate 0.6), and MLR model that, they have MAPE of 5.24%, 5.85%, and 6.02% respectively.

The best model to forecast the demand for cassava chips is BPN 7-14-1 with a learning rate of 0.5. It has the lowest MAPE of 2.42% while BPN 7-13-1 (learning rate 1.0), BPN 7-12-1 (learning rate 0.3), and MLR model have MAPE of 2.73%, 5.22%, and 6.25% respectively.

For the cassava pellets, the best model to forecast the demand cassava pellets is MLR with a MAPE of 21.07% that, lowest error when it is compared with BPN 7-12-1 (learning rate 0.4), BPN 7-13-1 (learning rate 0.8) and BPN 7-14-1 (learning rate 0.2), that MAPE of 25.94%, 27.47%, and 29.61% respectively.

The best model to forecast the demand for sago is BPN 7-13-1 with a learning rate of 0.4 and the MAPE of 0.63%, while, another models have BPN 7-12-1 (learning rate 0.5) with MAPE of 2.08, MLR with MAPE of 2.62, and BPN 7-14-1 (learning rate 0.9) with MAPE of 2.81, respectively.

Table 3: MAPE of cassava products demand

Product	MAPE of BPN Model				MAPE of MLR
	Learning Rate	BPN 7-12-1	BPN 7-13-1	BPN 7-14-1	
Cassava starch	0.1	6.03	7.25	4.70	6.02
	0.2	6.71	6.70	5.86	
	0.3	5.51	6.99	7.42	
	0.4	5.42	7.82	6.65	
	0.5	6.24	8.39	6.31	
	0.6	**4.49**	**5.85**	**5.24**	
	0.7	6.79	6.47	6.94	
	0.8	7.36	6.87	7.87	
	0.9	7.77	6.97	6.63	
	1.0	7.62	6.92	7.82	
Cassava chip	0.1	5.88	5.91	4.63	6.25
	0.2	5.65	6.27	4.53	
	0.3	**5.22**	2.98	4.59	
	0.4	5.57	4.64	10.75	
	0.5	5.64	5.49	**2.42**	
	0.6	6.58	3.57	5.11	
	0.7	5.39	2.87	2.77	
	0.8	6.74	2.97	3.84	
	0.9	6.79	3.40	6.26	
	1.0	6.27	**2.73**	4.76	
Cassava pellet	0.1	30.44	28.08	44.55	**21.07**
	0.2	56.87	29.06	**29.61**	
	0.3	37.21	35.00	45.47	
	0.4	**25.94**	29.37	43.12	
	0.5	44.04	29.51	43.82	
	0.6	26.45	30.70	38.26	
	0.7	48.40	36.85	46.16	
	0.8	39.82	**27.47**	46.51	
	0.9	33.05	31.51	44.49	
	1.0	50.30	29.55	42.91	
Sago	0.1	2.70	6.88	6.59	2.62
	0.2	8.03	2.34	4.49	
	0.3	6.67	3.79	6.92	
	0.4	3.60	**0.63**	7.10	
	0.5	**2.08**	4.95	8.90	
	0.6	3.85	4.03	5.34	
	0.7	4.21	1.99	6.95	
	0.8	2.08	3.21	8.90	
	0.9	3.39	1.89	**2.81**	
	1.0	3.47	3.90	8.90	

6 Maximum Profit for Cassava Products and Optimization of Cassava Planting Area

The results for the accurate forecasting model are used for finding the optimal supply of cassava products for exporting and for maximizing profit. The data of domestic market are calculated from proportion of 8% of the total supply.

6.1 *Maximum profit of cassava products: Part III*

Linear programming is applied to calculate the production volume of cassava products including cassava chips, cassava pellets, cassava starch, and sago that match the demand of the domestic and export markets in order to generate the maximum profit.

The objective function of the LP program can be written as follows in equation (12).

$$Max\ Z_x = \sum_{i=1}^{8} a_i X_i \tag{12}$$

a_i = profit coefficient of a specific cassava product in the respective market, USD per ton
i = 1, 2, 3, ... , 8.
X_1 = quantity cassava chips for domestic
X_2 = quantity cassava pellets for domestic
X_3 = quantity cassava starch for domestic
X_4 = quantity sago for domestic
X_5 = quantity cassava chips for export
X_6 = quantity cassava pellets for export
X_7 = quantity cassava starch for export
X_8 = quantity sago for export

According to the results obtained from the BPN and MLR models, the total cassava production in 2016 is forecasted to be 31,022,075 tons. The demand for cassava products in the export market is 29,952,347 tons, which included 17,402,482 tons of cassava chips, 59,200 tons of cassava pellets, 12,375,375 tons of cassava starch, and 115,291 tons of sago. Considering the demand for cassava products in domestic markets, which is calculated based on the data from previous year, it is forecasted to reach 2,481,766 tons (8% of supply) in 2016.

The profit per ton of each cassava product is also calculated according to the following relevant data: 1) raw material cost, 2) production cost, 3) domestic sales prices, and 4) export sales prices, which were collected from the Office of Agricultural Economics, the Department of Export Promotion, and the Thai Tapioca Trade Association. These relevant data, demand for cassava products in 2016 and profit for each cassava product are applied as the constraints of the linear programming model (Table 4).

Table 4: Forecasting demand for cassava products in 2016 and profit for each cassava product

Cassava Product	Demand (X_i) (tons of cassava fresh)	Profit (a_i) (USD/ton)
Cassava chip for domestic	2,481,766 (8% of supply)	20.43
Cassava pellet for domestic		18.90
Cassava starch for domestic		24.39
Sago for domestic		22.87
Cassava chip for export	17,402,482	21.98
Cassava pellet for export	59,200	21.80
Cassava starch for export	12,375,375	27.53
Sago for export	115,291	27.44

The objective function determining the maximum profit can be written as follows (13).

$$Max\ Z = 20.43X_1+18.90X_2+24.39X_3+22.87X_4+ 21.98X_5+21.80X_6+27.53X_7+27.44X_8 \quad (13)$$

The constrains are as follows;

$X_1+X_2+X_3+X_4+X_5+X_6+X_7+X_8 \leq 31{,}022{,}075$ (supply)

$X_1+X_2+X_3+X_4 \leq 2{,}481{,}766$ (demand for domestic)

$X_5 \leq 17{,}402{,}482$ (demand of cassava chip for export)

$X_6 \leq 59{,}200$ (demand of cassava pellet for export)

$X_7 \leq 12{,}375{,}375$ (demand of cassava starch for export)

$X_8 \leq 115{,}291$ (demand of sago for export)

$X_1+X_5 \leq 18{,}794{,}681$ (total quantity of cassava chip*)

$X_2+X_6 \leq 63{,}936$ (total quantity of cassava pellet*)

$X_3+X_7 \leq 13{,}365{,}405$ (total quantity of cassava starch*)

$X4+X_8 \leq 124{,}514$ (total quantity of sago*)

$X_i \geq 0$.

Remark: * Total quantity of cassava products such as cassava chip is calculated from demand of cassava chip for export plus 8% of demand of cassava chip for export ($X_1+X_5= X_5 + 8*X_5/100$).

Table 5: Optimization of cassava products from LP to get maximum profit in 2016

Cassava Product	Quantities (tons fresh root)		
	Domestic	Export	Total
Cassava chips	34,786	17,402,482	17,437,268
Cassava pellets	0	59,200	59,200
Cassava starch	1,025,388	12,375,375	13,400,763
Sago	9,553	115,291	124,844
Total productions	1,069,727	29,952,348	31,022,075
Total demand	2,481,766	29,952,348	32,434,114
Balance	-1,412,039	0	-1,412,039
Maximum profit (USD) 753,523,053			
Lost opportunity profit for merchants (USD) -28,836,002			
Lost opportunity for farmers (USD) - 86,099,939			

The results for the LP are shown in Table 5; the optimal total production of cassava chips is 17,472,956 tons (fresh root), 70,474 tons for domestic market, and 17,402,482 tons for export. The total production of cassava pellets is 59,200 tons, which is the most suitable for export. Couse of the cassava pellets are the lowest profit then can be substituted by cassava chips.

The total productions of cassava chips are 17,437,268 tons, and of these 34,786 tons are for the domestic markets and 17,402,482 tons are for export markets. The total 59,200 tons of cassava pellets are produced only for export purposes. The total productions of cassava starch are 13,400,763 tons, and of these 1,025,388 tons are for domestic markets and 12,375,375 tons are for export markets. The total quantity of sago products are 124,844 tons, of which 9,553 are for domestic markets and 115,291 tons are for export markets.

According to the results from the LP technique, which are calculated based on the maximum profit and relevant constraints, the domestic supply for cassava products are 1,412,039 tons lower than the domestic demand. On the other hand, the production volume of cassava products for export markets is found to meet the demand. This is because the production for export purposes has a higher profit per unit than the production for domestic consumption.

It is also found that there are attempts to import cassava products to serve the demands of both domestic and export markets, which lead to the loss of opportunities in cassava production and the processing of 28,836,002 USD. If there were effective management procedures (explained in Recommendations), this loss amount can be reduced and the farmers can gain higher income from fresh root sales. In addition, if the production volume of cassava products can be increased to meet the demand, the farmers' income can possibly reach 86,099,939 USD.

6.2 *Optimization of planting area: Part IV*

Linear programming is applied to calculate the appropriate cassava plantations that give the minimum planting area in order to get optimal benefit of area for cultivating.

This part of the research is related to the constraints, objective function coefficient, and LP program determining the minimum of planting area. The objective function can be written as follows (14).

$$Min\ Z_y = \sum_{j=1}^{10} Y_i \quad (14)$$

The constraints are as follows:
$Y_1 \leq 43{,}511$ (area zone 1)
$Y_2 \leq 164{,}999$ (area zone 2)
$Y_3 \leq 342{,}088$ (area zone 3)
$Y_4 \leq 245{,}068$ (area zone 4)
$Y_5 \leq 921{,}094$ (area zone 5)
$Y_6 \leq 572{,}363$ (area zone 6)
$Y_7 \leq 143{,}445$ (area zone 7)
$Y_8 \leq 216{,}510$ (area zone 10)
$Y_9 \leq 331{,}272$ (area zone 11)
$Y_{10} \leq 554{,}088$ (area zone 12)
$Y_j \geq 0$;
$j = 1, 2, 3, \ldots, 10$.
$\sum a_j Y_j = 32{,}434{,}115$ (total demand)
a_j = percent yield of cassava production in each area zone (tons per acre)

The percent yield (a_j) for zone 1, 3, 4, 7, 10 and 11 is 8.85 tons per acre. The percent yield for zone 2 is 8.88 tons per acre, zone 5 is 9.49 tons per acre, zone 6 is 9.33 tons per acre, and zone 12 is 9.42 tons per acre (see Table 6).

Table 6: Input variables (percent yield and planting area in each zone) and output variables (optimum area and cassava production volume in each zone)

Zone Area	Input: Coefficient and Constrains		Output: Optimization	
	% Yield (a_j) (tons/acre)	Planting Area (acres)	Optimum Area (acres)	Production (tons)
Zone 1 (Y_1)	8.85	43,511	42,933	380,106
Zone 2 (Y_2)	8.88	164,999	164,999	1,465,909
Zone 3 (Y_3)	8.85	342,088	341,510	3,023,278
Zone 4 (Y_4)	8.85	245,068	244,495	2,164,402
Zone 5 (Y_5)	9.49	921,094	921,094	8,739,120
Zone 6 (Y_6)	9.33	572,363	572,363	5,339,973
Zone 7 (Y_7)	8.85	143,445	142,867	1,264,776
Zone 10 (Y_8)	8.85	216,510	215,932	1,911,590
Zone 11 (Y_9)	8.85	331,272	330,694	2,927,528
Zone 12 (Y_{10})	9.42	554,088	554,088	5,217,433
Total			3,530,972	32,434,115
Minimum planting area (acres)			3,530,972	
Average percent yield (tons/acre)			9.19	
Income for farmers : Farm price (tons/USD) 63-68			USD 2,043,349,245 - 2,205,519,820	

After calculating all of the cassava planting in 10 zones, it is found that the total optimum area resulting from the LP program (solver in Microsoft Excel 2010) is 3,530,972 acres. The results also suggest that the farmers can gain a total income of 2,043,349,245 to 2,205,519,820 USD if the total cassava production can reach 32,434,115 tons and the minimum planting area is 3,530,972 acres, and percent yield is 9.19 tons per acre therefore, we should get optimal benefit of area for cultivating.

7 Conclusions and Recommendations

The objectives of this research are 1) to generate models that can effectively and accurately forecast the yields and the demand for four cassava products; and 2) to calculate the suitable production volume for each cassava products for local market and export demands and 3) to calculate the cassava planting area that can minimize planting area.

7.1 *Conclusions*

1. The best model for forecasting the volume of cassava production (supply) is BPN 4-14-1. Considering the demand for cassava products, the best forecasting models for cassava starch, cassava chips, cassava pellets, and sago are BPN 7-12-1, BPN 7-14-1, MLR, and BPN 7-13-1 respectively.

2. According to the results from the forecasting model, the cassava yield in 2016 is 31,022,075 tons. The export demand for cassava chips, cassava pellets, cassava starch, and sago is 17,402,482 tons, 59,200 tons, 12,375,375 tons, and 115,291 tons, whereas the domestic demand for cassava products is 2,481,766 tons. Therefore, the total demand for cassava products is 32,434,115 tons.

7.2 *Recommendations*

The contribution of this research is to propose a more accurate methodology to manage the cassava product production in Thailand and how to maximize the profit. The results based on the forecasting model can be effectively and accurately used as information to appropriately plan and manage the production of cassava products in advance. This can bring out the most appropriate benefit for cassava farmers, manufacturers,

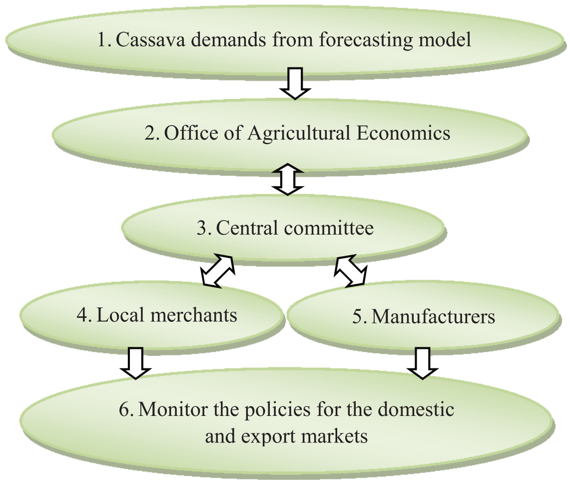

Figure 7: Recommended management of cassava products for domestic and export markets.

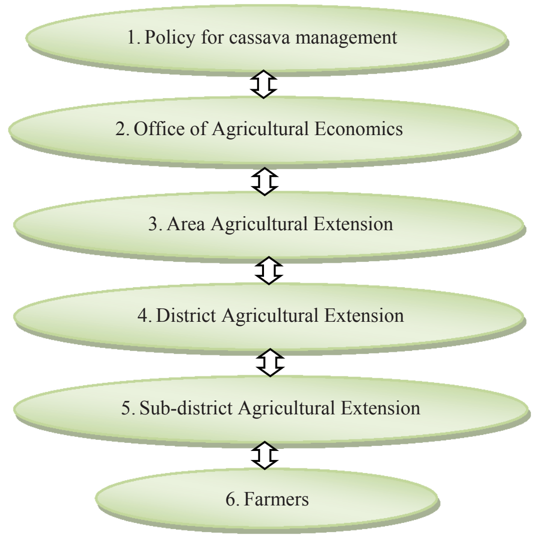

Figure 8: Management of cassava production for farmers.

and merchants. The recommended management system for cassava demand is depicted in Figure 7.

The processes show in Figure 7 can be described as follows.

1. The cassava yield in 2016, resulting from the forecasting model, is found to be 31,022,075 tons. The cassava demand in the domestic and export markets are forecasted to be 32,434,115 tons (fresh root).

2. The data relevant to the domestic and export demands for cassava products are submitted to the Office of Agricultural Economics, a Governmental agency responsible for developing agricultural strategies and development plans and measures.

3. Central committee should be established, which consists of representatives from various cassava-related sectors such as cassava farmers, manufacturers, merchants, and governmental staff from the Office of Agricultural Economics, and should be appointed to determine the policies concerning cassava management. These in order to reduce conflicts that are caused by farmers want to produce in large volumes of cassava and sold at high prices. On the other hand, the manufacturers want to get cassava in limited volume and at low prices. The central committee formulates the cassava policies, which includes fixing a minimum price of cassava fresh root in order to help the farmers earn maximum benefits, assigning cassava planting areas, setting effective plans to get maximum yield per each particular area, then we can determining the proportion of cassava production to meet the demand of markets. According to the forecasting demand for cassava products in 2016, the total optimum areas for cassava planting is calculated to be 3,530,972 acres.

4. Cassava farmers distribute their products to local merchants in the amount of 18,908,507 tons of fresh root for processing total amount of cassava chips and cassava pellets.

5. Cassava farmers sell their products to cassava product manufacturers in the amount of 13,525,607 tons of fresh root for processing to cassava starch and sago.

6. The central committee monitors the implementation of cassava policies and establishes mutual agreement on cassava trading based on predetermined proportions and prices. This can enable the manufacturers to produce cassava products appropriately to meet the demand of both domestic and export markets.

After the cassava management policies are established by the central committee, the relevant governmental agencies shall implement them to the farmers, as shown in Figure 8.

The processes show in Figure 8 can be described as follows.

1. The central committee establishes the policy for cassava management.

2. The Office of Agricultural Economics announces the policy to relevant stakeholders. The central committee monitors the implementation to ensure accurate policy compliance.

3. The Area Agricultural Extension adopts the policy from the Office of Agricultural Economics to study and develop agricultural data for each particular area, monitoring reports, make evaluations, and make impact summaries and suggestions for the related agencies and farmers.

4. The Area Agricultural Extension recognizes the relevant agricultural data and implements the policy to the District Agricultural Extension. Then the District Agricultural Extension can determine cassava planting promotion plans and find out solutions for cassava production and marketing, especially regarding cassava prices and purchasing sources with predetermined purchasing proportions that meet the demand of the market.

5. The District Agricultural Extension holds meetings with the Sub-district Agricultural Extension in order to implement the policy for cassava planting promotion, to clarify solution slumps in cassava prices, and to provide information on the predetermined minimum prices as well as the purchasing proportion of cassava fresh root. According to the previous example, the farmers can sell 18,908,507 tons of raw materials to the cassava chips and pellets manufacturers, while the other 13,525,607 tons of fresh root can be sold to the cassava starch and sago manufacturers. After that the Sub-district Agricultural Extension can implement the policy to the farmers and survey the planting area by encouraging the farmers to register and provide information about the size of their planting area, and the planting and cultivating time. Then, the District Agricultural Extension can collect the data and submit it to the Area Agricultural Extension to urgently find an effective solution. If the supply exceeds the demand, the measure to find new potential markets should be determined.

6. The farmers in particular areas adopt the policy for cassava management from the Sub-district Agricultural Extension. They can finally realize the importance of policy implementation in terms of productive cassava production, including appropriate cassava planting areas, optimal yields per area, and effective cassava pricing, which can contribute to their maximum benefits and correspond to the market demand. These would help resolve the imbalance between supply and demand, as mentioned in the above problems.

Future research related to cassava product management should be done as valuable tool in order to create plans for the management of the demand and supply of cassava for domestic demand forecasting, import cassava products demand and the determination of cassava cultivation areas suitable for both domestic and export market needs. Moreover, patterns or models of forecasting should be adapted to other agricultural products domestically and internationally as an efficient approach for upgrading agricultural product management standards for Thailand or for other tropical neighboring countries. These measures are part of extending agricultural product potential domestically and globally in particular the ASEAN Economics Community comes into full force.

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