

Modeling and Forecasting of the Supply of Durian for Consumption in Domestic and Export Markets

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Abstract

This research aimed to design and construct a forecasting support system on demand of fresh durian of Thailand by applying 2 mathematical models which were Time Series model and Artificial Neural Network model in order to find an accurate model of forecasting support system on demand of durian yield to forecast durian yield quantity of Thailand in advance and use the forecast results to plan and determine quantity of fresh durian and durian product conforming with domestic consumption and export in order not to be over demand and cheap durian sold price.

The forecast models were applied with Time Series model by using Moving Average, Weighted Moving Average, Single Exponential Smoothing and Holt's Linear Exponential Smoothing techniques and Back Propagation of Artificial Neural Network model which used 4 input variables relating to durian yield. All of the forecast models were used to forecast total durian yield quantity in 26 provinces of durian cultivated area all around Thailand. Durian yield quantity data used was from 1996 to 2008. After that, the forecast results were used to find the errors of MAE, MSE, RMSE and MAPE. Then, the errors of each forecast model were compared. The forecast model which had the least error was the most accurate forecast model. The research result is following. Back Propagation with 4-8-1 structure of Artificial Neural Network model had the least error so that it was the most accurate forecast model to forecast fresh durian yield quantity in advance.

Keywords: Durian, Forecasting, Time Series Model, Artificial Neural Networks Model.

1. Introduction

According to durian production situation in 2008, Thailand was the major country of the world that exported fresh durian and processed durian products. There was more than 290,000 acres of durian cultivated area in Thailand, the area providing durian yield was 266,975 acres and fresh durian yield totaled about 637,790 tons. Export durian were the kinds of fresh durian, frozen durian and processed durian products such as durian preserve and dehydrated durian. The export price in 2009 was 122.46 million Dollar. When the quantity and the export price in 2009 and 2008 were compared, it indicated that the export quantity increased extremely but the export price increased a bit. Durian sale price tended to be inexpensive continually that was opposed to durian production capital which raised. In 2009, Mhontong durian average price sold by gardeners was 0.47 Dollar /kg. but in 2008, it was 0.54 Dollar /kg so the price decreased 12.96%. (The Center of Agricultural Information, 2008)

1.1 Durian production power of Thailand

Durian cultivated areas in Thailand were in 26 provinces (See figure 1.) which the important areas were in the South and the central part of Thailand. The provinces in the central part such as Chanthaburi, Rayong and Trat provided 50% of total yield of Thailand. The harvest duration was from March to July and the most abundant yield duration was from April to May. The provinces in the South such as Chumphon, Surat Thani and Nakhon Si Thammarat provided 30% of total yield. The harvest duration was from June to October and the most abundant yield duration was from July to August. (The Office of Agricultural Economics, 2008)

Table 1 List of provinces containing durian cultivated area in Thailand

Northern	North-eastern
1. Sukhothai	3. Si Sa Ket
2. Utharadit	4. Nakhon Rachasima
Central	Southern
5. Nonthaburi	13. Chumphon
6. Prachinburi	14. Ranong
7. Chachoengsao	15. SuratThani
8. Chanthaburi	16. Phangnga
9. Trat	17. Phuket
10. Rayong	18. Krabi
11. Chonburi	19. Trang
12. Prachuap Khiri Khan	20. Nakhon Si Thammarat
	21. Phatthalung
	22. Songkhla
	23. Satun
	24. Pattani
	25. Yala
	26. Narathiwat

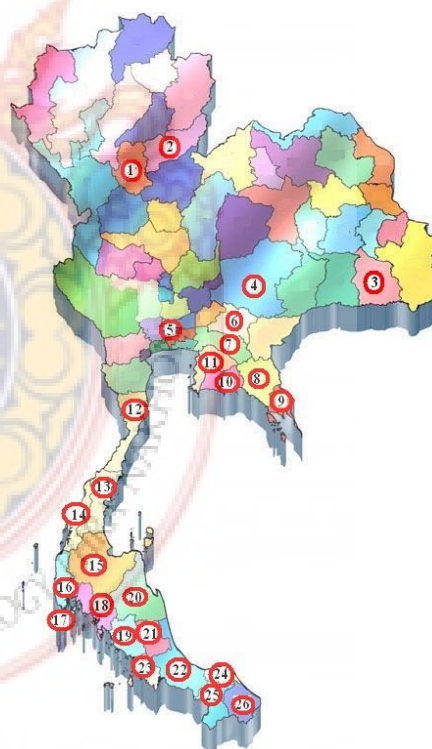


Fig. 1 Map of provinces containing durian cultivated area in Thailand

Proportion of fresh durian yield in each province as shown in figure 2 indicates that the provinces providing the most durian yield were Chanthaburi, Chumphon and Rayong, respectively.

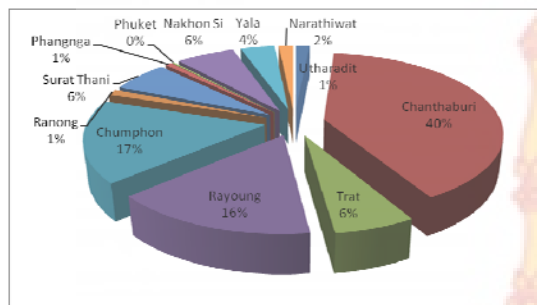


Fig. 2 Proportion of fresh durian yield in each province in 2008

The problems were abundant durian yield and being seasonal fruit, especially, the same period of harvest in the central part and the South from June to August. Those problems caused flooded fresh durian and inexpensive sale price. Figure 3 indicates that gardeners' sale price in June and July was very cheap, especially, in August, sale price was less than production capital because domestic fresh durian consumption rate in abundant durian duration was less than production rate. Those events have happened continually until present.

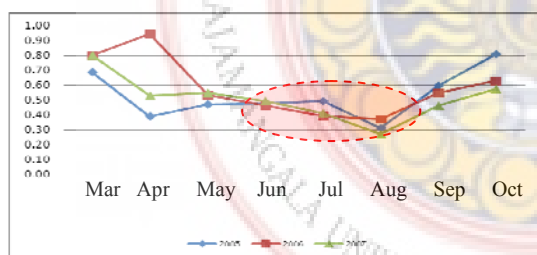


Fig. 3 Gardeners' sale price per year in 2005-2007 (Dollar) (The Office of Agricultural Economics, 2008)

This study aimed to construct forecast models applying accurate mathematical models to forecast fresh durian yield quantity in 26 provinces of

durian cultivated area in Thailand in advance. After that, the forecast results were used as the data to plan and determine appropriate fresh durian production and processed durian production in long-term period in order to decrease the problems of superabundant durian production and inexpensive durian price.

2. Research Methodology

2.1 The information of fresh durian yield quantity all around Thailand and in Agro-Economics Zones of durian of Thailand was studied.

2.2 Durian cultivated area, area providing yield and durian yield quantity per acre in Agro-Economics Zones of durian of Thailand was investigated.

2.3 Domestic durian consumption quantity and fresh durian and processed durian product export quantity was researched.

2.4 Proportion of fresh durian consumption and processed durian product consumption was studied.

2.5 Variables affecting durian yield quantity was investigated.

2.6 Models of durian yield quantity forecast in advance was researched and developed.

2.7 Time Series methods as follows were studied.

- Moving Average
- Weighted Moving Average
- Single Exponential Smoothing
- Holt's Linear Exponential Smoothing

2.8 Artificial Neural Networks Model (ANNs) determining 4 input variables as follows was researched.

- Variable1 = Harvested area. (Acres)
- Variable2 = Farm price. (Dollar/Ton)
- Variable3 = Export price.(Dollar/Ton)
- Variable4 = Rainfall. (mm)

2.9 The forecast model based on Back propagation type of Artificial Neural Networks was constructed.

2.10 The models of durian yield quantity forecast using the information in 1996-2008 were tried out.

2.11 The errors of forecast between Time Series models and Artificial Neural Networks model were compared to inspect the forecast accuracy. The errors were compared as follows.

- Mean Absolute Deviation (MAE)
- Mean Square Error (MSE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percent Error (MAPE)

2.12 Mathematical models were studied to determine proportion of fresh durian and processed durian product conforming with domestic consumption demand and export.

2.13 Mathematical models were used to determine appropriate proportion of fresh durian and processed durian product by using authentic data in order to plan durian production.

Nonthaburi	1248		276
Prachinburi	3339		2417
Chachoengsao	385		165
Chanthaburi	310641		243808
Trat	36878		37306
Rayong	132143		94290
Chonburi	675		482
Prachuap Khiri Khan	3143		3133
Chumphon	85593		100584
Ranong	25807		7514
Surat Thani	20869		37513
Phangnga	3456		4495
Phuket	696		1371
Krabi	3964		4563
Trang	3077		2761
Nakhon Si Thammarat	17510		38222
Phatthalung	3252		1378
Songkhla	16800		7111
Satun	6303		927
Pattani	4537		3028
Yala	17855		22161
Narathiwat	18154		9472
TOTAL	726806	→	637790

3. Mathematical models used in the research

3.1 Time Series model

Time Series model is based on the assumption saying that “Future is function of past.” by considering that what have happened in that period of time and the data series were used to forecast. Numerical data used can be divided into a week, a month, three months or a year. In this research, the data used to forecast was the yearly durian yield quantity data in each province of 26 provinces containing durian cultivated area in Thailand. (See table 2.)

Table 2 Fresh durian yield quantity data in each province in 1996-2008

Provinces	Year	1996	→	2008
	Sukhothai		1954	
Utharadit		7749		9023
Si Sa Ket		469		1795
Nakhon Rachasima		309		34

Four Time Series models used in this research are as follows.

3.1.1 Moving Average Model

Moving Average Model is the smooth forecasting which averages 1 series of observed data in the past and uses the average to be the forecast value in the next period. In this research, there is the durian yield quantity forecast in advance using retrospective durian yield quantity data in 2-10 years. We can calculate by:

$$MA_n F_{t+1}^p = \frac{1}{n} \left(\sum_{t=i+1-n}^i A_t^p \right)$$

Where

$MA_n F_{t+1}^p$ = Moving average of n forecasted product quantity in period $t+1$

$t+1$ = Period of forecast

i = The last year in that period use for calculating

t = The first year in that period at

start for calculating

n = Number of periods in moving average as yearly start at $n = 2, 3 \dots 10$ years
 p = The provinces of durian cultivated area
 A_t^p = Actual product quantity at time period t

3.1.2 Weighted Moving Average Model

Weighted Moving Average Model is the average of produce quantity in the past consecutively. To value the importance weight to produce quantity close to current then in descending order based on the past. The result is a forecast value of next period. We can calculate by:

$$WMA_n F_{t+1}^p = \sum_{t=i+1-n}^i W_t A_t^p$$

Where

$WMA_n F_{t+1}^p$ = Weighted Moving average of n forecasted product quantity in period $t+1$
 $t+1$ = Period of forecast
 i = The last year in that period use for calculating
 t = The first year in that period at start for calculating
 n = Number of periods in moving average as yearly start at $n \geq 2$
 p = The provinces of durian cultivated area
 W_t = The weight for period t , between 0 and 100 percent
 A_t^p = Actual product quantity at time period t

3.1.3 Single Exponential Smoothing Model

A single exponential smoothing model allows us to vary the importance of recent product quantity to the forecast. We can calculate by:

$$ESF_{t+1}^p = \alpha A_t^p + (1-\alpha)ESF_t^p$$

Where

ESF_{t+1}^p = Single Exponential Smoothing forecasted in period $t+1$

ESF_t^p = Single Exponential Smoothing forecasted in period t

$t+1$ = Period of forecast

α = Smoothing constant when $0 \leq \alpha \leq 1$

t = Period before forecast

p = The provinces of durian cultivated area

A_t^p = Actual product quantity at time period t

3.1.4 Holt's Linear Exponential Smoothing Model

This is an extension of exponential smoothing to take into account a possible linear trend. There are two smoothing constants α and β . We can calculate by:

$$LESF_{t+1}^p = L_t + b_t$$

Where

$LESF_{t+1}^p$ = Holt's Linear Exponential Smoothing forecasted in period $t+1$

L_t, b_t = Respectively (exponentially smoothed) estimates of the level and linear trend of the series at time t . We can calculate L_t and b_t by:

$$L_t = \alpha A_t^p + (1 - \alpha)(L_{t-1} + b_{t-1})$$

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}$$

Where

α = Smoothing constant when
 $0 \leq \alpha \leq 1$

β = Smoothing constant for
trend when $0 \leq \beta \leq 1$

t = Period before forecast

p = The provinces of durian
cultivated area

A_t^p = Actual product quantity at
time period t

3.2 Artificial Neural Networks Model (ANNs)

Artificial Neural Networks is computer construction which models human brain's working or can think and remember as human Artificial Neural Networks in order that computer can understand human language, read and recognize. The structure of Artificial Neural Networks consists of input units and output units and determines the weight for each input unit route. Back-propagation Algorithm is used to write for the construction of Neural Network learning in order to think as human. Back-propagation Neural Networks (BPN) will have high or low efficiency, it depends on the selection of network construction which are numbers of hidden layers, hidden units and parameters of learning. The working principle of Artificial Neural Networks Model is shown in figure 4.

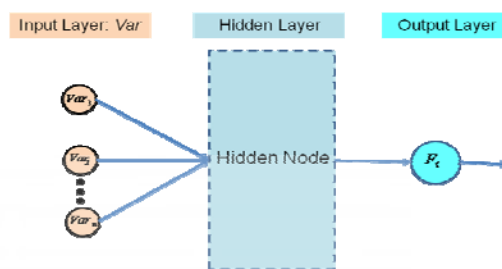


Fig. 4 Working principle of Artificial Neural Networks Model

Input variables for Artificial Neural Networks Model were:

Var_1 = Harvested area. (At the time t-1)

Var_2 = Farm price. (At the time t-1)

Var_3 = Export price. (At the time t-1)

Var_4 = Rainfall. (At the time t-1)

Output variable for Artificial Neural Networks Model was:

F_y = Forecast of durian production quantity (At the time t)

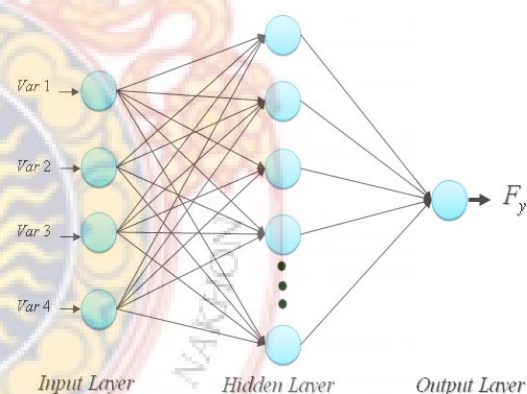


Fig. 5 Structure of Artificial Neural Networks Model In the research

In this research, the data was divided to be 2 series which were the training series containing 260 data sequences and the testing series containing 52 data sequences. The infrastructure consisted of 4 input variables, 1 hidden layer, changing 1-10 hidden nodes and the parameter of

learning. The error goals were 0.007, 0.009, 0.01 and 0.05. The results of Neural Networks forecast testing are shown as MAPE. (See table 4.)

Table 4 MAPE calculated by Neural Networks forecast Model

Error goal \ Hidden Node	0.007	0.009	0.01	0.03
1	31.47	39.49	43.00	56.01
2	26.01	28.29	29.58	67.74
3	22.41	21.59	26.15	28.71
4	24.73	25.22	28.96	91.66
5	21.93	30.85	33.53	49.24
6	62.75	78.49	84.41	96.20
7	65.70	79.40	83.45	47.32
8	24.12	12.95	11.63	48.80
9	36.38	29.06	24.79	15.83
10	28.37	27.52	27.38	41.58

3.3 Comparison of model efficiency

The forecast model efficiency compares the forecast errors by comparing MAE and MAPE resulting from forecast models. Mean absolute percentage error (MAPE) can be calculated by using the following equation.

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

Where

F_t = Actual of Durian production quantity in period t

A_t = Forecasted of Durian production quantity in period t

t = Period at consider

n = Total number of periods

4. Results

The efficiency of Time Series forecast model and Back-propagation Neural Networks were compared about fresh durian yield quantity forecast in 1 year in advance. The forecast model

efficiency was found by comparing the forecast errors as MAE, MSE, RMSE and MAPE. The results are shown as follows. The forecast model of Back propagation Artificial Neural Networks with 4-8-1 structure had the least forecast error so that the forecast of Back propagation Neural Networks was more accurate than the forecast of Time Series forecast model and the second efficient forecast model was Weighted Moving Average forecast model.

Table 5 Comparison of forecast errors

Forecast Model	MAE	RMSE	MAPE
Moving Average	91,230.33	104,499.71	12.36
Weighted Moving Average	89,694.14	104,691.78	12.22
Single Exponential Smoothing	92,612.77	106,879.15	12.61
Holt's Linear Exponential Smoothing	93,441.26	113,296.89	12.77
Back propagation Neural Networks	82,391.28	100,424.39	11.63

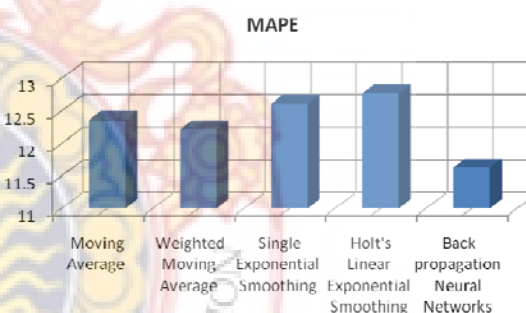


Fig. 6 Comparison of Mean Absolute Error

5. Conclusions

Comparison of forecast fresh durian product quantity in advance between the Moving Average Model, Weighted Moving Average Model, Single Exponential Smoothing Model, Holt's Linear Exponential Smoothing Model and Artificial Neural Networks model applied to be a forecast model was Back propagation. The research results were

found as follows. Artificial Neural Networks Model applied to be a forecast model was back propagation containing 4-8-1 structure had the least error. Its MAE was 82,391.28 tons, MAPE was 11.63% and the forecast accuracy was 88.37%. Forecasting by Artificial Neural Network model tends to forecast lower than actual product quantity.

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