ENHANCING SUPPLY FORECASTING FOR A PINEAPPLE CANNING COMPANY

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ABSTRACT

Traditionally, statistical time series methods such as Moving Average (MA), Exponential Smoothing, Regression or Decomposition, are used for demand forecasting. This project shows how these demand forecasting techniques have been employed for supply forecasting. Formerly, the company conducted the pineapple supply forecast by a judgmental method and assessment of surveys and historical data. A quantitative forecast method was not applied.

In this project, the historical pineapple supply data of the company was first used to investigate the data pattern. The Coefficient of Variance and Autocorrelation Functions were examined to select suitable forecasting techniques. In the results, the data showed a stationary pattern, and so the Moving Average and Simple Exponential Smoothing forecasting approaches were selected. Two years' supply data for 2006 to 2007 were used in the models. The implementation of a new proposed forecasting technique was measured for accuracy by comparing the Mean Absolute Percentage Error (MAPE). The results demonstrated that MAPE was reduced from 29% to 20% by the Simple Exponential Smoothing approach.

The improvement of forecast accuracy is evidence that a quantitative forecasting technique is favorably considered as part of pineapple supply forecast improvement. The new forecast enables the preparation of efficient sales and production planning.

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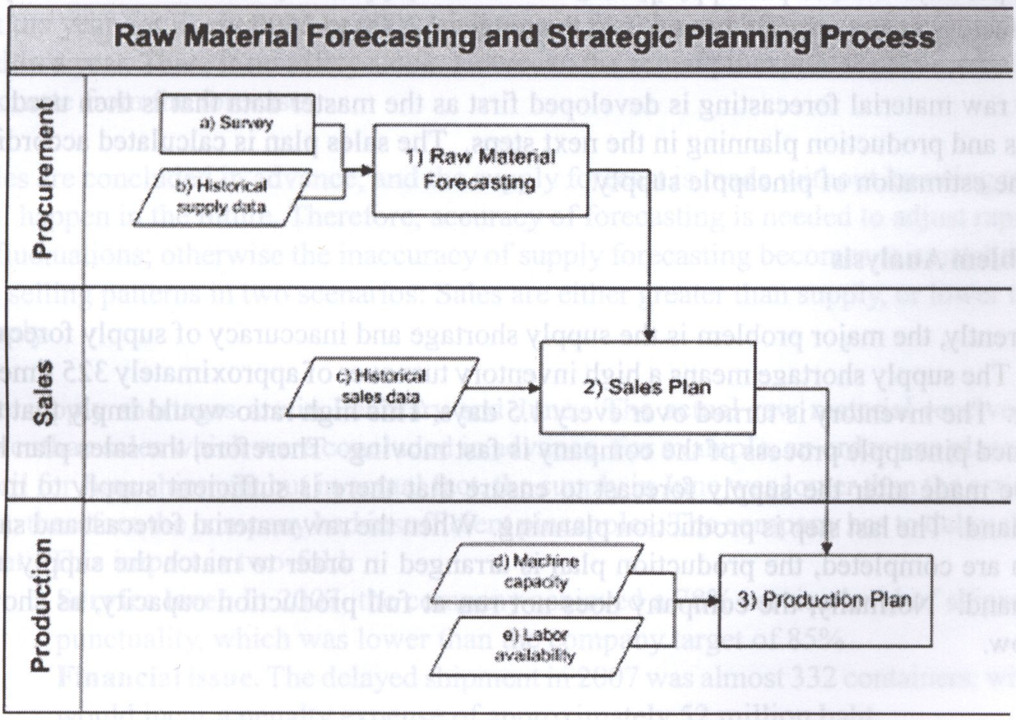
INTRODUCTION

The canned pineapple factory in this case study is one of the largest such factories in Thailand. The supply of fresh pineapples comes mainly from plantations in a southern Province which account for nearly 60% of all pineapple grown in Thailand. Fresh pineapples are received daily and processed by the end of the day. The company produces a wide range of products, but the main product is canned pineapple, which in 2007 accounted for 72% of the total sales.

All the products are exported globally, to North and South America, Europe, Asia, Middle East and Australia. The company's export volume is 50,000 containers per year. Most of the orders are "make-to-order" and packed for private labels. The company has implemented the strategic planning of supply, demand and production. Currently, the planning is undertaken at the beginning of the calendar year, by three departments. The company strategic planning process is depicted in this Figure:



Procurement Department:
For Raw Material Forecasting, the company rarely applies a statistical method to predict the future supply. Instead it uses a judgmental method that relies heavily on subjective assessments of surveys and historical data. A plantation survey is done before the crop

starts, to obtain crop data such as the quantities of each farm, and size and quality of pineapple. Also, historical data is used, of seasonal factors of rainfall and temperature affect supply quantities.

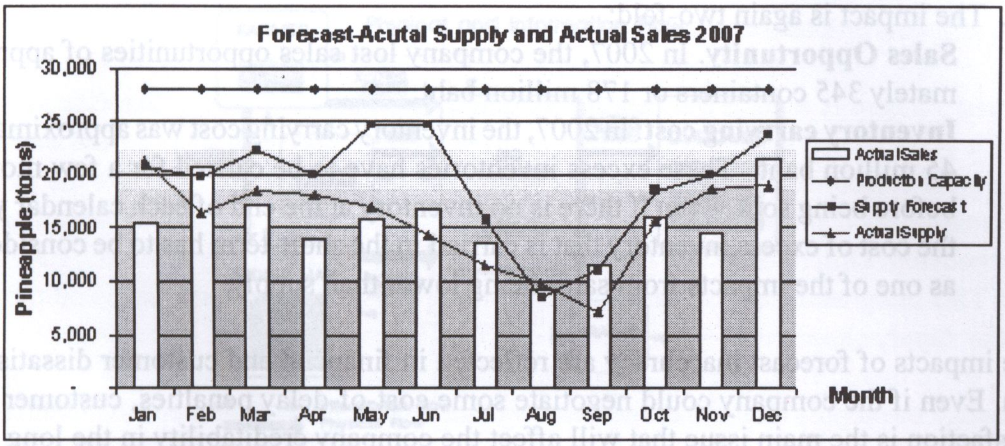
Sales Department:
A Sales plan is produced once a year. Normally, the demand of orders to the company is higher than the supply. Hence, the production is almost sold out in advance. The selling policy is to have regular three-months contracts. Historical Sales data is used to analyze the pattern of actual sales and set the sales target. The raw material forecasting from Procurement is also used to plan simultaneously.

Production Department:
Production planning is adjusted to match with the sales plan and does not exceed the production capacity and available labor. The evaluation of machine capacity and of labor availability is used as the data input for production planning. Machine utilization is evaluated to estimate the factory production capacity, which is approximately 800 tons per day. Canned pineapple production is labor intensive. The labor availability of the factory at any specific period is in the range of 2000 to 2500.

The raw material forecasting is developed first as the master data that is then used for sales and production planning in the next steps. The sales plan is calculated according to the estimation of pineapple supply.

Problem Analysis

Currently, the major problem is the supply shortage and inaccuracy of supply forecasting. The supply shortage means a high inventory turnover of approximately 325 times a year. The inventory is turned over every 1.5 days. This high ratio would imply that the canned pineapple process of the company is fast moving. Therefore, the sales plan has to be made after the supply forecast to ensure that there is sufficient supply to meet demand. The last step is production planning. When the raw material forecast and sales plan are completed, the production plan is arranged in order to match the supply and demand. Normally, the company does not run at full production capacity, as shown below.



This chart reveals that the actual sales and supply are below the company production capacity. Therefore, the machine capacity and labor availability are ignored in this study, as the case is focused only on supply. The average supply and sales quantities throughout the year are likely to be equal, which means that the production is almost sold out within a year. There is no safety stock. However, the actual pineapple supply is likely to fluctuate from the forecast.

Sales are concluded in advance, and the supply forecast is made without knowing what will happen in the future. Therefore, accuracy of forecasting is needed to adjust rapidly to fluctuations; otherwise the inaccuracy of supply forecasting becomes mismatched to the selling patterns in two scenarios: Sales are either greater than supply, or lower than supply.

The supply shortages are in February and June. The actual raw material received is lower than sales which were concluded in advance. For example, an order was placed in April for June shipment but in actual fact, the supply in June was lower than the estimation; therefore the company had insufficient pineapples. The company has to delay shipment. This impact is two-fold:

Service level. In 2007, the company achieved a 78% service level of shipment punctuality, which was lower than the company target of 85%.

Financial issue. The delayed shipment in 2007 was almost 332 containers, which would incur a penalty expense of approximately 52 million baht.

On the other hand, the supply was greater than actual sales in January, March, April and May. For example, an order was placed in January for March shipment. When the actual supply was more than sales, there would be pineapples left over, to keep as inventory. This inventory is carried over a certain period waiting for a spot order or kept for shipping later. There is a possibility that supply will be greater than sales in some periods. The impact is again two-fold:

Sales Opportunity. In 2007, the company lost sales opportunities of approximately 345 containers or 178 million baht.

Inventory carrying cost: In 2007, the inventory carrying cost was approximately 45 million baht. These excess inventories have to be carried for a few months before being sold. Even if there is no inventory at the end of each calendar year, the cost of excess inventory that is carried in the short-term has to be considered as one of the impacts from sales being lower than supply.

The impacts of forecast inaccuracy are reflected in financial and customer dissatisfaction. Even if the company could negotiate some cost-of-delay penalties, customer dissatisfaction is the main issue that will affect the company creditability in the long run. Therefore, this case study is focused on the importance of supply forecasting accuracy that would result in the efficient sales and production planning of the company.

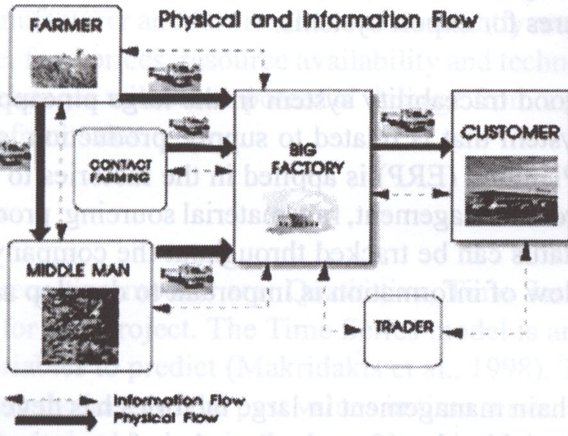
LITERATURE REVIEW

Supply Chain of the Canned Pineapple Industry

Thailand is the largest exporter of canned pineapple in the World. This Industry is the integration of Agricultural and Industrial sectors that add value to agricultural products. The supply chain consists of farmers, contract farming, middle men, canned pineapple factories, logistics providers, and customers. The supply chain management for the canned pineapple business can be segmented into two groups (Wasusri, 2007): small factories; large factories. This project studies the latter.

The supply chain management for large factories

The physical and information flow of large canned pineapple factories are:



Physical and Information Flow of large canned pineapple factory

The purchasing order is sent directly to factories from customers, importers or end buyers. Traders represent another channel that orders pass through. The procurement department in each factory will source and buy pineapples from independent farmers, contact farming and middle men for production and delivery to the customers. 60% of pineapples is supplied from contact farming, 10-15% is from independent farmers, and 25-30% is the consolidation from middle men (Wasuri, 2007).

The supply chain management of large canned pineapple factories can be summarized according to The Supply Chain Operations Reference model (SCOR model).

Plan - The large factories have good supply chain planning. The demand and supply have been forecast in advance by using plantation survey results and historical data. However, the forecasting is less than accurate due to uncertainty factors of season, climate, rainfall, crop price and acreage yield.

Source - The large canned pineapple factories have a good sourcing system in evaluating and tracing sources of supply. The farmers have to be registered as contract farming. The plantation and harvesting process according to Good Agricultural Practice (GAP) will be learnt from those factories. With this support, the farmers are able to increase crop yield and quality.

Make - The factories have been certified by Good Manufacturing Process (GMP), Hazard Analysis and Critical Control Point (HACCP), International Organization for Standardization (ISO 9000 and 14000) which are an assurance of production quality.

Delivery - The delivering system is operated by factories and Logistic providers which have efficient procedures for export systems.

Return - There is a good traceability system in the large pineapple factories as these have a good record system that is related to supply, production, storage and delivery. Enterprise Resource Planning (ERP) is applied in the factories to integrate the overall information such as order management, raw material sourcing, production planning and warehousing. Order status can be tracked throughout the company with this ERP system. This integrated flow of information is important to develop an end to end process for the supply chain.

Although the supply chain management in large factories has developed efficiently, the factories still need to quickly identify and adjust their forecasting from uncertainty of supply, process and demand, so as to increase the competitiveness of the Thai canned pineapple industry. Thus the improvement of supply forecasting accuracy was selected to be studied first in this case. Generally, forecasting has been applied to both the demand and supply functions. A prerequisite for the effective use of forecasting is an understanding of forecast theory and the factors that impact on forecasting error.

Supply Forecasting

If the demand is limited by supply, there is no need to predict future demand. Whatever is produced, the company can sell because the demand is greater than the supply. Therefore, the fluctuation of supply has to be studied and analyzed to accomplish the supply forecast.

From research studies, the primary determinants of raw material supply fluctuation in the agricultural industry result from two main factors: the change in yield and the change of human response (Adams et al.,1998). The first factor, is due to the variation in external factors such as climate, humidity, temperature. Crop yield is directly affected by changes in climatic factors of temperature, and rain. Extreme events like El Nino can cause droughts and floods that directly impact on plant productivity. Nevertheless, some impacts from El Nino may benefit farmers, because in some areas El Nino provides plentiful water supplies and higher determinants of human well-being (Kelly et al., 2000).

The second factor, the change in crop acreage, results from the farmer's expectation of changes in relative crop prices and returns per acre. Crop yield and acreage will rise or decline depending on both factors. If the demand is more than supply, the crop price will increase. Farmers have a motivation to increase productivity to take advantage of high returns. Conversely, farmers are indirectly forced to divest from the industry if the crop price is not attractive enough.

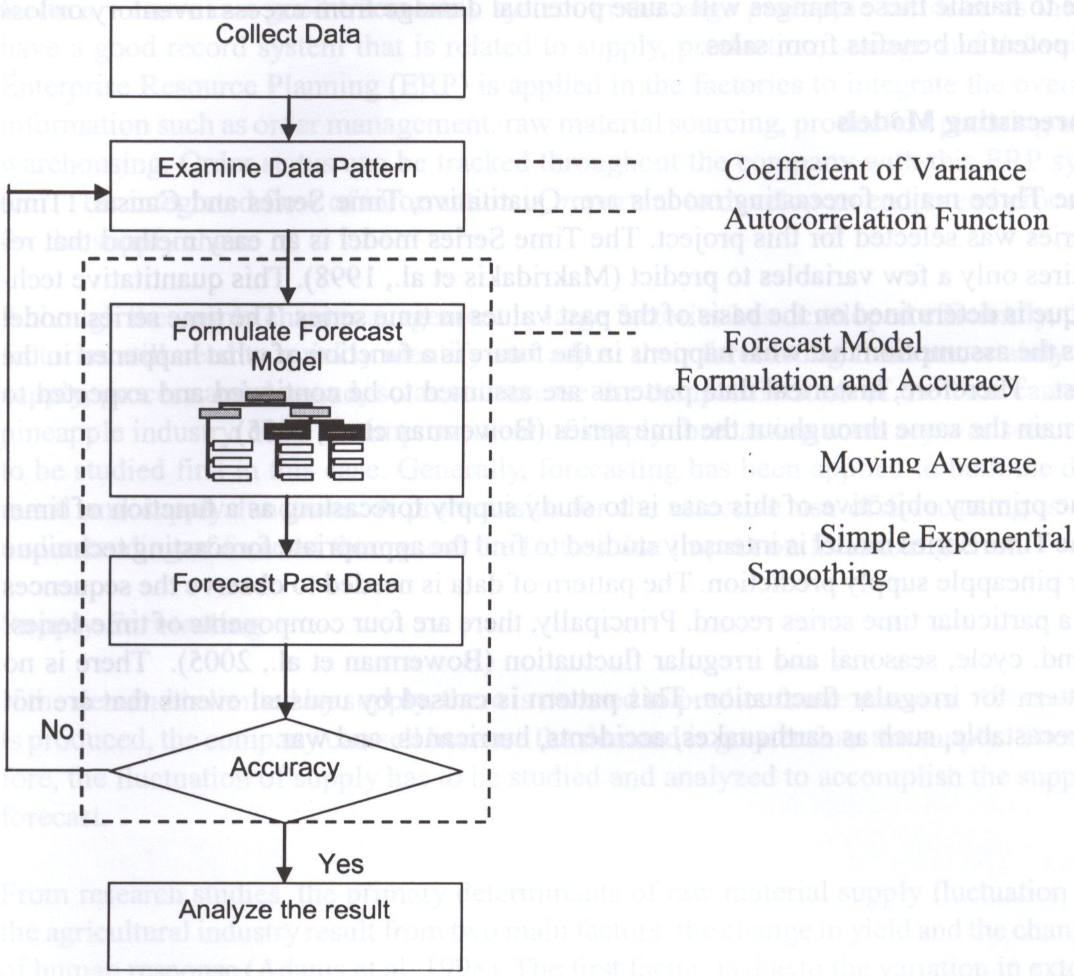
These biophysical effects and the human responses to the changes are complex and uncertain. Food Manufacturer and farmers have to constantly respond to the changes in crop yields and price, food prices, resource availability and technological change. Failure to handle these changes will cause potential damage from excess inventory or loss of potential benefits from sales.

Forecasting Models

The Three major forecasting models are: Quatitative, Time Series and Causal. Time Series was selected for this project. The Time Series model is an easy method that requires only a few variables to predict (Makridakis et al., 1998). This quantitative technique is determined on the basis of the past values in time series. The time series model has the assumption that what happens in the future is a function of what happened in the past. Therefore, historical data patterns are assumed to be continued and expected to remain the same throughout the time series (Bowerman et al., 2005).

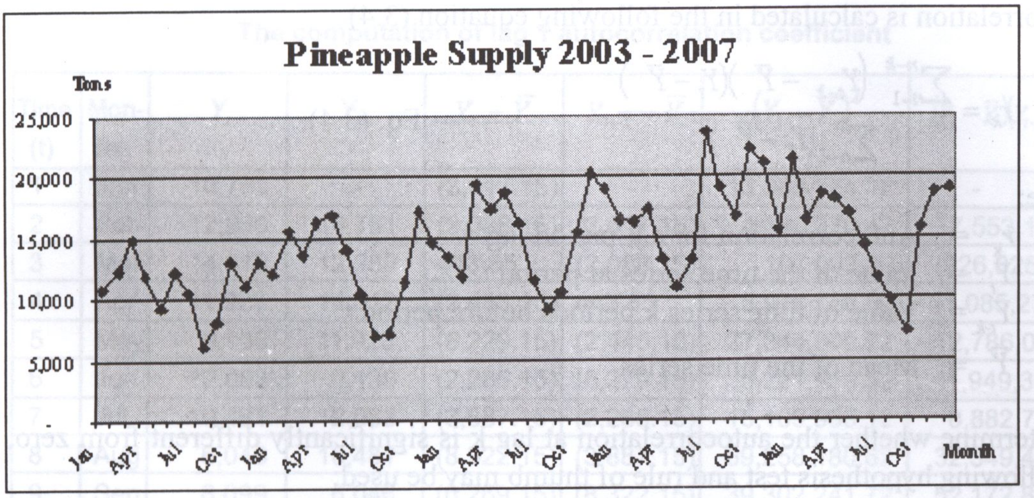
The primary objective of this case is to study supply forecasting as a function of time. The Time Series model is intensely studied to find the appropriate forecasting technique for pineapple supply prediction. The pattern of data is needed to observe the sequences of a particular time series record. Principally, there are four components of time series: trend, cycle, seasonal and irregular fluctuation (Bowerman et al., 2005). There is no pattern for irregular fluctuation. This pattern is caused by unusual events that are not forecastable, such as earthquakes, accidents, hurricanes, and war.

METHODOLOGY



In this forecasting model, the time series forecasting approach has been designed to increase the forecasting efficiency instead of judgmental assessment of surveys and historical data.

The historical supply data of pineapples from 2003 to 2007 was collected, and the movements in supply. These data were used to compute the Mean, Standard Deviation (SD) and the Coefficient of Variance (CV) to pre-determine the pattern.



Pre-analysis of data series by coefficient of variance

From the data of pineapple supply, the value of Mean, SD and CV were calculated, and the result depicted in the Table below.

Mean, SD and CV value of pineapple supply in years 2003 - 2007

Year	Period	Time series (months)	Pineapple supply (tons)	Mean	SD	CV
2003	Jan-Dec	12	132,515	11,042.92	2,386.38	0.216
2004	Jan-Dec	12	155,251	12,937.58	3,502.66	0.270
2005	Jan-Dec	12	181,889	15,157.42	3,865.53	0.255
2006	Jan-Dec	12	204,975	17,081.25	3,811.52	0.223
2007	Jan-Dec	12	187,459	15,621.58	4,181.13	0.267

Data pattern examination by Autocorrelation function

The data were assembled to find the patterns associated with a function of time. Autocorrelation function (ACF) is used to analyze this step. This is another measurement to evaluate the correlation between a variable, lagged one or more period, and itself (Hanke et al., 2001; Wilson & Keating, 1994). There are 3 scenarios:

1. Stationary data: the value of r_k should diminish rapidly toward zero as k increases.
2. Trend pattern: the value of r_k will decline toward zero slowly as k increases.
3. Seasonal pattern: the value of r_k will be significantly different from zero at k = 4 for quarterly data, or k = 12 for monthly data and may also be large.

The correlation is calculated in the following equation (3.4).

$$r_k = \frac{\sum_{t=1}^{n-k}\left(Y_{t-k} - \bar{Y}\right)\left(Y_t - \bar{Y}\right)}{\sum_{t=1}^{n}\left(Y_t - \bar{Y}\right)^2} \quad \text{---------- Eq. (3.4)}$$

Where:

r_k = Autocorrelation for a k-period lag
Y_t = Value of the time series at period t
Y_{t-k} = Value of time series k periods before period t
$\bar{Y}$ = Mean of the time series

To determine whether the autocorrelation at lag k is significantly different from zero, the following hypothesis test and rule of thumb may be used:

$H_0: \rho k = 0$
$H_1: \rho k \neq 0$

Where:

H_0 = Null Hypothesis
(Autocorrelation coefficients are not significantly different from zero)
H_1 = Alternative Hypothesis
(Autocorrelation coefficients are significantly different from zero)

For any k, reject H0 if $|r_k| > 2/\sqrt{n}$, where n is the number of observations. This rule of thumb is for a 95 percent confidence level which is shown by the two horizontal lines labeled "Upper limit"and "Lower limit".

The data series of pineapple supply from 2003 to 2007 (60 periods) was used to compute the autocorrelation coefficient in equation (3.4). The example of lag 1 autocorrelation coefficient (r_1) calculation is shown in the Table below:

The computation of lag 1 autocorrelation coefficient

Time (t)	Month	Y_t	Y_{t-1}	$Y_t - \overline{Y}$	$Y_{t-1} - \overline{Y}$	$(Y_t - \overline{Y})^2$	$(Y_t - \overline{Y})(Y_{t-1} - \overline{Y})$
1	Jan	10,751	-	(3,617.15)	-	13,083,774.12	-
2	Feb	12,280	10,751	(2,088.15)	(3,617.15)	4,360,370.42	7,553,151.77
3	Mar	14,812	12,280	443.85	(2,088.15)	197,002.82	(926,825.38)
4	Apr	11,923	14,812	(2,445.15)	443.85	5,978,758.52	(1,085,279.83)
5	May	9,139	11,923	(5,229.15)	(2,445.15)	27,344,009.72	12,786,056.12
6	Jun	12,083	9,139	(2,285.15)	(5,229.15)	5,221,910.52	11,949,392.12
7	Jul	10,481	12,083	(3,887.15)	(2,285.15)	15,109,935.12	8,882,720.82
8	Aug	6,046	10,481	(8,322.15)	(3,887.15)	69,258,180.62	32,349,445.37
9	Sep	8,099	6,046	(6,269.15)	(8,322.15)	39,302,241.72	52,172,806.67
10	Oct	12,930	8,099	(1,438.15)	(6,269.15)	2,068,275.42	9,015,978.07
11	Nov	10,973	12,930	(3,395.15)	(1,438.15)	11,527,043.52	4,882,734.97
12	Dec	12,998	10,973	(1,370.15)	(3,395.15)	1,877,311.02	4,651,864.77
t=60	....	....	....	....	....	....	
Total		**862,089**				**985,971,390**	**589,748,586**

Where; the mean was calculated, thus $\overline{Y} = \dfrac{862{,}089}{60} = 14{,}368.15$

The variable of Y_{t-1} is actually the Y_t values that have been lagged by one period. The value of pineapple supply in January, Y_t = 10,751 tons was the value of February, Y_{t-1} = 10,751 tons that was lagged by one period. To compute the autocorrelation coefficient, the sum values of $(Y_t - \overline{Y})^2$ and $(Y_t - \overline{Y})(Y_{t-1} - \overline{Y})$ were further used in an autocorrelation coefficient equation (3.4), thus

$$r_1 = \frac{589{,}748{,}586}{985{,}971{,}390} = 0.5981$$

The second, third, fourth till sixtieth lag were also computed in the same formula to find the autocorrelation coefficient, and compared to each other.

The hypothesis test and decision rule were developed to determine whether a particular autocorrelation coefficient was significantly different from zero.

Hypothesis Test:

$H_0 : \rho k = 0$

$H_1 : \rho k \neq 0$

Decision Rule:

For any k, reject H0 if $|r_k| > 2/\sqrt{n}$, where n is the number of observations. This rule of thumb is for a 95 percent confidence level. In this case 60 observations were used: the pineapple supply from year 2003 to 2007. Thus, $2/\sqrt{n} = 2/\sqrt{60} = 0.2581$. From this rule, the upper and lower limits of pineapple supply data were determined.

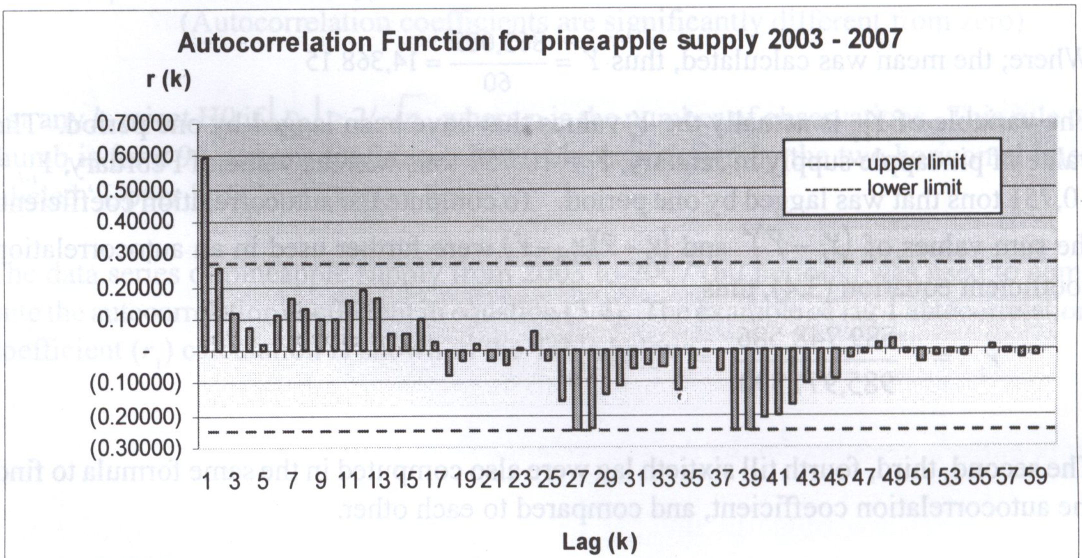
Confidence limit:

$2/\sqrt{60}$ = 0.2581

The upper limit = 0.2581

The lower limit = -0.2581

H_0 was rejected at the first period (0.5981 > 0.2578). After the first period lag, r_k has dropped below the confidence limits that is 0.2581 (0.2578 < 0.2581), and almost all the autocorrelation are within 95% confidence bounds. The upper and lower limit of confidence bounds and autocorrelation coefficient plot by Microsoft Excel is depicted in the Figure below:



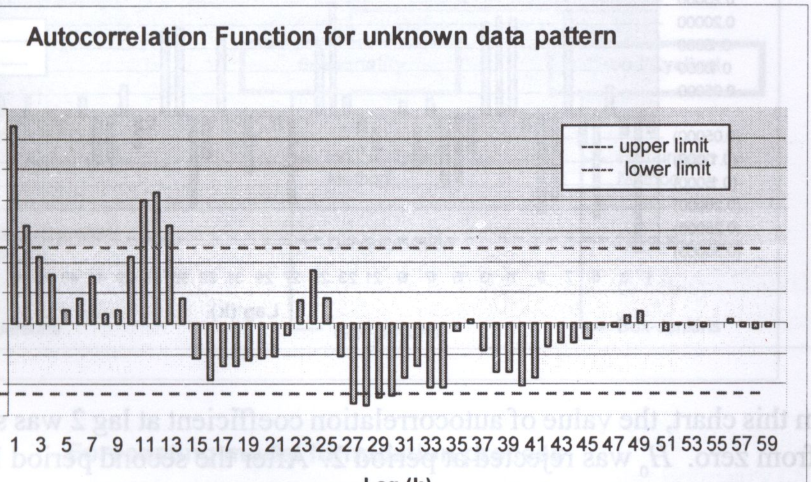
The autocorrelation coefficients of pineapple supply in years 2003 to 2007 dropped quickly toward zero since the first lag, thus the data series appeared to conclude that the pineapple supply data was stationary series.

Unknown Pattern

Alternatively, if the autocorrelation coefficient did not show a specific pattern, the series may be transformed into a stable one by using a differences transformation method. The difference is calculated as:

$$\textbf{Difference of data} = \textbf{data}_t - \textbf{data}_{t-1} \qquad \text{---------- Eq. (3.5)}$$

The example of unknown pattern was taken to show the computation in this part. The unknown data pattern is depicted as in the Figure below.

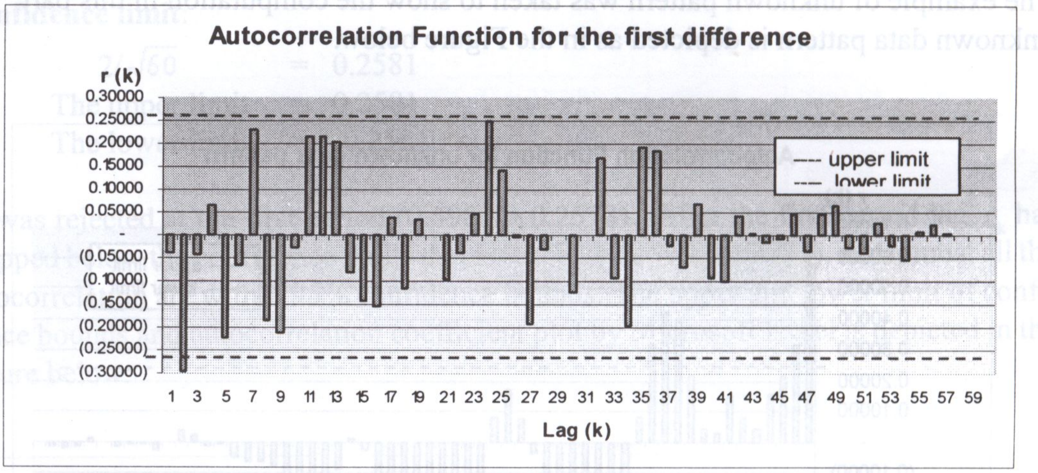


The autocorrelation coefficients (r_k) were significantly different from zero at periods 1, 2, 11, 12, 13, 27 and 28. At the initial notice, the autocorrelation coefficients were not repeated at the same time interval. The pattern was not able to be determined precisely. Hence, the first transformation, by taking the difference of autocorrelation, was determined in equation (3.5).

The first difference started in February at 1,529 (DY_1) which was calculated from the difference of the January and February values (12,280 - 10,751). The variable of DY_{t-1} is DY_1 that has been lagged by one period. And then the computation of the autocorrelation coefficient for first transformation was the same as in the autocorrelation coefficient equation (3.4), thus

$$r_1 = \frac{-30{,}152{,}047}{774{,}579{,}362} = -0.0389$$

The second, third, fourth till fifty-ninth lag were also computed in the same formula to find the autocorrelation coefficient and compare to each other. There were only 59 periods lagged because one was lost in calculating the first difference. To examine the hypothesis with 95% confidence level, the upper and lower limits were determined $2/\sqrt{59} = 0.26037$. The autocorrelation coefficient for the first difference is shown in the graph below:



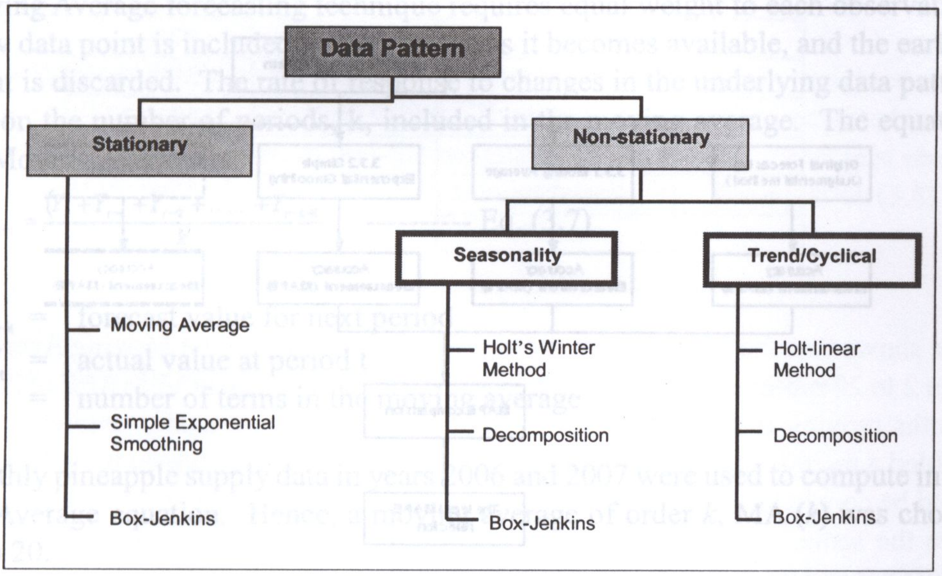
From this chart, the value of autocorrelation coefficient at lag 2 was significantly different from zero. H_0 was rejected at period 2. After the second period lag, r_k had dropped quickly toward zero, and almost all autocorrelation coefficients were within the 95% confidence bounds. At this stage, the autocorrelation structure for first difference of data had become stationary. In addition, if the first transformation has still not specified the pattern, the further transformation to the second difference, that is the difference in the first difference, is proposed for a case like this.

Seasonal and Trend/Cyclical Pattern

The transformation method by taking difference, is used in seasonal and trend pattern data series. The calculation processes are developed step by step until the data is transformed to the stationary pattern and has implemented the stationary forecasting approaches for the transformation data. By this technique, the noise created by seasonality, trend or cycle is removed. Once the transformation data is forecasted, the transformation can be reversed to forecast the original pattern as the last step.

Formulation forecast model and Measurement accuracy

Based on an analysis of the data pattern, the forecasting model was formulated as in the next chart.

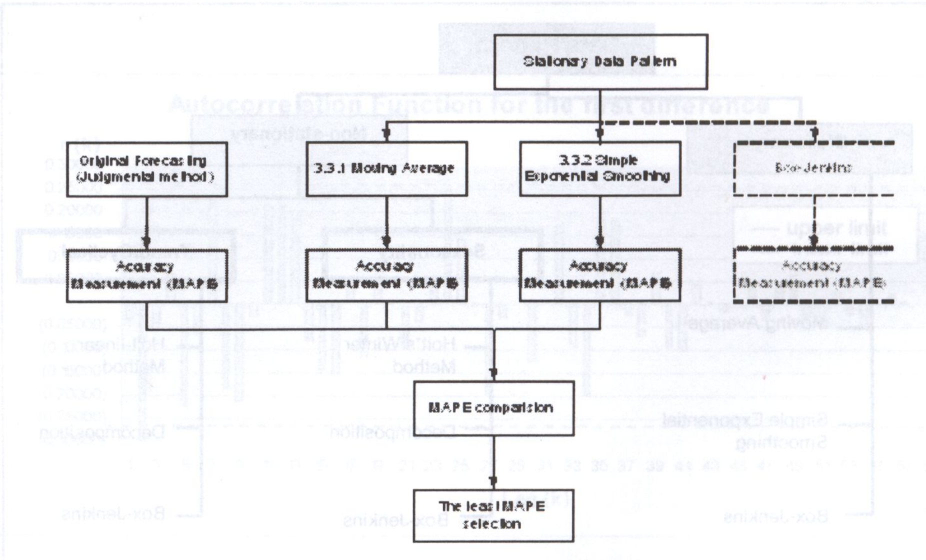


Forecasting model formulation process

From the data pattern examination, there are two types of data patterns, stationary and non-stationary data. The data are considered stationary when there is neither a positive nor a negative trend (Wilson and Keating, 1994). The forecasting models for stationary data are Moving Average, Simple Exponential Smoothing and Box-Jenkins. If the data is non-stationary, the seasonality and trend/cyclical pattern have to be examined in the next step. The Holt's Winter method, Decomposition and Box-Jenkins are proposed for Seasonal patterns. On the other hand, the Holt's Linear method, Decomposition and Box-Jenkins are suitable for trend/cyclical patterns. Also, the appropriate method depends on the applications and limitations of each technique.

Examination and data analysis of pineapple supply for the past five years by comparing the coefficient of variance (CV) and determining the correlation between a variable by Autocorrelation Function, were able to analyze that the historical supply of pineapple had a stationary pattern. From the limitation, the method of Box-Jenkins requires 40 observations or more to develop the model. In this case, pineapple supply is an agricultural product supplied directly from farms. The uncontrollable factors such as climate, temperature or the natural disaster are the factors that cause the fluctuation of supply.

There is also no supportive evidence and analysis of these factors in the case. Therefore, all past five years data is not suitable to formulate a Box-Jenkins model, otherwise the forecast value will lead to misinterpretation. The forecast value will not correspond accurately enough to develop further analysis. Thus, in the samples of two recent years, 24 observations were selected instead, to formulate and test the forecasting models.



Forecasting Model Formulation and Accuracy Measurement

As in the model above, the Moving Average and Simple Exponential Smoothing techniques were investigated, and predicted the new forecasting series. The forecast accuracy before and after the implementation of new approaches was measured to evaluate the impact of the new approach. The forecasting accuracy method selected for the case is Mean Absolute Percentage Error (MAPE), because more than one forecasting technique is formulated in this case. MAPE is suitable to compare the accuracy of different forecasting technique which used the same data series. The Mean Absolute Percentage Error formula is shown in equation (3.6).

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|Y_t - \hat{Y}_t|}{Y_t}}{n} \quad \text{---------- Eq. (3.6)}$$

Where

MAPE = Mean Absolute Percentage Error (%)

Y_t = Value of a time series at period t

$\hat{Y}_t$ = Forecast value of

n = Number of observations

The MAPE value from each forecasting method and the original forecasting were compared. The least error of any technique was selected for the case.

Moving Average

The Moving Average forecasting technique requires equal weight to each observation. Each new data point is included in the average as it becomes available, and the earliest data point is discarded. The rate of response to changes in the underlying data pattern depends on the number of periods, k, included in the moving average. The equation (3.7) of Moving Average is:

$$\hat{Y}_{t+1} = \frac{(Y_t + Y_{t-1} + Y_{t-2} + \ldots\ldots + Y_{t-k+1}}{k} \quad \text{---------- Eq. (3.7)}$$

Where

$\hat{Y}_{t+1}$ = forecast value for next period

Y_t = actual value at period t

k = number of terms in the moving average

The monthly pineapple supply data in years 2006 and 2007 were used to compute in the Moving Average equation. Hence, a moving average of order *k*, MA (*k*) was chosen from 2 to 20.

The first forecasting and accuracy measurements were done in a Moving Average of order 2. MA (2) would take the last two observations in January (Y_{t-1}) and February (Y_t), and then divided by 2 periods to find the forecasting value $\hat{Y}_{t+1}$.

The 24 observations of pineapple supply in years 2006 to 2007 were selected to evaluate the efficiency of the Moving Average approach. After implementing the Moving Average of order 2, the new forecasting series were reduced to 22 observations and used to measure the error by equation (3.8); thus the sum value of $\frac{|Y_t - \hat{Y}_{t+1}|}{Y_t}$ in table 3.8 was computed as follow:

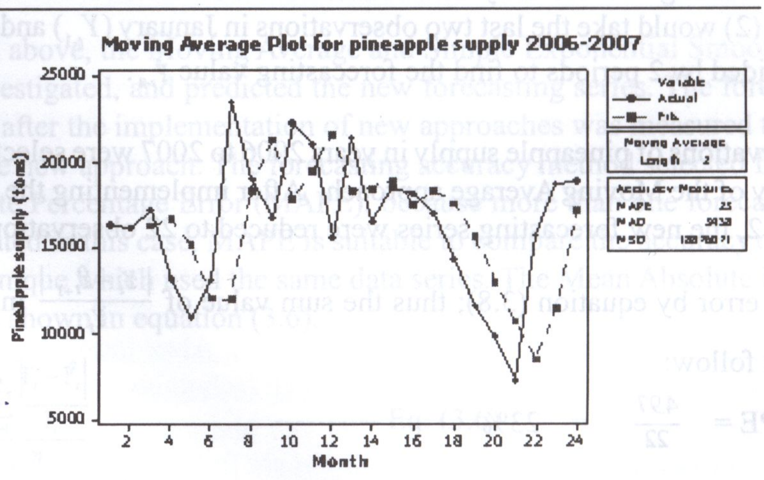
$$\text{MAPE} = \frac{4.97}{22} = 23\%$$

The moving average order (*k*) from 3 to 20 periods was forecasted and compared to the MAPE, as summarized in the following Table.

Mean Absolute Percentage Error of Moving Average of k from 2 to 20

MA (k)	MAPE %	MA (k)	MAPE %
2	23%	12	32%
3	25%	13	32%
4	26%	14	35%
5	27%	15	37%
6	28%	16	39%
7	26%	17	43%
8	28%	18	47%
9	29%	19	47%
10	30%	20	40%
11	30%		

This shows that the MAPE were increasing substantially in the Moving Average order from 2 to 20 months moving period. As a result, the least error of MAPE at 23% was 2 months moving order. This illustrated figure that was manually predicted by Excel enabled a reconfirmation of the result by MINITAB. After implementing MINITAB, it could be concluded that the result from the manual calculation and software generation were the same. Therefore, the Moving Average Plot for 2 months moving order by MINITAB is depicted in the next graph.



From this graph, the actual variable from pineapple supply from 2006 to 2007 was plotted along with the predicted value (fits value) that was computed from moving average length 2 months. The Moving Average forecast from MINITAB generated three accuracy measurement, MAPE, MAD and MSD or MSE at 23%, 3458 and 1,887,671 respectively. However, MAPE was selected in the case only because MAPE allows the comparison of different techniques on the same data series. The error from the Moving Average approach would be further used to compare with the Simple Exponential Smoothing approach and original forecast, and therefore the MAPE technique is more appropriate for this case than MAD and MSD.

Simple Exponential Smoothing

The Simple Exponential Smoothing technique provides an exponentially weighted moving average of all previously observed values. The observed values are weighted by the smoothing constant (α) that determines the weight given to the most recent past observation and therefore controls the rate of smoothing or averaging. The equation (3.8) for Simple Exponential Smoothing is:

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \qquad \text{----------- Eq. (3.8)}$$

Where

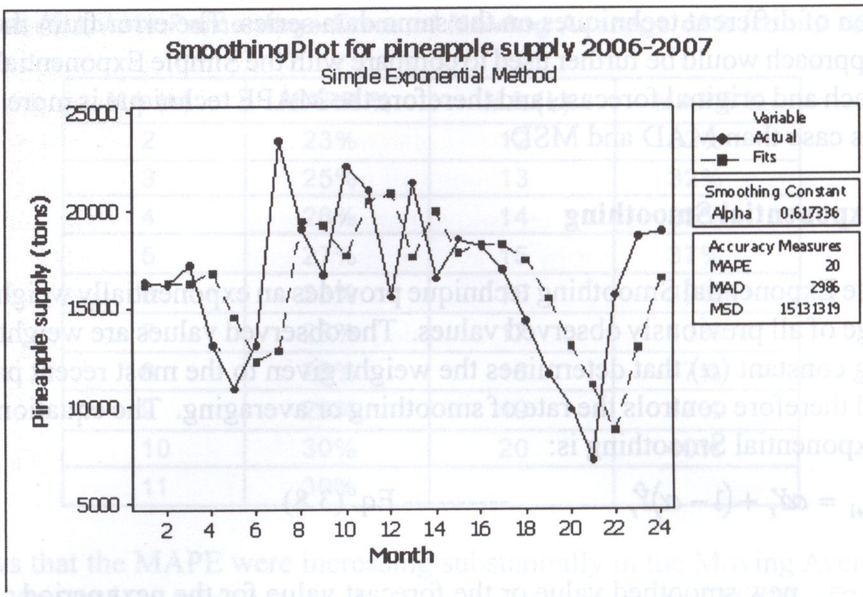
$\hat{Y}_{t+1}$ = new smoothed value or the forecast value for the next period

α = smoothing constant ($0<\alpha<1$)

Y_t = new observation or actual value of series in period t

$\hat{Y}_t$ = old smoothed value or forecast for period t

To simplify the forecasting and obtain the optimal smoothing constant, monthly pineapple supply data in years 2006 and 2007 were used to be analyzed in the MINITAB program by selecting the Simple Exponential Smoothing technique. The most favorable value of smoothing constant (α) that produced the least error was 0.617336, and generated the MAPE at 20%. The Simple Exponential Smoothing is plotted by MNITAB in the next graph.



Smoothing Plot for Pineapple supply forecast in years 2006-2007

The fits or predicted value were calculated from the simple exponential smoothing equation (3.8) by trial and error of the application of alpha (α) from 0 to 1. MINITAB could search the optimal alpha for this actual variable at 0.617336. This optimal alpha value generated the least MAPE, MAD and MSE at 20%, 2986 and 1,513,319 respectively. As well as the Moving Average technique, the MAPE of Simple Exponential Smoothing technique was only selected for analyzing further.

The MAPE values between the Moving Average technique and the Simple Exponential Smoothing technique for the pineapple supply forecasting in years 2006 and 2007 were 23% and 20% respectively. Therefore, the least error of MAPE was generated by Simple Exponential Smoothing method at smoothing constant (α) 0.617336. This technique will be used further to predict the future supply for the case.

RESULT AND ANALYSIS

Data pattern analysis

The actual supply plot did not obviously reveal the seasonal period of pineapple crop because in some periods the company also sourced pineapple from other parts of Thailand in addition to the local area. This small supply from distant plantations is not examined in the case. Thus, the raw data of historical supply was used to examine the pattern, by computing the Coefficient of Variance (CV) and Autocorrelation Coefficient. The Coefficient of Variance revealed approximately 0.2 every year. These results could be explained by the dispersion of data series in each year towards the mean looking rather similar from year to year, despite the varying of the mean. There was little variation of the data between years. Such data fluctuation indicated that the series were relatively stable. There is no trend or seasonality effect.

The data series were further supported by qualitative methods by calculating Autocorrelation Functions (ACF), which is the statistical tool for examining time series patterns. As for CV calculation, 60 observations of pineapple supply in years 2003 to 2007 were calculated. If a series is stationary, the autocorrelations between a variable lagged one or more periods and are close to zero. Since the second period lag (0.2578), almost all the autocorrelations coefficients were within the confidence levels (+/-0.2581). Whenever an autocorrelation coefficient is outside the confidence limits, the null hypothesis of zero autocorrelation is rejected. By rule of thumb at 95% confidence interval, the autocorrelation coefficient dropped quickly toward zero after the first period lag (0.59841) and within the confidence interval, and thus the data was defined as the stationary pattern. Minitab program was also used to generate the correlogram or Autocorrelation Function and individual value of autocorrelation coefficient for 60 times lags to reconfirm the result.

Forecasting and Accuracy Measurement Analysis

For the stationary data pattern of the case, the Moving Average and Simple Exponential Smoothing techniques were selected, and evaluated the forecast accuracy before and after the implementation by comparing the Mean Absolute Percentage Error (MAPE). Based on the results, the least MAPE 20% was from Simple Exponential Smoothing at smoothing constant 0.61733. The Forecasting value and MAPE of two techniques compared with the original forecasting that was formerly done by judgmental and assessment of historical data, are shown in the next Table.

Forecasting Value of each forecasting technique

Month 2006-2007	Actual Supply (Tons)	Forecasting Value (tons)		
		Original Method	Moving Average (MA2)	Simple Exponential Smoothing ($\alpha = 0.61733$)
Jan	16,328.00	18,940.00	*	16,195.00
Feb	16,198.00	18,086.00	**	16,277.10
Mar	17,194.00	20,246.00	16,262.50	16,227.70
Apr	13,167.00	18,287.00	16,695.00	16,823.60
May	10,922.00	22,607.00	15,180.00	14,566.20
Jun	13,128.00	22,607.00	12,044.00	12,315.90
Jul	23,528.00	14,368.00	12,024.00	12,816.60
Aug	19,041.00	7,837.00	18,327.50	19,429.10
Sep	16,687.00	10,047.00	21,284.50	19,189.50
Oct	22,217.00	16,980.00	17,864.00	17,644.60
Nov	20,997.00	18,287.00	19,451.50	20,466.70
Dec	15,568.00	21,703.00	21,606.00	20,793.50
Jan	21,373.00	18,850.00	18,282.00	17,567.60
Feb	16,451.00	18,000.00	18,470.50	19,916.80

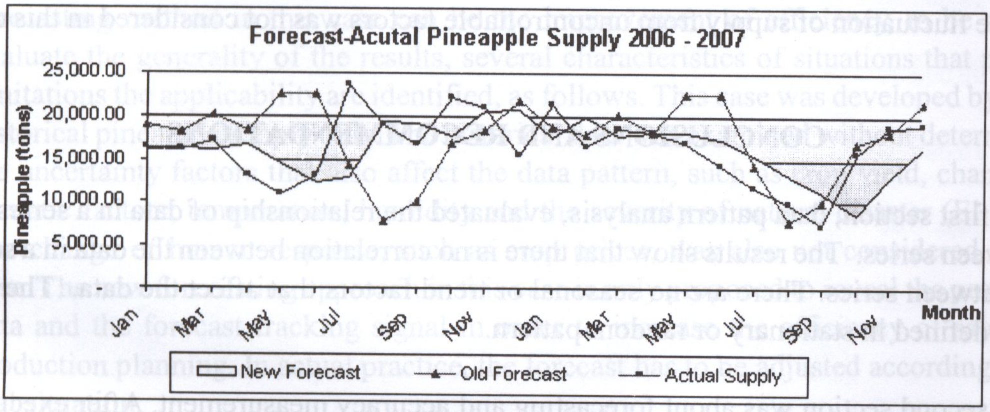
Month 2006-2007	Actual Supply (Tons)	Forecasting Value (tons)		
		Original Method	Moving Average (MA2)	Simple Exponential Smoothing ($\alpha = 0.61733$)
Mar	18,479.00	20,150.00	18,912.00	17,777.20
Apr	18,104.00	18,200.00	17,465.00	18,210.50
May	16,973.00	22,500.00	18,291.50	18,144.70
June	14,279.00	22,500.00	17,538.50	17,421.40
July	11,599.00	14,300.00	15,626.00	15,481.50
August	9,816.00	7,800.00	12,939.00	13,084.70
September	7,207.00	10,000.00	10,707.50	11,066.80
October	15,633.00	16,900.00	8,511.50	8,684.00
November	18,650.00	18,200.00	11,420.00	12,973.90
December	18,895.00	21,600.00	17,141.50	16,477.90
Total	**392,434.00**	**418,995.00**	**356,044.00**	**389,552.50**

From this we see that the sum of new forecasting value, 389,552.50 tons on Simple Exponential Smoothing method, was close to the actual supply of 392,434.00 tons. When compared to the original forecasting, the accuracy was also significantly improved, from 29% to 20%, as depicted in the next Table.

The MAPE of each forecasting technique

Forecasting Error Measurement Method	Forecasting Technique		
	Original	Moving Average (MA2)	Simple Exponential Smoothing (α = 0.61733)
MAPE	29%	23%	20%

Therefore, the Simple Exponential Smoothing was selected as the new forecasting approach to the case. The improvement of this new forecasting approach is the result of error reduction between actual and new forecasting of supply.



New forecasting plot with old forecasting and actual supply for 2006-2007

The graph above reveals the plot of new forecasting that results from Simple Exponential Smoothing at smoothing constant (α) 0.61733, compared with old forecasting and actual supply.

After implementation of the Simple Exponential Smoothing approach, the forecast accuracy was improved. New forecasts are close to the actual supply. This satisfied the main objective of the case. The evidence of better forecast accuracy proved that the quantitative forecasting technique is favorably considered as a part of the improvement in pineapple supply forecasting. The new forecasting is enabled for use as the guideline for strategic planning. Thus, sales and production plans are conducted more efficiently.

The sales department could implement the sales plan from this new forecasting. Therefore, to simply show the improvement of the new forecast, the Simple Exponential Smoothing forecast value above was used to be the new sales level to compare with the original performance.

The inventory cost from the Simple Exponential Smoothing forecast decreased by 2.1 million baht, or approximately 2%, from the original value. In addition, more accurate forecasts would help the company to sell more. Therefore, the opportunity loss of sales was reduced by 8.4 million baht, or approximately 2% from the original value. The company could generate additional revenue and save costs of around 10.5 million baht by this new forecasting approach. This result illustrates the improvement of statistical forecasting application to pineapple supply in this case study.

However, the implementation of a quantitative approach to predict pineapple supply was based on the historical data in years 2006 and 2007 only. The uncertainty of demand or the fluctuation of supply from uncontrollable factors was not considered in this case.

CONCLUSIONS AND RECOMMENDATIONS

The first section, data pattern analysis, evaluated the relationship of data in a series and between series. The results show that there is no correlation between the data in a series or between series. There are no seasonal or trend factors that affect the data. The data was defined in stationary or random pattern.

The second section was about forecasting and accuracy measurement. After execution of the new approach, the forecasting efficiency was significantly increased, resulting from the improvement of MAPE from 29% to 20% by the Simple Exponential Smoothing method. This error reduction generated a cost saving to the company of around 10.5 million baht.

Based on the improvement of forecast accuracy in this case study, the new forecast from a quantitative approach could enable the facilitation of successful sales and production planning for the company.

The sales plan was produced by analyzing the pattern of the new supply forecast. The new forecast is like a quantitative guideline that sales people could evaluate along with the demand forecast from the customer side. Therefore, the sales plan will be quicker to reflect the real fluctuations of both demand and supply movement. To investigate the supply pattern and forecast by using Simple exponential smoothing that is continually revising a forecast in the light of more recent data, would help to keep the supply situation on the right track. If there is any change in the supply, the sales plan could be adjusted quicker. The plan is made much simpler and can adjust more rapidly than had previously been possible.

For production planning, the production capacity of the company is normally higher than demand and supply, and the evaluation of machine capacity and required labor are limited to the supply forecast and sales plan. When the supply forecast and sales plan are more accurate and close to each other, the production capacity can be planned efficiently. The factory can estimate how many tons per day for the production, and assign the optimal processing procedure and required labor for such a supply volume. The problems from traffic processing in some production lines, as well as the vacuum time of no production in any machines, are reduced when the production plan is developed on a more accurate supply and sales forecast. Resource utilization is efficiently planned.

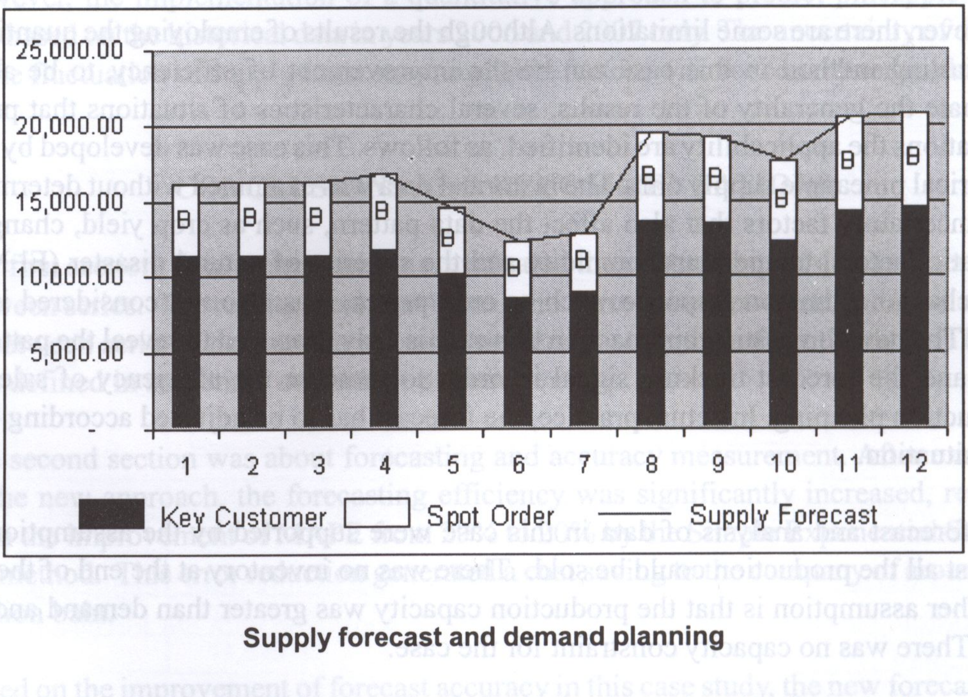
However, there are some limitations. Although the results of employing the quantitative forecasting method in this case can be the improvement of efficiency, to be able to evaluate the generality of the results, several characteristics of situations that present limitations the applicability are identified, as follows. This case was developed by using historical pineapple supply only. The historical data was examined without determining the uncertainty factors that also affect the data pattern, such as crop yield, changes in climatic factors, temperature, humidity and the severity of natural disaster (El Nino). The change of human response, such as crop prices, was also not considered in this case. The new forecasting approach in this case is only proposed to reveal the pattern of data and the forecast tracking signal in order to increase the efficiency of sales and production planning. In actual practice, the forecast has to be adjusted according to the real situation.

The forecast and analysis of data in this case were supported by the assumption that almost all the production could be sold. There was no inventory at the end of the year. Another assumption is that the production capacity was greater than demand and supply. There was no capacity constraint for the case.

Arising from this project are some recommendations. Obviously, the value of this new forecasting approach cannot be conclusively established based on a quantitative method only, because the case is about agricultural produce. The qualitative adjustment could potentially improve the forecasting and reflect the real life situation. Judgmental methods could be better supported and made more efficient. Thus, the useful combination of judgmental and statistical forecasting could be developed and studied further. The sample of methodologies for integrating forecasts are judgmental adjustments of quantitative forecasting. The judgmental method is adjusted to the prior quantitative forecasting and the quantitative forecast is adjusted to the preliminary judgmental forecast. Both methodologies should be studied to define the most appropriate technique for the pineapple supply.

One of the constraints in this case is that of no inventory. Because the supply is not sufficient to meet the demand, the production proceeds based on available supply. Therefore, to find the inventory level of safety stock would reduce the impact of a pineapple shortage. However, the inventory level should be carefully determined because pineapple is a food product. The remaining shelf life of products in the inventory is a critical issue needing cautious control.

The result of quantitative forecasting is a prerequisite useful resource to develop the sales or demand planning. The idea is simply shown by the Figure below.



Supply forecast and demand planning

From this Figure, the supply forecast is set as the tracking signals of supply that will be determined, like the ceiling level, to control the advance selling operation. The demand could be segmented based on the volume of key customer (A) and spot orders (B). The proportion for key customer should be properly determined and the remaining proportion is for serving spot orders. This would help the company to manage the demand and quickly adjust if the supply is changed.

BIBLIOGRAPHY

Adams, R. M., Hurd, B. H., Lenhart, S., & Leary, N. (1998). Effects of global climate change on agriculture: an interpretative review. ***Climate Research***, 11: 19-30.

Bowerman, B. L., O'Connell, R. T., & Koehler, A. B. (2005). ***Forecasting, Time Series, and Regression An Applied Approach*** (Fourth ed.): Curt Hinrichs.

Hanke, J. E., Wichern, D. W., & Reitsch, A. G. (2001). ***Business Forecasting*** (Seventh ed.): Prentice Hall.

Kelly, M., Granich, S., & Ninh, N. H. (2000). The Impact of El Nino And La Nina On Southeast Asia. Hanoi, Vietnam: The Center for Environment Research Education and Development.

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). ***Forecasting Methods and Applications*** (Third ed.): John Wiley & Sons, Inc.

Montgomery, D. C., & Johnson, L. A. (1976). ***Forecasting And Time Series Analysis*** (First ed.): McGraw-Hill.

Phatcharee, S. (2005). ***Comparison of Forecasting Techniques for Export Quantity and Production Quantity of Canned Pineapple***. Bangkok, Kasetsart University.

Render, B., Stair, R. M., & Hanna, M. E. (2006). ***Quantitative Analysis for Management*** (Ninth ed.): Prentice Hall.

Sanders, N. R., & Ritzman, L. P. (2004). Integrating Judgmental and quantitative forecasts methodologies for pooling marketing and operations informaton. ***International Journal of Operation and Production Management***, 24(5): 514-529.

Wacker, J. G., & Lummus, R. R. (2002). Sales Forecasting for strategic resource planning. ***International Journal of Operation and Production Management***, 22(9): 1014-1031.

Wasusri, T. (2007), ***Prachachart Thurakij***, Vol. 3922 (3122).

Watcharin, P., & Thanaya, W. (2007). ***Forecasting and Production Planning: Case study of Coconut Milk Company***. Paper presented at the Proceedings of the 7th Industrial Academic Annual Conference on Supply Chain and Logistics Management.

Wilson, J. H., & Keating, B. (1994). ***Business Forecasting*** (Second ed.): Richard D. Irwin, Inc.