Aggregate Planning for Production Cost Efficiency in Agribusiness and Technology Park of Bogor District

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Abstract**—***The agricultural sector is growing rapidly, with the crystal guava variety emerging as one of the most popular commodities. Known for its unique crunchy texture, near seedlessness, and high vitamin C content, crystal guava is highly valued. Its cultivation is relatively simple but requires significant human labor, especially during the harvesting period. Labor costs represent the largest operational expense for crystal guava plantations, making effective labor planning critical. Inadequate planning can lead to inefficiencies and increased production costs. Additionally, crystal guava is a high-risk product, as its quality can deteriorate if harvesting is delayed. This is particularly important for plantations that supply supermarkets, where product quality is a top priority. The focus of this study is the Agribusiness and Technology Park (ATP) in Bogor Regency, which frequently faces labor shortages during the harvest season, resulting in fruit that is not properly sorted. This study applies an aggregate planning strategy using the linear programming transportation method, alongside forecasting through time series decomposition. The time series decomposition method was chosen due to its superior accuracy, achieving the smallest MAPE value of 2.365%. The results of the aggregate planning process showed that it successfully reduced ATP's total production costs by IDR 10,667,600, or 13.059%.*

Index Terms**—** *Seasonal data forecasting, aggregate planning, cost efficiency*

I. INTRODUCTION

The agricultural business in Indonesia is growing, marked by an increase in GDP value which has contributed to the increase in Indonesia's national economy by 12.40% (Kementerian Pertanian 2023). One of the popular agricultural businesses is crystal guava plantations with production centers in Bogor Regency (Badan Pusat Statistik 2024). This is because crystal guava is a unique fruit. It has a crunchy texture and sweet taste and has few seeds that's only 3% of the fruit. In addition, crystal guava is high in vitamin C and can cure various diseases (Suhendar 2021).

Crystal guava cultivation in Indonesia is still simple and uses human labor, especially in harvesting. However, it is now increasingly difficult to find human labor in the agricultural sector, especially in the land labor. This is due to the lack of interest of young people in Indonesia to work in agriculture. It is recorded that in Indonesia there has been a decline in the number of farmers by 7.45% and the majority of farmers are Generation X aged 44 to 59 years (Badan Pusat Statistik 2024). This makes it increasingly difficult to find agricultural workers for land labors. In addition, the need for agricultural labor often fluctuates according to harvest productivity in each period and increases during the peak harvest period. Human labor costs are also the highest operational costs in the crystal guava business, so poor labor planning will cause waste and inefficiency.

Crystal guava fruit is usually harvested before the peak of maturity to get a crunchy flesh texture, because if the crystal guava has reached the peak of maturity, it will have a soft texture, tend to be unpopular with consumers, and be prone to rot. This can reduce the quality of crystal guava and will be a problem for companies that supply their products to supermarkets. One of the crystal guava plantation business units in Bogor Regency that supplies its products to supermarkets is the Agribusiness and Technology Park (ATP). ATP experienced a shortage of labor during the main harvest, so around 21% of the crystal guava harvest did not pass sorting because it was too ripe. This can be overcome by implementing an aggregate planning strategy to organize regular labor, overtime, and subcontracts and streamline production costs.

Referring to the problem, there are several research objectives to be achieved including: (1) formulating an aggregate planning strategy to overcome the labor shortage during the harvest period at the Agribusiness and Technology Park, Bogor Regency; (2) analyzing efficiency cost production when aggregate planning strategy applied to the Agribusiness and Technology Park, Bogor Regency. Similar research that is used as a reference in this study is research by Uche (2024) who uses aggregate planning of transportation methods and decomposition forecasting in Nigerian rubber plantations, the results of the study obtained more efficient production costs and total regular, overtime and outsourcing working hours. Additionally, Escallón-Barrios et al. (2022) also applied aggregate planning with the same method but with Holt-Winters exponential smoothing forecasting in Columbia oil palm plantations, and the results of the study also obtained production cost efficiency and an increase in harvest yields.

Another study by Matuges & Wijaya (2023) applied an aggregate planning strategy using the overtime control method with moving average forecasting at CV Ikhwa, the results of the study obtained more efficient labor costs and working hours. Then Darmawan (2019) also applied the same strategy but with a different forecast, namely regression in the Madiun Home Industry, the results of the study also obtained production cost efficiency and were able to meet product demand. In addition, there are other studies by Pramodya Utami & Mandala (2024), Effendi et al. (2023), Julieta & Indrajaya (2023), Oey et al. (2020) and Hanum & Nahartyo (2020) with aggregate planning using the chase strategy method and Simanjuntak et al. (2022) with the mix strategy method.

II. METHOD

This research uses a descriptive quantitative approach, which refers to research that is based on data systematically collected from facts. According to Thomas (2021), in quantitative research, the data is generated through data collection and numerical analysis. This approach was chosen based on the research objectives and the type of data to be used. The type of data to be used is secondary data, which refers to data that has already been collected previously and obtained from parties not directly involved in the research. This data is sourced from the company's harvest report. However, the data used in this study comes from the company's internal records and includes information on harvest results from previous periods, as well as the number and capacity of permanent (regular) labor and labor costs. The data collected then will be analyzed using forecasting methods and aggregate planning strategies.

a. Selection of forecasting models
   The forecasting model will be selected based on the forecasting model selection criteria according to Wilson & Keating (2009:58), namely:
   1. The pattern shown by the data
      To detect data patterns, can using the autocorrelation coefficient (Paramu 2018:28-29) with formula:

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \overline{Y})(Y_{t-k} - \overline{Y})}{\sum_{t=1}^{n}(Y_t - \overline{Y})^2}$$

      Where r_k = autocorrelation coefficient for lags of k periods; Y_t = actual data in t period; $\overline{Y}$ = average value of actual data; Y_{t-k} = data in $(t-k)$period; t = data period and k = number period before t. Based on the autocorrelation coefficient value, it can be concluded that the harvest data is categorized as seasonal data because repeating data patterns are found every monthly time interval.
   2. Quantity of historical data available
      The available harvest data is for six years or from January 2018 to December 2023, totaling 72 data.
   3. Estimated horizon length
      The forecasting horizon length to be carried out is for one year or 12 months ahead.

b. Forecasting
   Forecasting will calculate by winter's exponential smoothing and time-series decomposition methods. The forecasting method is chosen based on the type of data which is seasonal data, according to Wilson & Keating (2009:58) the selection model criteria.
   1. Winter's exponential smoothing
      To calculate the winter's exponential smoothing method can use formula on Paramu (2018:87) as:

$$\widehat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p}$$

      The formula was developed based on the following formula.

$$L_t = \alpha\frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$
$$S_t = \gamma\frac{Y_t}{L_t} + (1-\gamma)S_{t-s}$$

      Where $\widehat{Y}_{t+p}$ = forecast at period p of t; L_t = smoothed at t period with α weight; T_t = trend estimate at t period with β weight; S_t = seasonal estimate at t period with γ weight; and s = length of season.
   2. Time series decomposition
      There are two models in time series decomposition, namely the additive and the multiplicative component model. The additive component model is suitable for predicting data which has same variability, while the multiplicative component model is suitable for increases or decreases data variability. Harvest data has increase or decrease variability that suitable to use the multiplicative component model. The formula of multiplicative component model formula as (Paramu, 2018:130).

$$Y_t = T_t \times S_t \times C_t \times I_t$$

      Where Y = variable to be predicted; T = trend component, S = seasonal component; C = cyclical component; and I = Irregularity component.

c. Forecast accuracy measure
   According to Paramu (2018:141), of the seven forecasting accuracies, ME and MPE are rarely used because they are based on residual error so that positive errors can be covered by negative errors. More accurate forecasting errors are MAE and MAPE because they are based on the absolute value of the error, and MSE, RMSE and Theil's U because they are based on squared residuals so that negative errors will become positive. And according to Heizer et al. (2020:152), MAPE is better used for data that has thousands of items, because the evaluation of the value is expressed in percentage. Harvest data has thousands of items so its suitable using MAPE with formula as (Paramu, 2018:65):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \widehat{Y}_t|}{Y_t}$$

   Where Y_t = actual value at t; $\widehat{Y}_t$ = estimated value at t; and n = number of periods.

d. Aggregate planning strategy
   The aggregate planning technique that will be used is a mathematical approach with the linear programming transportation method according to Stevenson (2021:481) as in Table 1.

Table 1. Planning aggregate method transportation linear programming

Period		Period 1	Period 2	Period 3	…	Period n	Unused capacity	Capacity	
Beginning inventory		0	h	2h	…	(n − 1)/h	0		r = Routine production costs per unit f = Overtime costs per unit s = Subcontract cost per unit h = Storage cost per unit period b = Advance order cost per unit per period n = Number of periods in the planning horizon
1	Regular	r	r + h	r + 2h	…	r + (n − 1)/h	0		
	Overtime	t	t + h	t + 2h	…	t + (n − 1)/h	0		
	Subcontract	s	s + h	s + 2h	…	s + (n − 1)/h	0		
2	Regular	r + b	r	r + h	…	r + (n − 2)/h	0		
	Overtime	t + b	t	t + h	…	t + (n − 2)/h	0		
	Subcontract	s + b	s	s + h	…	s + (n − 2)/h	0		
3	Regular	r + 2b	r + b	r	…	r + (n − 3)/h	0		
	Overtime	t + 2b	t + b	t	…	t + (n − 3)/h	0		
	Subcontract	s + 2b	s + b	s	…	s + (n − 3)/h	0		
Demand					…				

Source: Stevenson (2021:481)

Aggregate planning can also be performed by POM-QM for Windows 5.4 by using the aggregate planning transportation method module.

III. Results and Discussion

Data used in this research are collected from the company's internal resource. Table 2, 3 and 4 below show the harvest, harvest capacity and cost data of Agribusiness and Techlogy Park Bogor from January 2018 to December 2023.

a. Harvest data

Table 2 presents 72 harvest yields data from January 2018 until December 2023.

Table 2. Harvest yields data from January 2018 until December 2023

Year	Month	Yields	Year	Month	Yields	Year	Month	Yields
2018	January	2793	2020	January	2461	2022	January	2177
	February	4242		February	3951		February	3685
	March	3035		March	2542		March	2116
	April	3453		April	3074		April	2505
	May	3415		May	2879		May	2290
	June	2456		June	2333		June	1926
	July	2933		July	2806		July	2217
	August	3619		August	3212		August	2871
	September	2712		September	2689		September	2389
	October	2772		October	2591		October	2195
	November	2706		November	2501		November	2018
	December	2409		December	2104		December	1843
2019	January	2596	2021	January	2399	2023	January	1971
	February	4094		February	3796		February	3485
	March	2835		March	2336		March	1865
	April	3204		April	2813		April	2230
	May	3019		May	2756		May	2223
	June	2519		June	2230		June	1840
	July	2863		July	2580		July	2067
	August	3483		August	3103		August	2585
	September	2863		September	2521		September	2181
	October	2689		October	2353		October	1836
	November	2693		November	2335		November	1781
	December	2356		December	1991		December	1600

Source: Agribusiness and Technology Park

b. Labor capacity data

The maximum capacity per month for regular labor is 1980 kg/month, overtime 450 kg/month and subcontracts 1120 kg/month which can be seen in Table 3.

Table 3. Regular, overtime and subcontract labor capacity

Regular					
Monday Friday			Saturday		
Number of labors	3	person	Number of labors	3	person
Working days in a month	20	day / month / person	Working days in a month	4	day / month / person
Total working days	60	day / month	Total working days	12	day / month
Working hours daily	8	hour / day / person	Working hours daily	4	hour / day / person
Total working hours daily	24	hour / day	Total working hours daily	12	hour / day
Harvest capacity per day	30	kg / day / person	Harvest capacity per day	15	kg / day / person
Harvest capacity per hour	3.75	kg / hour / person	Harvest capacity per hour	3.75	kg / hour / person
Harvest capacity per month	600	kg / month / person	Harvest capacity per month	60	kg / month / person
Total harvest capacity per month	1800	kg / month	Total harvest capacity per month	180	kg / month
Capacity regular per month	1980	kg / month			
Overtime					
Saturday			Sunday		
Number of labors	3	person	Number of labors	3	person
Overtime days in a month	4	day / month / person	Overtime days in a month	4	day / month / person

Total overtime days	12	day / month	Total overtime days	12	day / month
Overtime hours daily	4	hour / day / person	Overtime hours daily	8	hour / day / person
Total overtime hours daily	12	hour / day	Total overtime hours daily	24	hour / day
Harvest capacity per day	12.5	kg / day / person	Harvest capacity per day	25	kg / day / person
Harvest capacity per hour	3,125	kg / hour / person	Harvest capacity per hour	3,125	kg / hour / person
Harvest capacity per month	50	kg / month / person	Harvest capacity per month	100	kg / month / person
Total harvest capacity per month	150	kg / month	Total harvest capacity per month	300	kg / month
Capacity overtime per month	450	kg / month			
Subcontract					
Monday- Sunday					
Number of labors	2	person			
Subcontract days in a month	28	day / month / person			
Total subcontract days	56	day / month			
Subcontract hours daily	8	hour / day / person			
Total subcontract hours daily	16	hour / day			
Harvest capacity per day	20	kg / day / person			
Harvest capacity per hour	2.5	kg / hour / person			
Harvest capacity per month	560	kg / month / person			
Total harvest capacity per month	1120	kg / month			
Capacity subcontract per month	1120	kg / month			

Source: Agribusiness and Technology Park

c. Labor cost data

Regular labor costs are IDR 3030/kg, overtime IDR 3840/kg and subcontracts IDR 5200 which can be seen in Table 4.

Table 4. Labor costs per capacity

Labor	Capacity		Cost (IDR)	
Regular	30	Kg/ day /person	90,909	Rp/ day /person
	3.75	Kg/hour/person	11,364	Rp/hour/person
	1	Kg	3,030	Rp/kg
Overtime	25	Kg/ day /person	96,000	Rp/ day /person
	3,125	Kg/hour/person	12,000	Rp/hour/person
	1	Kg	3,840	Rp/kg
Subcontracting	20	Kg/ day /person	104,000	Rp/ day /person
	3.75	Kg/hour/person	13,000	Rp/hour/person
	1	Kg	5,200	Rp/kg

Source: Agribusiness and Technology Park

Data collected was then further analyzed using forecasting and aggregate planning.

a. Forecasting

Forecasting will be calculated using winter's exponential smoothing and time series decomposition with Microsoft Office Excel 2019 and the formula according to Paramu (2018:87-93).

1. Winter's exponential smoothing

The steps to forecasting using winte'rs exponential smoothing are as follows:

a. Input the data

Inputting 72 crystal guava harvest data starting from January 2018 to December 2023.

b. Determine initial parameters L_1, T_1 and S_1

According to Hanke and Wichern in Paramu (2018:89), the value L_1 is equal to the value in the first observation period, T_1 assumed to be 0 and S_1 assumed to be 1.

c. Determine initial weighting of smoothed value (α), trend estimate (β) and seasonal estimate (γ)

Initial weighting can be determined by a combination of random values between 0 and 1. Initial weighting α is set at 0.1; β at 0.2; and γ at 0.3.

d. Calculate the smoothed value (L_t)

The value L_2 can be calculated using the following formula (Paramu, 2018:89).

$$L_2 = \alpha \frac{Y_2}{S_{2-s}} + (1-\alpha)(L_1 + T_1)$$

Where L_2 = smoothed value in period 2; The smoothed value weighted (α) is 0.1; Y_2 = actual harvest data for period 2; S_{2-s}= seasonal estimate for period $2-s$; with s or the season length for L_2 up to L_{12} is assumed to 1; and L_1 = smoothed value in period 1; and T_1 = trend estimate for period 1. Meanwhile, L_{13} up to L_{72} is calculated by value $s = 12$ because its monthly data.

e. Calculate the trend estimate (T_t)

The value T_2 can be calculated using the following formula (Paramu, 2018:90).

$$T_2 = \beta(L_2 - L_1) + (1-\beta)T_1$$

Where T_2 = trend estimate in period 2; The trend estimate weighted (β) is 0.2; L_2 and L_1 = smoothed value in period 2 and 1; and T_1 = trend estimate in period 1. The formula can used for calculated T_3 until T_{72}.

f. Calculate the seasonal estimates (S_t)

The value S_2 can be calculated using the following formula (Paramu, 2018:90).

$$S_2 = \gamma \frac{Y_2}{L_2} + (1-\gamma)S_{2-s}$$

Where S_2 = seasonal estimate in period 2; The seasonal estimate weighted (γ) is 0.3; Y_2 = actual harvest data in period 2; L_2 = smoothed value in the period 2; and S_{2-s}= seasonal estimate in period $2-s$; with s or season length for S_2 up to S_{12} is assumed to 1. Meanwhile for S_{13} up to S_{72} is calculated by value $s = 12$ because its monthly data.

g. Winter's exponential smoothing forecasting

Forecasting can be calculating from $\hat{Y}_{13}$ to $\hat{Y}_{84}$ due to limitations in the seasonal estimates used, namely S_{t-s+p}, which is the value s in the monthly data is 12. The winters exponential smoothing forecast for period 13 ($\hat{Y}_{13}$) can be calculated using the following formula:

$$\hat{Y}_{13} = (L_{12} + 1T_{12})S_1$$

With $\widehat{Y}_{13}$ = forecasting for period 13; with $p = 1$ future period; L_{12} = smoothed value in period 12; T_{12} = trend estimate in period 12; and S_1 = seasonal estimated in period 1. Values $p = 1$ can be used from $\widehat{Y}_{13}$ up to $\widehat{Y}_{73}$. Meanwhile, for $\widehat{Y}_{74}$ to $\widehat{Y}_{84}$ can use p adjusted to the number of future periods, such as $\widehat{Y}_{74}$ using $p = 2$; $\widehat{Y}_{75}$ use $p = 3$; $\widehat{Y}_{76}$ use $p = 4$; and until $\widehat{Y}_{84}$ use $p = 12$. Forecasting results for $\widehat{Y}_{73}$ up to $\widehat{Y}_{84}$ will be presented in Table 5.

Table 5. Forecasting winter's exponential smoothing from $\widehat{Y}_{73}$ up to $\widehat{Y}_{84}$ with weighting $\alpha = 0{,}1$, $\beta = 0{,}2$ and $\gamma = 0{,}3$

t	Month	Forecasting ($\widehat{Y}_t$)
73	Jan-2024	1783,339
74	Feb-2024	2764,517
75	Mar-2024	1753,447
76	Apr-2024	2017,888
77	May-2024	1946,357
78	Jun-2024	1640,606
79	Jul-2024	1824,983
80	Aug-2024	2173,782
81	Sep-2024	1831,908
82	Oct-2024	1662,565
83	Nov-2024	1598,281
84	Dec-2024	1430,477

The results of the winter's exponential smoothing forecast with weighting α=0.1, β=0.2 and γ=0.3 are presented graphically in Figure 1.

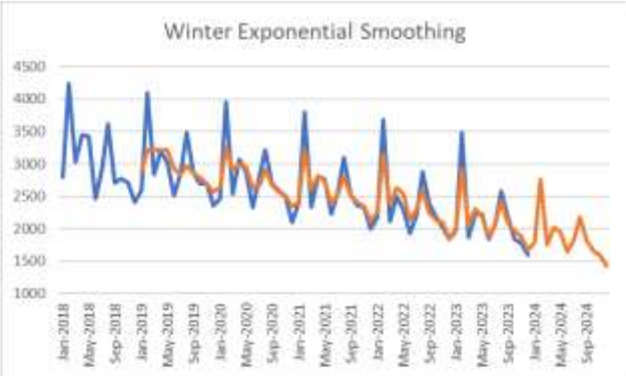

Figure 1. Graph of actual and forecast data winters exponential smoothing with weighting $\alpha = 0{,}1$, $\beta = 0{,}2$ and $\gamma = 0{,}3$

h. Calculate the forecasting accuracy with MAPE
The MAPE forecast accuracy value for winters exponential smoothing forecasting with weighting $\alpha = 0{,}1$, $\beta = 0{,}2$ and $\gamma = 0{,}3$ was obtained at 6.430%.

i. Find a combination of weights α, β and γ which minimizes the error value
The combination of weighting α, β and γ can be found through the Solver feature on the Data Analyze menu in Microsoft Office Excel 2019. This feature will change the combination of weighting α, β and γ with the constraints is $\alpha, \beta, \gamma \leq 1$ and non-negative numbers. After the feature is activated, then obtained the combination weighting is $\alpha = 0{,}020$, $\beta = 0{,}481$ and $\gamma = 0{,}898$ with a MAPE value of 3.428%. The forecasting results $\widehat{Y}_{73}$ until $\widehat{Y}_{84}$ will be presented in Table 6.

Table 6. Forecasting winter's exponential smoothing from $\widehat{Y}_{73}$ up to $\widehat{Y}_{84}$ with weighting $\alpha = 0{,}020$, $\beta = 0{,}481$ and $\gamma = 0{,}898$

t	Month	Forecasting ($\widehat{Y}_t$)
73	Jan-2024	1774,218
74	Feb-2024	3115,958
75	Mar-2024	1679,399
76	Apr-2024	2004,975
77	May-2024	1979,053
78	Jun-2024	1636,076
79	Jul-2024	1838,238
80	Aug-2024	2300,085
81	Sep-2024	1932,534
82	Oct-2024	1640,191
83	Nov-2024	1581,284
84	Dec-2024	1420,522

The results of the winter's exponential smoothing forecast with weighting $\alpha = 0{,}020$, $\beta = 0{,}481$ and $\gamma = 0{,}898$ are presented graphically in Figure 2.

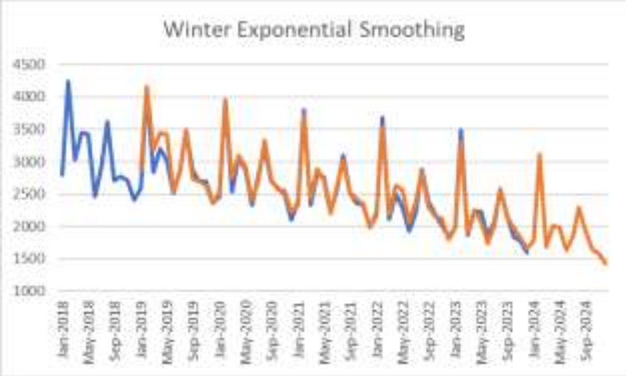

Figure 2. Graph of actual and forecast data winters exponential smoothing with weighting $\alpha = 0{,}020$, $\beta = 0{,}481$ and $\gamma = 0{,}898$

2. Time series decomposition

Forecasting will be calculated using the multiplicative component model because the harvest data has varying values over time. The following are the stages in forecasting (Paramu, 2018:129):

a. Deseasonalizing data

The deseasonalizing data is the stage of removing short-term fluctuations consisting of seasonal components and irregularities by using a moving average with an order according to the length of the season in the data. The harvest data is monthly data so the order used is 12. The value calculated in the moving average at this stage will be placed in the middle (centered) of the season length. The following is the formula for the moving average of order 12 (Paramu, 2018:131):

$$\mathrm{MA_t} = \frac{\mathrm{Y_{t-6} + Y_{t-5} + Y_{t-4} + Y_{t-3} + Y_{t-1} + Y_t + Y_{t+1} + Y_{t+2} + Y_{t+3} + Y_{t+4} + Y_{t+5}}}{12}$$

With $\mathrm{Y_{t-6}}$ = actual data 6 periods before t; $\mathrm{Y_t}$ = actual data in period t; and $\mathrm{Y_{t+5}}$ = actual data 5 periods after t.

Furthermore, to place the moving average value in an even order right in the middle of the season length, this can be done with a centered moving average using the following formula (Paramu, 2018:132):

$$\mathrm{CMA_t} = \frac{\mathrm{MA_t + MA_{t+1}}}{2}$$

With $\mathrm{MA_t}$ = moving average value of the period t and $\mathrm{MA_{t+1}}$ = moving average value one period after the period t.

b. Determine seasonal factors

After obtaining data that no longer has a seasonal components, the next stage is to determine the seasonal factor using the following formula (Paramu, 2018:134):

$$\mathrm{SF_t} = \frac{\mathrm{Y_t}}{\mathrm{CMA_t}}$$

Where = $\mathrm{Y_t}$ actual harvest data in period t and $\mathrm{CMA_t}$= centered moving average in period t.

If the SF > 1 means the data in that period is greater than the average of all data, SF $= 1$ means that it is the same as the average of all data, and SF < 1 means that it is smaller than the average of all data.

The SF value must be consistent in every multiple of the season period. However, if the SF value is inconsistent, the standardization must be carried out or called a seasonal index. The following are the stages for obtaining the seasonal index (Paramu, 2018:136-138):

1. Summing SF for the same seasonal period
   SF is summed over each of the 12 equal seasonal periods.
2. Calculate the average SF for each season
   SF is averaged over each of the 12 equal seasonal periods.
3. Adding the average SF
   If the average number of SF is not the same as the number of seasonal periods, which is 12, then it needs to be normalized by multiplying the average ratio of SF for each period by the number of seasons. The average ratio of SF is obtained by dividing the average value of SF for each period by the average number of SF. The normalized value of SF will be used as the seasonal index value.
4. Calculate deseasonalized data
   Deseasonalized data can be calculated using the following formula (Paramu, 2018:137).

$$\mathrm{DD_t} = \frac{\mathrm{Y_t}}{\mathrm{SI_t}}$$

   Where $\mathrm{Y_t}$ = actual harvest data in the period t and $\mathrm{SI_t}$ = seasonal index in the period t.

c. Find the trend patterns

The trend pattern used is a linear trend model because the harvest data tends to increase or decrease with a trend that resembles a straight line. The linear trend model in the time series decomposition method can be calculated using the following formula (Paramu, 2018:140).

$$\widehat{\mathrm{CMA}}_\mathrm{t} = \mathrm{b_0 + b_1 t}$$

Where $\widehat{\mathrm{CMA}}_\mathrm{t}$ = centered moving average trend (CMAT) in the period t; $\mathrm{b_0}$ = intercept coefficient; and $\mathrm{b_1}$ = coefficient x variable.

The value $\mathrm{b_0}$ and $\mathrm{b_1}$ can be calculated using the Data Analysis feature and selecting Regression in Microsoft Office Excel 2019, with the x variable being t and the y variable being the centered moving average (CMA). Obtained $\mathrm{b_0} = 3196{,}473$ and $\mathrm{b_1} = -15{,}090$.

d. Calculate the cyclical components

The cyclical component is calculated with the cycle factor (CF) using the following formula (Paramu, 2018:141).

$$\mathrm{CF_t} = \frac{\mathrm{CMA}}{\mathrm{CMA_t}}$$

Where CMA is the centered moving average (CMA) value and $\mathrm{CMA_t}$ is the centered moving average trend (CMAT) for each period t.

If $\mathrm{CF} > 1$, it means that the deseasonalized data for that period is above the long-term trend projection, while $\mathrm{CF} < 1$ it is below the long-term trend projection.

The cyclical component can only be calculated for $\mathrm{CF_7}$ to $\mathrm{CF_{66}}$ due to the limited centered moving average (CMA) value. Meanwhile, we need up to $\mathrm{CF_{84}}$. So, to get $\mathrm{CF_{67}}$ until $\mathrm{CF_{84}}$ can estimate using Holt's exponential smoothing (Paramu, 2018:144).

e. Time series decomposition forecasting

The next stage is to forecast time series decomposition using the formula (Paramu, 2018:143):

$$\mathrm{Y_t} = \mathrm{T_t} \times \mathrm{S_t} \times \mathrm{C_t} \times \mathrm{I_t}$$

Where $\mathrm{Y_t}$ = forecast in the period t; $\mathrm{T_t}$ = trend component in the period t which is centered moving average trend (CMAT); $\mathrm{S_t}$ = seasonal component in the period t which is seasonal index (SI); $\mathrm{C_t}$ = cyclical component in the period t which is cyclical factor (CF); and $\mathrm{I_t}$ = irregularity component in the period t which is assumed to be 1. Forecasting is carried out starting from $\mathrm{Y_7}$ to $\mathrm{Y_{84}}$. Forecasting using the time series decomposition method obtained a MAPE value of 2.365%. The forecasting results $\hat{\mathrm{Y}}_{73}$ up to $\hat{\mathrm{Y}}_{84}$ will be presented in Table 7.

Table 7. Forecasting time series decomposition from $\hat{\mathrm{Y}}_{73}$ up to $\hat{\mathrm{Y}}_{84}$

t	Month	CMAT($\mathrm{T_t}$)	SI($\mathrm{S_t}$)	CF($\mathrm{C_t}$)	Forecasting ($\hat{\mathrm{Y}}_t$)
73	Jan-2024	2094,920	0.882	0.959	1771,754
74	Feb-2024	2079,830	1,460	0.957	2904,341
75	Mar-2024	2064,740	0.895	0.954	1762,489
76	Apr-2024	2049,651	1,064	0.952	2075,800
77	May-2024	2034,561	1,021	0.949	1972,093
78	Jun-2024	2019,471	0.847	0.947	1618,655
79	Jul-2024	2004,381	0.981	0.944	1857,605
80	Aug-2024	1989,292	1,201	0.942	2249,599
81	Sep-2024	1974,202	0.979	0.939	1815,911
82	Oct-2024	1959,112	0.941	0.937	1727,384
83	Nov-2024	1944,022	0.920	0.934	1671,846
84	Dec-2024	1928,932	0.809	0.932	1454,422

The results of time series decomposition forecasting are presented graphically in Figure 3.

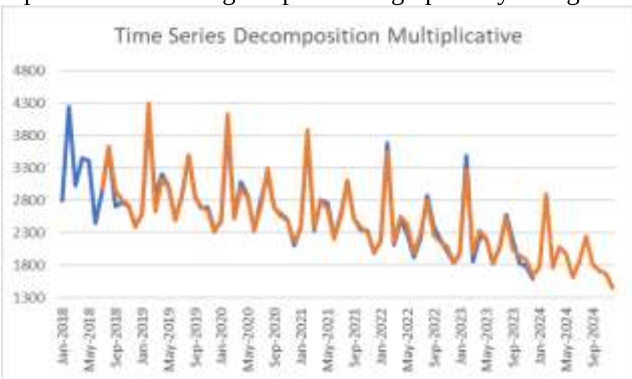

Figure 3. Graph of actual and forecast data time series decomposition

b. Comparison of forecasting accuracy

After forecasting using the winter's exponential smoothing and time series decomposition methods, the next step is to compare the forecasting accuracy of the two methods. The comparison is presented in Table 8.

Table 8. Comparison of the forecasting accuracy of winter's exponential smoothing and time series decomposition

Method	α	β	γ	MAPE
Winters exponential smoothing	0.020	0.481	0.898	3.428%
Time series decomposition				2.365%

The minimum error accuracy value is with the time series decomposition method because it has the smallest MAPE of 2.365%. So, this method will be selected as a forecasting model for the aggregate planning stage.

c. Aggregate planning

Aggregate planning is used to organize labor during the peak harvest season. The method used is the linear programming transportation mathematical approach which is chosen because it uses formula-based calculations so it is more accurate. Aggregate planning can be calculated by using POM-QM for windows version 5.2 because the calculations are in accordance with the aggregate planning theory according to Heizer et al., (2020:567-568) and Stevenson (2021:481). The selected module is the Aggregate Planning Transportation Model. The steps for carrying out aggregate planning using this application are as follows:

1. Open the POM-QM 5.2 and select the required module

   Before planning, the first step is to open the POM-QM for Windows version 5.2 application and select the Aggregate Planning module and then select the Transportation Model. Then after the box display appears, fill in the title section, the number of periods is 12 and the row name is based on the month starting from January.

2. Input the required data on the POM-QM 5.2 display
   The required data is the forecast of the crystal guava harvest data using the time series decomposition method from January to December 2024, the capacity and costs of regular labor, overtime and subcontract.
   The maximum capacity per month of regular labor is 1980 kg/month, overtime 450 kg/month and subcontract 1120 kg/month. Meanwhile, regular labor costs are IDR 3030/kg, overtime IDR 3840/kg and subcontract IDR 5200.
3. Aggregate planning with POM-QM 5.2
   Aggregate planning is done by pressing the solve button on POM-QM 5.2 with the efficient regular, overtime and subcontract labor costs results will be presented in Figure 4.

Optimal cost = $71.022.000	January	February	March	April	May	June	July	August	September	October	November	December	Excess Capacity	Capacity
January RegTime	1772												208	1980
January Overtime													450	450
January Subcontract													1120	1120
February RegTime		1980												1980
February Overtime		450												450
February Subcontract		474											646	1120
March RegTime			1762										218	1980
March Overtime													450	450
March Subcontract													1120	1120
April RegTime				1980										1980
April Overtime				96									354	450
April Subcontract													1120	1120
May RegTime					1972								8	1980
May Overtime													450	450
May Subcontract													1120	1120
June RegTime						1619							361	1980
June Overtime													450	450
June Subcontract													1120	1120
July RegTime							1858						122	1980
July Overtime													450	450
July Subcontract													1120	1120
August RegTime								1980						1980
August Overtime								270					180	450
August Subcontract													1120	1120
September RegTime									1816				164	1980
September Overtime													450	450
September Subcontract													1120	1120
October RegTime										1727			253	1980
October Overtime													450	450
October Subcontract													1120	1120
November RegTime											1672		308	1980
November Overtime													450	450
November Subcontract													1120	1120
December RegTime												1454	526	1980
December Overtime													450	450
December Subcontract													1120	
Demand	1772	2904	1762	2076	1972	1619	1858	2250	1816	1727	1672	1454	19718	

Figure 4. Aggregate planning using POM-QM 5.2

Details of the calculation of regular, overtime and subcontract labor costs with aggregate planning will be presented in Table 9.

Table 9. Details of regular, overtime and subcontract labor costs in aggregate planning

Month	Aggregate planning (kg)			Total cost (Rp)		
	Regular	Overtime	Subcontract	Regular	Overtime	Subcontract
January	1772	-	-	5,369,160	-	-
February	1980	450	474	5,999,400	1,728,000	2,464,800
March	1762	-	-	5,338,860	-	-
April	1980	96	-	5,999,400	368,640	-
May	1972	-	-	5,975,160	-	-
June	1619	-	-	4,905,570	-	-
July	1858	-	-	5,629,740	-	-
August	1980	270	-	5,999,400	1,036,800	-
September	1816	-	-	5,502,480	-	-
October	1727	-	-	5,232,810	-	-
November	1672	-	-	5,066,160	-	-
December	1454	-	-	4,405,620	-	-
Total	21,592	816	474	65,423,760	3,133,440	2,464,800
Sum total			22,882			71,022,000

Based on the research that has been conducted, the results show that the aggregate planning strategy through the optimal combination of regular labor, overtime, and subcontracting using linear programming transportation methods yields the minimum cost and meets the labor requirements during the harvest season. The next step is to compare the costs incurred by the company before and after the implementation of the aggregate planning strategy. Before implementing the aggregate planning strategy, to meet the labor needs during the main harvest, the company employs two subcontract employees every main harvest month, when in February and August. If there is still a shortage of harvest labor, the company will set overtime hours for regular employees. The following is a comparison of the costs incurred by the company before and after implementing the aggregate planning strategy presented in Table 11.

Table 11. Comparison before and after implementing the aggregate planning strategy

Method	Labor cost (IDR)			Total cost
	Regular	Overtime	Subcontract	
Company (before strategy implementation)	72,000,000	537,600	9,152,000	81,689,600
Aggregate planning transportation *linear programming*	65,423,760	3,133,440	2,464,800	71,022,000

The labor cost budgeted using the company's calculation method for regular harvest labor is IDR 72,000,000, overtime is IDR 537,600, and subcontracting is IDR 9,152,000. Thus, the total labor cost for the crystal guava harvest for ATP is IDR 81,689,600. However, after implementing aggregate planning strategy, the labor cost for regular harvest labor is IDR 65,423,760, overtime is IDR 3,133,440, and subcontracting is IDR 2,464,800. Therefore, the total labor cost for the crystal guava harvest for ATP after implementing the aggregate planning strategy is IDR 71,022,000. This shows that the aggregate planning strategy produces more efficient costs. The cost efficiency obtained is IDR 10,667,600 or 13.059%. Therefore, it is recommended that the companies use this strategy to make production costs more efficient, especially regular labor costs, overtime and subcontracts.

IV. CONCLUSION

This study aims to formulate a strategy for overcoming labor shortages during the peak harvest season of crystal guava and to identify an efficient production cost at the Agribusiness and Technology Park. This issue can be addressed using an aggregate planning strategy to manage regular labor, overtime, and subcontracting to ensure that labor is available exactly when needed, in line with the productivity of the crystal guava plants, thereby optimizing production costs.

Before formulating the aggregate planning strategy, forecasting is necessary to project harvest yields for the next 12 months. The methods that can be used for seasonal data are winter exponential smoothing and time series decomposition. Forecasting was carried out using spreadsheets, and the time series decomposition method was found to have the best accuracy with a MAPE of 2.365%, which became the basis for formulating the strategy. This study employs the aggregate planning strategy using the linear programming transportation method with the POM-QM for Windows 5.2. Based on the calculations, a cost efficiency of IDR 10,667,600 or 13.059% was achieved. Therefore, the Agribusiness and Technology Park can consider this aggregate planning strategy as an alternative to optimize production costs, particularly labor costs for the crystal guava harvest, as well as to plan the workforce according to the company's needs.

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