Modelling Raw Material Policy in the Palm Sugar Industry While Considering Sustainability Aspects: A Dynamic System Approach

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Abstract. The availability of raw materials is one important factor in managing the supply chain to support the sustainability of the palm sugar industry. The number of raw materials in the palm sugar industry is influenced by various aspects stemming from the environment, economy and the coconut trees themselves. These aspects are interconnected and interact with each other to support the availability of raw materials in the palm sugar industry. This study is conducted in Purbalingga, Indonesia. The dynamic system analysis of palm sugar inventory will be compared to the demand for palm sugar. Inventory and demand analysis is used to influence policy decisions on how to manage the raw material production area. A model for raw material policy in the palm sugar industry is developed using the dynamic system. Model divided into a demand model and a model of neera coconut inventory and backlog demand. The model in this research can be used to simulate the palm sugar industry in a broader system, because validation for this model gives a small value error of $\hat{\mu}_M$ and MAPE.

1. Introduction
The food supply chain has a significant impact on our daily life. Enhancement of the food supply chain can thus improve the standard of living. However, there are various problems caused by food supply chains, including high chain costs, food waste, food losses and environmental issues, that still exist in the food industry [1]. Based on the time horizon impact, researchers have classified supply chain decisions into three categories, which are strategic, tactical and operational decisions. For strategic decisions, the time horizon is in years, and an example is the location of facilities. Tactical decisions have a time horizon of months, and include planning aspects that relate to inventory management. Operational decisions are made on the daily time horizon, and include items such as distribution decisions [2].

Perishable products are an important issue for the food industry. Because of their limited shelf life, if there is unsuccessful inventory management in the supply chain, it will cause a rise in system costs, including ordering costs, shortage costs, inventory handling costs and outdating costs [3]. Each entity in the supply chain tries to minimize the cost incurred by the same facility without considering the implications on upstream or downstream entities of the supply chain. Research by Coelho, et al [4]
highlighted that the inventory routing problem with transshipment needs to be thoroughly taken into account.

The palm sugar industry is one of the leading industries in Purbalingga, Central Java, Indonesia. Lately, the market share of palm sugar has been popular among consumers. The development of the palm sugar industry in Purbalingga is important. Therefore, the expansion of coconut palm as a raw material is also very important in supporting the sustainability of the palm sugar industry. Mapping the coconut tree locations has previously been done with some knowledge of the coconut tree characteristics and consumer demand, which served as inputs into the palm sugar inventory model. Coconut palm is affected by many factors, such as climate, plant age and the number of coconut trees themselves. These aspects are interconnected, and they interact with each other to support the availability of raw materials for the palm sugar industry. The availability of coconut palm and the demand in palm sugar have recently increased significantly and become rather complex. Hence, a system of calculating the availability of the basic materials, which contain various complex factors, is needed.

Dynamic system simulations are generally used for complex systems. Some cases that employ the dynamic system approach are public health management [5] and the ship breaking industry [6]. A dynamic system is a system that is used to analyze inventory characteristics in a perishable product that possesses a complex endurance factor [7]. Past research has indicated that proper management of perishable products in an inventory model will reduce the sale price, making the customers more willing to buy, and also minimize lost values in supply chains [8],[9],[10]. In contrast, [11] also find that a good production and distribution plan is critical when the production periods are given. Climate is also dynamic. Hargreaves, et al [12], Tresnawati, et al [13], Mirawati, et al [14] and others have employed the Kalman Filter algorithm to estimate climate. We employed the El Nino index, as conducted by Tresnawati, et al [13], for the rainfall predictions in our model.

The aim of this research is to formulate the policy for the palm sugar industry. This study is conducted in Purbalingga, Indonesia. The dynamic system analysis of palm sugar inventory will be compared to the demand for palm sugar. Inventory and demand analysis is used to shape policy decisions regarding whether or not an increase raw material production area is justified. Demand, inventories, economy and environmental issues will be considered in developing a model for the raw materials policy of the palm sugar industry. Model verification and validation is conducted with data from a palm sugar producer in Purbalingga. Models that have been validated and verified can then be used to take policy in the sugar industry. The policy is the extended to the acquisition of raw materials.

2. Material and Methods

This research, conducted on the palm sugar industry of Purbalingga, central Java, Indonesia, employs modelling using a dynamic system approach to guide raw materials policy. We obtained data from a palm sugar producer, Sari Bumi, a small and medium enterprise (SME) in Purbalingga, from January 2015–August 2017, were analysed against the model simulations for model verification and validation. The data taken includes area of the palm sugar plantations, organic and inorganic palm sugar production, organic and inorganic demand and production capacity served as model parameters to shape the final results and recommendations.

The palm sugar industry serves the demand for organic and inorganic palm sugar and Javanese sugar. The raw materials for these three types of demand are coconut and organic coconut neera. When the amount of raw materials does not meet the demand, policy for land expansion needs to be taken into consideration. The raw materials in the palm sugar policy system are influenced by various factors, such as climate, demand and supply, inventory, the economy and the number of plants in production. The causal loop for raw material policy in the palm sugar industry is illustrated in Figure 1. The causal loop for organic and inorganic sugar production can essentially be defined by the same model in Figure 1.
Neera coconut is affected by the tapping process. The tapping process is only affected by the climate and the number of trees being tapped. The number of coconut trees that can be tapped is influenced by the company’s policy regarding the percentage of coconut trees that can be tapped. The process of making palm sugar begins with cooking neera into wet palm sugar. The amount of coconut neera that becomes palm sugar is influenced by the Javanese sugar demand. Next is the drying process. Drying is done with ovens that possess a certain capacity. Additional oven capacity is required when the amount of processed wet palm sugar exceeds the current oven capacity. Dry palm sugar is stored in inventory before it is delivered to the customer. Backlog occurs when the inventory cannot meet the demand for palm sugar. If a backlog occurs, the company creates a land expansion policy when the maximum percentage of coconut neera is unable to meet the demand.

The model assumptions are:
- the tapping process is not influenced by sap tapping techniques;
- the process of plant regeneration is done continuously by the company and does not affect the amount of production; and
- climate estimates use the Kalman Filter method based on rainfall data

3. Result and Discussion

3.1. Modelling raw material policy in palm sugar industry
The model is divided into two submodels:
A. Demand submodel
Palm sugar demand is defined by the demand for Javanese sugar and palm sugar, which is assumed to increase every year (Figure 2).
B. Neera coconut inventory and backlog sub model

Neera coconut is obtained from the coconut tree, yielding 3 L of sap per tree. Trees are planted at a 5-m grid spacing over the total coconut production area, of which 43% of the area produces coconut trees. Climate change affects the tapping results, such that the rainy season production is three times greater than the dry season production. The dry season is denoted by seasonal rainfall of less than 150 mm. Climate forecasting for the 2015–2017 time period is estimated using the Kalman Filter algorithm and data from climatedata.org as the model inputs. The rainfall calculations are done using Matlab before being simulated in Vensim. The Kalman Filter algorithm for the climate prediction is as follows:

1. Prediction phase (Time Update)
   a. Project the state
      \[ \hat{x}_{k} = A\hat{x}_{k-1} \]  
   b. Project the error covariance
      \[ P_{k}^{-} = AP_{k-1}A^T + Q \]  

2. Renewal Phase
   a. Compute the Kalman Gain
      \[ K_k = P_{k}^{-}H^T(HP_{k}^{-}H^T + R)^{-1} \]  
   b. Update estimate with measurement \( z_k \)
      \[ \hat{x}_{k-1} = \hat{x}_{k} + K_k(z_k - H\hat{x}_k) \]  
   c. Update the error covariance
      \[ P_{k}^{-} = (I - K_kH)P_{k}^{-} \]  

Notation:
- \( \hat{x}_{k} \) = prior estimates
- \( P_{k}^{-} \) = prior error covariance
- \( K_k \) = Kalman Gain
- A = the state transition matrix of the process from the state at k-1 to the state at k
- Q = the covariances of the noise models
- H = the noiseless connection between the state vector and the measurement vector

In theory Kalman filter has two different phases, namely Predict and Renewal. The first phases is Predict using state estimates from the previous time phase to generate state estimates at the current time phase (1), but does not include information from observations in them. At the renewal phase, a prior estimates is combined with the observational information for refining the estimation phase (3), the improvement of the resulting estimate is update estimate with measurement \( z_k \) (4) and update the error covariance (5). [13] For notations A, Q and H are assumed stationary overtime. [15]

We use the simple form for the climate prediction, such that our inputs are numerical values and not a matrix. We also assume \( A = 1, H = 1, X_0 = 0 \) and \( P_0 = 1 \). Table 1 lists the rainfall predictions for 2015–2017 time period.
Table 1. Rainfall Prediction (mm)

| Number | Month | 2015 | 2016 | 2017 | Number | Month | 2015 | 2016 | 2017 |
|--------|-------|------|------|------|--------|-------|------|------|------|
| 1      | January | 374  | 387  | 365  | 7      | July  | 74   | 76   | 79   |
| 2      | February | 336  | 339  | 313  | 8      | August | 77   | 77   | 78   |
| 3      | March   | 401  | 378  | 392  | 9      | September | 122  | 115  | 119  |
| 4      | April   | 291  | 294  | 271  | 10     | October | 307  | 310  | 314  |
| 5      | May     | 223  | 211  | 218  | 11     | November | 370  | 384  | 397  |
| 6      | June    | 129  | 131  | 132  | 12     | December | 408  | 413  | 418  |

The 2015–2017 rainfall predictions 2015–2017 were validated with data from climate-data.org, and these rainfall predictions were then used as a model input to evaluate and validate the raw material policy model.

is the neera coconut inventory and backlog demand model. Company policy 1 is an increase in the number of tapped coconut trees, while company policy 2 is the expansion of the raw material acquisition area. The production of inorganic palm sugar is recognised by the amount of Javanese sugar production. The palm sugar production is calculated as the reduction in neera production due to the need to meet the demand of Javanese sugar. Sugar powder is a wet palm sugar that then undergoes the oven process to reduce the water content in the sugar. The inventory model is used to infer the magnitude of the difference between the amount of available palm sugar and the demand for sugar. The ratio result between inventory and demand will thus shape the company’s policy for increasing/decreasing the amount of land used and increasing/decreasing the number of customers. This inventory model can also determine whether or not additional capacity is required to meet the demand. If there are still unprocessed sugars with existing capacity, it will then be necessary to increase the capacity.
3.2. Verification and validation model
Model verification was performed to test the model using the Vensim PLE 7.1 software. Data were obtained from Sari Bumi, a SME palm sugar producer in Purbalingga. The model validation consisted of comparing the actual palm sugar demand and production of the SME with model results. The high degree of agreement between the model and the SME highlight that our model can be extended for further analysis that encompasses wider area of Purbalingga. According to [16], the error in $\hat{\mu}_M$ provides details on both the validity and final results of the model, as follows:

$$\text{Error in } \hat{\mu}_M = |\hat{\mu}_M - \mu_S| = |\hat{\mu}_M - \mu_M + \mu_M - \mu_S|$$

Here they construct a simulation model, where the correspondent mean is $\mu_M$ and the system mean is $\mu_S$. They run the simulation and obtain an estimated $\hat{\mu}_M$ of $\mu_M$. The first absolute value of the above error equation carries the greatest amount of weight in determining the validity of the model, whereas the second absolute value carries the greatest amount of weight for verifying the model results.

The simulation was run for 31 months from January 2015 until August 2017, to validate the model results.

1. Validation test for climate
From the data in Table 1, we used the Mean Absolute Percent Error (MAPE) as a measure of the reliability of the rainfall predictions.

| Number | Month | 2015  | 2016  | 2017  | Number | Month | 2015  | 2016  | 2017  |
|--------|-------|-------|-------|-------|--------|-------|-------|-------|-------|
| 1      | Jan   | 0.0049| 0.0015| 0.0071| 8      | Aug   | 0.0087| 0.0075| 0.0064|
| 2      | Feb   | 0.0025| 0.0014| 0.0092| 9      | Sep   | 0.0026| 0.0082| 0.0049|
| 3      | Mar   | 0.0021| 0.0077| 0.0043| 10     | Oct   | 0.0047| 0.0036| 0.0025|
| 4      | Apr   | 0.0030| 0.0019| 0.0098| 11     | Nov   | 0.0088| 0.0054| 0.0021|
| 5      | May   | 0.0037| 0.0094| 0.0060| 12     | Dec   | 0.0053| 0.0042| 0.0030|
The MAPE values for the rainfall prediction were quite small, totalling 0.54% for each year. This strong degree of agreement between our climate model and the rainfall observations validated the use of our model to predict rainfall in the raw material policy model.

2. Validation test for palm sugar production

![Figure 4. Modelled output of palm sugar production](image)

**Table 3. The error in μ̂_M for palm sugar production (tons)**

| Number | Month  | 2015 | 2016 | 2017 | Number | Month  | 2015 | 2016 | 2017 |
|--------|--------|------|------|------|--------|--------|------|------|------|
| 1      | January| 0.70 | 2.87 | 0.48 | 8      | August | 1.14 | 1.70 | 0.12 |
| 2      | February| 0.76 | 3.81 | 1.37 | 9      | September | 2.00 | 1.87 | -    |
| 3      | March  | 1.77 | 1.62 | 0.70 | 10     | October | 0.14 | 0.81 | -    |
| 4      | April  | 0.53 | 4.06 | 1.61 | 11     | November | 0.87 | 0.62 | -    |
| 5      | May    | 1.63 | 1.58 | 0.01 | 12     | December | 0.37 | 1.06 | -    |
| 6      | June   | 0.99 | 1.54 | 0.03 | Average| 0.98 | 1.86 | 0.64 |
| 7      | July   | 0.88 | 0.75 | 0.79 |        |        |      |      |      |

The errors in μ̂_M for palm Sugar production are small. The SME data highlighted average monthly palm sugar demands of 18 tons in 2015, 19 tons in 2016 and 20 tons in 2017; our model simulations yielded similar demands (Figure 4). This close agreement between our model results and the SME data demonstrate that we can simulate the company’s policy of increasing/decreasing the raw material production area to keep pace with demand.
Backlog occurred from July until September, because inventory and production could not meet demand. Therefore, the company must enact policies to increase the amount of raw material supply as needed (Figure 5).

4. Conclusion

Modelling raw material policy in the palm sugar industry is influenced by various environmental, economic and characteristic coconut tree aspects. A model can be divided into a demand model and a model of neera coconut inventory and backlog demand. The model validation gives a small value error of $\hat{\mu}_M$ and MAPE. Future research can thus use the model to simulate the palm sugar industry in a broader system with various scenarios.

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