An Integrated Sugarcane Phenology and an Optimization Approach to Set Plant and Harvest Schedules Within a Mill Region

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ABSTRACT

As a result of separated planning between rain-fed sugarcane growers and sugar mills in Northeastern Thailand, the supply of sugarcane to the mills were fluctuated. This situation led both sugarcane farmers and sugar plants to produce below their profit maximization level. During the harvest season, the quantity of sugarcane harvested did not match the capacity level of the mills. Hence, the supply of sugarcane was under capacity in the early and late harvest season, but it was over capacity in the middle of the season. This problem portrayed the loss of the mills to operate under capacity and the loss of farmers when the cut-to-crush time exceeded 15 hours as a result of the over supply of the sugarcane on that particular day. This problem, however, could be solved through the supply chain management using the database management, sugarcane phenology modeling such as the DSSAT-CANEGRO and a heuristic method. The database was used to record land information, climate zones, soil structures, land sizes, and farm management. The information, then, was fed into the CANEGRO, which combined weather data, genetic characters, management strategies, and soil data in order to simulate expected outputs. The results of these simulations were used in heuristic programming to identify varieties, plant and harvest date for a particular sugarcane plot so that the capacity of a sugar processing plant was optimized as well as the farmer's revenue. The simulated maximum quantity of sugar that could be produced was 810 million kilograms; it was obtained from the start of the harvest season on January 6 until the end of November 9. The simulated result using the purposive algorithm was greater than the average of simulated randomly grown sugarcane by 243 million kilograms. Moreover, the results of the simulated randomly grown sugarcane depicted that the supply of sugar exceeded the capacity by 4 times and under it by 20 times on the average.

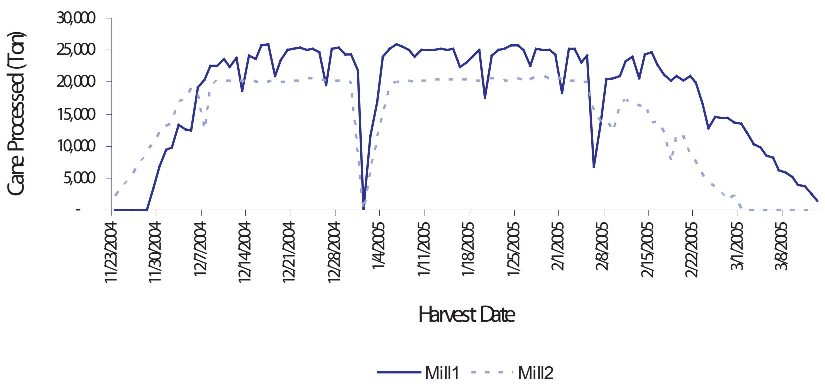
Keywords: Supply Chain Management, Heuristic, Sugar Industry, Quantitative Analysis, CANEGRO

INTRODUCTION

In recent years, sugar exporters have been competing fiercely in driving down their cost or pushing up their productivity. Severals engage in quest for better management. Hence, researchers have been conducting research for clearer vision on this matter. Most of them have concluded that collaboration between cane growers and sugar mills would pave the way to their ultimate goals. This collaboration plan is known as supply chain management. The collaboration will enable planners to set harvesting dates which will give optimum benefits to the sugar industry as a whole. Moreover, it possesses promising future application in marketing, transportation and warehouse management, etc. However, the road to this promising future has not been neatly paved.

In the Thai sugar industry, the unpaved road is traditionally adopted. Most of the Thai cane is rainfed, and the plant date is naturally fixed by the mother of nature. Also, growers' copycat habit leads them to grow the same variety of cane. Combining the two events, the sugarcane inevitably ripens at the same period. This incident triggers a big road block as shown in Fig. 1. The amounts of cane supplied to mills are under crushing capacity at the beginning and at the end of the harvest season while they are over capacity in the middle of the season. The under capacity operation causes high per unit fixed cost for mills while the over capacity one prolongs cut-to-crush delay which leads to lower recoverable sugar yield. From an interview with growers, the cut-to-crush delay sometimes lasts four days, and that portrays an unnecessary loss of 60 kg. per ton.

Figure 1. Tons of sugar produced daily in the 2004/2005 harvest season



Solutions for this phenomenon are as follows: First, exploiting genotypes of cane varieties is needed. Varieties of cane may differ in their mature characteristics or ripening time. As suggested by Gilbert et al.(2004), some varieties are early season mature; some are mid, and some are late season mature. Hence, a certain combination of varieties will enable capacity and yield optimization. Second, enhancing the ability to predict sugar yield is to be conducted. This element is a consequence of the first one. If a variety selection is a preferred method to solve this problem, an accurate yield forecast is needed so that decision makers can decide harvest schedules accordingly. Third, a mathematical tool to lay out estimated yield into a collaboration plan is to be applied. Because the plan involves numbers of participatory growers, together with daily yield prediction, the problem can be unimaginary large. Therefore, decision makers need a mathematical tool to sort it out.

LITERATURE REVIEW

Engineering/management researchers have been trying to combine yield estimation and mathematical programming to smooth out this problem for years. Their mathematical concepts are rather more advanced while they are still struggling with yield prediction. Whan, Scott and Jefferson (1978) were among very first researchers who dealt with the application of cane yield prediction. Their predicted methodology was a quadratic equation which was a function of cane age, years of crop cycles and cross products between cane age and years of crop cycles. Although they attempted to imitate a pattern of real cane yield over time, their method did not cover crucial factors such as weather distribution. Years later, Hahn and Ribeiro (1999) suggested a daily planning of the transportation of sugar cane to mills which minimized cost and waiting time. Although it was a big leap forward for the cane industry, they assumed the amount of ripening cane was known and given. Cane growers were free to make decisions regarding pant dates, varieties, and the amount of land to grow. Therefore, the situation ended up as the Thai case. Their solution seemed to fix the waiting time, but the growers were not able to harvest at their possible optimal level.

Another study by Higgins et al. (1998) portrays a close concept to this study. They obtained a monthly average yield from historical data of each region to set up a harvest schedule. Although they demonstrated an elegant framework, using monthly average data implicitly assumed the same weather distribution across the year. Recently Jiao, Higgins and Prestwidge(2005) have proposed a combination of statistical and optimization approaches to resolve harvest schedule problems. They divided cane varieties into groups of early, middle and late mature varieties. Then, they estimated the sugar content of cane(CCS) as a polynomial function of number of weeks after the harvest season started. Finally, they applied a linear programming to optimize the predicted CCS under respective constraints. Similar to Higgins et al., Jiao, Higgins and Prestwidge assumed the same weather pattern across the year.

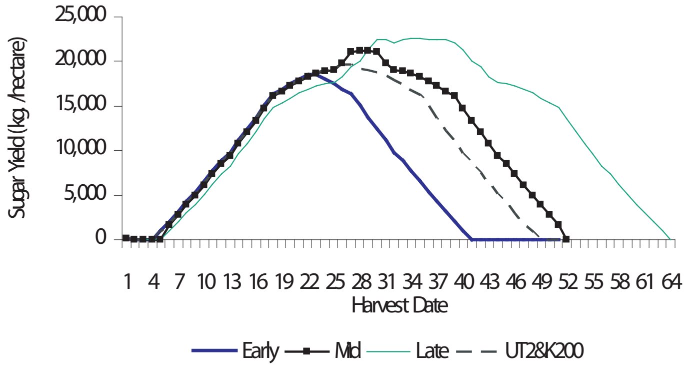
Plant phenologists have long been working on sugar yield estimation paralleled to the groups stated earlier. They successfully develop the state of art software programs for yield prediction. Two programs that have been widely used in cane industries are APSIM and DSSAT-CANEGRO. The two take similar approaches in dividing cane development into certain stages. Each stage differs in requirements of crucial factors such as solar radiation, water, temperature, nutrients, etc. A simulating process is created to imitate the development of plant growth in each stage. Hence, the program considers each important factor and each land plot separately and carefully. Although the simulated result possesses a promising future, it has not been applied for a group management. Rather, a single farm management is more commonly exploited.

To solve the problem of uneven cane supply and sugar mills' crushing capacity, we propose an integration of plant phenology programming and a heuristic approach. The details of this integration will be stated in the next section.

PLANT PHENOLOGY

Firstly, cane yield is simulated by the use of the DSSAT-CANEGRO. Due to the unavailable genetics coefficient for Thai cane except for UT2&K200, genetics of three varieties bundled with the DSSAT package, N14, NCo376, and GEOFF'S FAV were used. The coefficients were modified so that they could represent early, mid, and late season maturity. Degree-days(degree of highest temperature accumulated) from emergence to the harvest maturity of NCo376, N14, and GEOFF'S FAV were changed to 8.5, 7.0 and 6.5 thousand °C which represented late, mid and early season maturity consecutively. And the coefficient of UT2&K200 were obtained from Jintrawet et al.(1997).

Figure 2. Simulated results of 4 varieties on Chaiyaphum loamy sand planted in March



In this study, the management was assumed to be the same across the board and was constructed according to normal practice for Thai cane. The studied sugar mill is a mill located in Khon Kaen province. Growers who supplied cane to this mill, are in the provinces of Khon Kaen, Chaiyaphum and Loei. Therefore, weather distributions were separately created from the distribution of these provinces. There are two types of typical soil structures in these provinces, loamy sand and sandy clay. Combining the three weather stations together with the two types of soil, the studied areas were, then, classified into six different regions. As for planting periods, normal planting periods were around February, March and October. In summary, the simulated case was classified into 4 varieties, 6 regions, and 3 planting date. Therefore, it summed up to 72 different cases.

The examples of simulated yields were shown in Fig. 2. These yields were created from 4 varieties, planted in March on Chaiyaphum loamy sand. As indicated in Fig. 2, graphs of cane yield were crisscrossing. One interpretation is that each variety is to be harvested at a different date. If the harvest before period of 23 is needed, the early season mature variety should be chosen. Whilst, the period of 25, the UT&K200 will give more yields, and for the mid season mature variety, it is suitable for harvesting at the period of 27. Additionally, the harvesting beyond the period of 27, the late season mature should be selected.

INTEGRATION INTO A MATHEMATICAL PROGRAMMING MODEL FOR OPTIMIZATION

After predicted yields were obtained, we applied heuristic Algorithm to set plant and harvest dates which would give the highest amount of total sugar. The objective function of maximizing group outputs takes the following form:

$$\text{Max } Z = \sum_{s=1}^{n}\sum_{t=1}^{n}\sum_{k=1}^{4}\sum_{j=1}^{6}\sum_{i=1}^{3} Q_{ijkt}A_{ijkt}B_{s}$$

where Z is total sugar produced, Q_{ijkt} is the sugar yield from cane planted at period *i* in region *j* with variety *k* and harvested during period *t*, A_{ijkt} is the amount of land where cane was planted at period *i* in region *j* with variety *k* and harvested during period *t*, and B_s is the binary number which equals to 1 when it is harvested in the season and 0 otherwise

I	set of planting dates and $i \in I$, i equals to 1 to 3
J	set of regions and $j \in J$, j equals 1 to 6
K	set of varieties and $k \in K$, k equals 1 to 4
T	set of harvest dates and $t \in T$
S	set of harvest seasons and $s \in S$

Constraints

1. $\sum_{t=1}^{n}\sum_{k=1}^{4}\sum_{j=1}^{6}\sum_{i=1}^{3} A_{ijkt} \le L_j,\ \forall\, i \in I, \forall\, j \in J, \forall\, k \in K, \forall\, t \in T, s \in S$

   The first constraint ensured that sum of Area *j* which planted Variety *k* at Time *i* would not exceeds its maximum level. The total land available for the studied mill is 48 thousand hectares. Due to limitation of the detailed data, we assumed each region has equal amount of land, L_j equals to 8 thousand hectares.
2. $\sum_{k=1}^{4}\sum_{j=1}^{6}\sum_{i=1}^{3} Q_{ijkt} A_{ijkt} \le CAP_t,\quad \forall\, i \in I, \forall\, j \in J, \forall\, k \in K, t \in T, s \in S$

   This constraint is to say that the total amount of cane being harvested did not exceed crushing capacity, CAP_t.
3. The amount of land used were positive numbers.

   $A_{ijkt} \ge 0,\quad i \in I,\ j \in J,\ k \in K,\ t \in T,\ s \in S$
4. Only one harvest season was selected for a particular year. The interpretation is that the harvest season was to be continuous. Hence, the process would go on until the running out of land.

   $\sum_{s=1}^{n} B_s = 1,\ \forall\, s \in S$

SIMULATION MODEL

We constructed a heuristic algorithm to optimize the objective function. The detailed logic of the algorithm is described as follow:

1. Given 72 different cases simulated yield from the DSSAT-CANEGRO, the optimization model would start its first scenario, $s = 1$, by beginning the harvest season on $t = 1$.
2. First, it would search for the best sugar yield per hectare during that period, and fill up capacity with the best yield up to the amount of land available. Nonetheless, if after the harvesting best yield, the supply of cane was still insufficient to fill up the mill's capacity, the algorithm would search for the next best. The process would go on until the capacity was sufficiently filled. Then, the program would move on to the next harvest date and so on.
3. The filling up process went on until the amount of land subsided to zero. Then, the iteration process would start the next scenario $s = 2$ meaning the harvest season had begun on $t = 2$ and Step 2 was repeated. The process went on until $s = n$.

The optimization process is described by using the following pseudo codes.

Algorithm

```
SET each land = Maximum of land
SET capacity for each period equals to its maximum capacity
FOR each starting the harvesting season date
  FOR each harvesting time
    DO
      FOR each region
        FOR each variety
          FOR each planting period
            Obtain 'Current_Solution' from the result of DSSAT
            IF Current_Solution is an improvement over Best_Solution check
               if the solution is feasible (there is some land available for
               growing sugarcane and there is some capacity left to be filled
               up) THEN Best_Solution = Current_Solution
            ENDIF
          REPEAT
        REPEAT
      REPEAT
        Calculate sugar_produced which will be produced by land available
        IF sugar_produced is less than capacity THEN
        UPDATE capacity needed to be filled
        SET land available to grow next t equal to 0
        ELSEIF sugar_produced is greater than capacity THEN
        calculate land available for the next t and set capacity needed to be
           filled equal to 0
    UNTIL land_available = 0 or capacity_be_filled = 0
    RESET capacity and capacity_be_filled to initial value
    UPDATE total_sugar_accumulated
  REPEAT
  RESET total_sugar_accumulated = 0 and land_available to its maximum
     initial value
REPEAT
```

At the end of each scenario, the total amount of sugar is calculated. Then, these summation sugar yields were compared in order to retrieve an optimum solution from these calculated yields.

SIMULATING RESULTS

The result of comparison total simulated yields as shown in Fig. 3 suggested that the harvest season should start on January 6 and end on November 19 with an optimum sugar yield of 813 million kg.

Also, the proposed algorithm recommended a harvest schedule. The example of the schedule is shown in Table 1. It shows that, from January 6 until March 2,

Figure 3. Total simulated yields for each harvest season

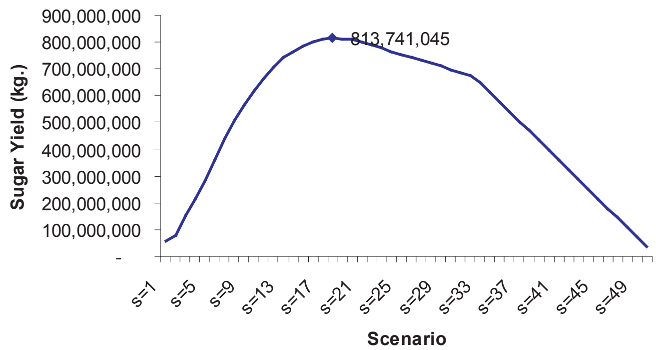


Table 1. Recommended harvest schedule

Harvest Date	Harvest Area (Hectare)	Variety	Plant Date	Region
Jan 6	1,582.0	UT2&K200	February	Chaiyaphum Loamy Clay
Jan 20	1,510.0	UT2&K200	February	Chaiyaphum Loamy Clay
Feb 3	1,458.0	UT2&K200	February	Chaiyaphum Loamy Clay
Feb 17	1,416.0	UT2&K200	February	Chaiyaphum Loamy Clay
Mar 2	1,416.0	UT2&K200	February	Chaiyaphum Loamy Clay
Mar 16	618.0	Mid Season	February	Chaiyaphum Loamy Clay
	810.0	Mid Season	February	Chaiyahum Sandy Loam
Mar 30	1,443.0	Mid Season	February	Chaiyahum Sandy Loam
Apr 13	1,443.0	Mid Season	February	Chaiyahum Sandy Loam
Apr 27	1,417.0	Late Season	February	Chaiyahum Sandy Loam
May 11	1,381.0	Late Season	February	Chaiyahum Sandy Loam
May 25	1,338.0	Late Season	February	Chaiyahum Sandy Loam
Jun 8	168.0	Late Season	February	Chaiyahum Sandy Loam
	2,178.0	Late Season	February	Chaiyahum Sandy Loam
Jun 22	2,476.0	Late Season	February	Chaiyahum Sandy Loam

Table 2. Recommended plant dates, areas, and varieties for each region

Region	Variety	Area (Hectares)	Planting Date
Chaiyaphum Sandy Loam	Mid season	3,696.0	February
	Late season	4,304.0	February
Total		8,000.0	
Loei Sandy Loam	Late season	7,226.0	February
	Late season	774.0	March
Total		8,000.0	
Khon Kaen Sandy Loam	Late season	8,000.0	February
Chaiyaphum Loamy Clay	UT2&K200	7,382.0	February
	Mid season	618.0	February
Total		8,000.0	
Loei Loamy Clay	Late season	8,000.0	February
Khon Kaen Loamy Clay	Late season	8,000.0	February

UT2&K200 planted on Chaiyaphum loamy clay in February should have been harvested with the amount of land indicated in the table. Whilst, from March 16 to April 13, the mid season variety grown on Chaiyaphum loamy clay and sandy loam should have been harvested. Next, the late season on Chaiyaphum sandy loam should have been harvested from April 12 to June 22.

According to the recommended planting schedule, the late season variety planted in February was recommended to grow on Chaiyaphum sandy loam, Loei sandy loam, Khon Kaen sandy loam, Loei loamy clay and Khon Kaen loamy clay for amount of land stated in Table 2. The mid season variety planted in February was recommended to grow on Chaiyaphum sandy loam and loamy clay. Finally, UT2&K200 planted in February was recommended to grow on Chaiyaphum loamy clay.

Because the result from optimization is a simulated one, its benefits are not known unless the model is supplied with the real world data. To show a potential benefit of this framework, we created 25 randomly grown scenarios. For each scenario, cane growers were to select a variety, the plant date and the amount of land on their own wishes and to harvest their canes when it was ripe. All 25 random scenarios showed lower total sugar yields, with an average of 570 million kg. The average randomly grown was 243 million kg. less than the former. Moreover, the result of these random scenarios showed uneven supply of cane which exceeded the sugar mill's capacity by an average of 4 times and was lower than the capacity by an average of 20 times.

CONCLUSIONS

The contribution of this research is to combine plant phenology with an optimization technique in solving supply chain management problems. Although the Thai cane industry will not be able to adopt this framework at this moment, we intend to illustrate a promising future application of the two fascinating tools which will lead to enhancing productivity of the industry as a whole. To get on track of this paved road, farmers' database is essential to the task. The mill needs to know the location, the amount of land, soil structures and the farm management style of each individual farmer. This information, then, will be fed to the optimization program to retrieve recommendations of plant dates, varieties and harvest dates.

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