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Sugarcane harvest planning with yield and quality consideration

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Abstract

In this paper, the sugarcane harvesting problem with sugarcane yield and sugar content (Commercial Cane Sugar: C.C.S.) consideration is addressed. The sugarcane yield and its quality are varied along its age and based on the growing environments. The farmer's revenue is depended on the weight and C.C.S. of sugarcane they sold. Generally, cane weight and C.C.S. may not follow the same pattern. At a specific period, cane may reach high weight but low sugar content. Farmer normally pays more attention to yield than C.C.S even though mills are willing to pay an extra for sugarcane with high C.C.S. A framework which is an integration of artificial neural network (ANN) approach and mathematical model is proposed to solve the problem. Two sets of ANN models are developed to forecast sugarcane yield and C.C.S., separately. The mathematical model is developed to determine an optimal harvesting plan in order to maximize farmer revenues. The data used in this study are collected from one of the largest sugar mills in Thailand. The results showed that both ANN models are quite suitable in yield and C.C.S. forecasting with the average of mean absolute percent errors (MAPE) 11.30 % and 6.86 %, respectively. Farmer revenues could be raised up 11,847.86 Baht by this proposed plan. The optimal harvesting plan with maximizing farmer revenues can be obtained with reasonable computational time for the small size problems.

Keywords: Artificial neural networks, Harvest planning, Mathematical model, Sugarcane

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1. Introduction

Sugarcane is one of the most valuable plants mostly grown in the northeastern part of Thailand and uses as raw material in the sugar industry. Commercial value of sugar has been increased continuously every year, especially in exporting market. It makes the sugar industry becomes one of the most important businesses in Thailand. Even though the business is getting bigger and wealthier, the farmers are still lack of properly benefit. One of the reasons is an inefficient harvest planning. Traditionally, harvesting plan, in Thailand, is set in order to fulfill sugar mill's capacity, which does not concern the farmer revenue. The farmer's revenue is depended on the weight and C.C.S. of the cane sold to the mill. The cane price will increase 60 Baht (i.e., US \$2) per ton for every 1 increased C.C.S. The prices of sugarcane are varied based C.C.S. as shown in Figure 1. For example, if the price of 10 C.C.S. cane is 1,000 Baht/ton, then the price of cane with 11 C.C.S. is 1,060 Baht/ton.

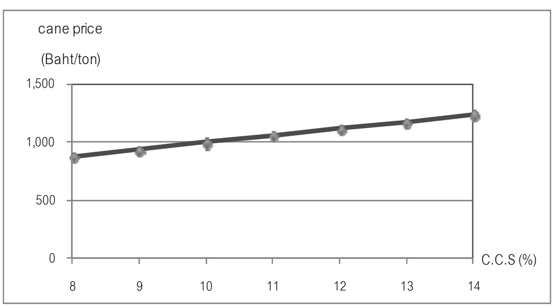

Figure 1 Sugarcane prices with various C.C.S. values

C.C.S. was originally known as Pure Obtainable Cane Sugar or POCS. It provides an estimation of the percentage of recoverable sucrose from cane which explains that 1 ton (i.e., 1,000 kilograms) of sugarcane is equal to 100 kilograms of refined sugar. To calculate C.C.S. value, both brix and pol values in cane must be known [1]. Two common equations used in calculating the C.C.S. are C.C.S. = pol in cane - 0.5 impurities in cane and C.C.S. = pol in cane - ½ (brix in cane - pol in cane), which were presented in [1] and [2], respectively.

However, cane weight and C.C.S. may not follow the same pattern. At a specific period, cane may be in the high weight situation but with low sugar content. Then, the sugarcane harvest scheduling can be planned appropriately if the values of yield and C.C.S. are known. Growth cycle of sugarcane has two prominent periods. First, the period when cane yield has reached its maximum level, the heaviest cane weight period. Second, it is the period when the C.C.S. has reached the peak level of sucrose storage. Theoretically, the yield will rise to the highest level and then slightly decreasing, while the C.C.S. will reach its peak after 1-2 months of the best yield time [3].

Therefore, the efficient harvesting time should be the period when the summation of the revenues from sugarcane weight and C.C.S. is maximized.

In this paper, we have set up a framework to obtain an efficient harvesting schedule with the objective to maximize farmer benefit by considering both yield and C.C.S. The ANN models have been developed to predict both yield and C.C.S. along the sugarcane age. Then, the mathematical model is employed to solve the optimal harvesting schedule.

2. Literature review

The studies of harvest planning was started since early 1950s in Europe when people began noticing that woods and natures had to be managed to supply for all demand in the future. The linear programming has been widely applied for harvest planning and aimed to calculate the optimal solution of cutting woods [4]. In addition, sugarcane harvest planning problem has been solved by various technical tools such as linear programming [5] [6], simulation [7], and experimental design [8].

Based on the literatures, it is obvious that sugarcane yield [9], C.C.S. [10], and harvesting method [11] affect to the sugar production cost, quantity of sugar produced and the mill profit. Therefore, the ability to accurately estimate the sugar yield and C.C.S. is essential to sugarcane business. There have been various methods employed in yield and C.C.S. forecasting such the ANN [12], the statistical equations [10] and growth function [13], [14].

In [12], the ANN model was developed for sugarcane yield prediction. The ANN approach is one of the popular tools that has been widely used in forecasting operation in various business functions such as financial (e.g., [15], [16], [17]), engineering (e.g., [18], [19]) and management (e.g., [20], [21]).

In [10], a mathematical model was proposed for sugarcane harvest planning problem with the objective function to maximize the C.C.S. The C.C.S. of each farm was estimated from the second-order polynomial equations, which were developed based on the historical data. The growth model was also used to forecast the total output of sugar of each sugarcane species in the different cultivar and the appropriate planting period were determined based on the output of the growth model in [13]. Another application of growth function was in [14]. In their paper, the growth function is employed to estimate sugarcane yield in order to determine the appropriate sugarcane types, planting area and the planting date.

Even though there have been various research works dealing with the application of either sugarcane yield or C.C.S. estimation in sugarcane harvest planning, but none of them has been concurrently considered both yield and C.C.S. in harvest planning.

3. Methods and model development

3.1 Neural network models for sugarcane yield and C.C.S. prediction

In this paper, the models based on ANN approach are developed for sugarcane yield and C.C.S. predictions. Input parameters for both yield and C.C.S. prediction models are cane cultivar, cane type, soil type, cane age, average rainfall, total rainfall, average maximum temperature, and average minimum temperature. The crop data of crop year 2011/2012, from the case study mill, are used in developing both yield and C.C.S. prediction models.

Since different sugarcane types are growing maturely in different period, in order to increase the accuracy of the models, we classify prediction models into three sub models for each prediction based on sugarcane types which are irrigation sugarcane (Model 1), late rained sugarcane (Model 2) and ratoon sugarcane (Model 3). Therefore, three models for yield prediction and another three models for C.C.S. estimation are developed in our work. In all ANN models development, the data were separated into three sets: training, model-validating and testing sets. For the purpose of training the models, approximately 70 % of the samples were randomly selected, whereas 20 %

were used for testing purposes and the remaining 10 % for cross validation and early stopping of the training processes. Note that early stopping prevents over fitting of neural network models.

For all prediction models, there are 5 input variables with 11 neurons to represent 3 sugarcane cultivars, 3 soil types, sugarcane age, 2 rainfall levels, and 2 temperature levels. The outputs of the yield prediction models are sugarcane yield in term of ton per Thai rai (i.e., 1 Thai rai = 0.04 ha.), while the output of C.C.S. models are C.C.S. values. The MATLAB 11.0 is applied as a tool to develop the models, while the three-layer feed-forward back propagation neural network is applied to correlate between inputs and outputs. The “logsig”, “tansig” and “purelin” transfer functions have been examined in the models. The number of neurons in the hidden layer is determined by investigating the suitable numbers ranging from 20 to 300 neurons. The learning cycles is set to 150,000. The number of hidden neurons providing the best output is selected as the optimal number.

Table 1 and Table 2 present the suitable parameters that provide the most accurate results and the best MAPEs of the yield and C.C.S forecasting models, respectively. The minimum MAPEs for predicting the yield of irrigation cane, late rained cane and ratoon cane are 11.42%, 11.80% and 10.68%, respectively. The C.C.S. prediction models are more accurate than the yield models. The best MAPEs are 6.12%, 6.79% and 7.66% for the irrigation cane, late rained cane, ratoon cane respectively. The accuracies of the models are acceptable for the case study mill.

Table 1 The MAPEs of sugar cane prediction model

Output: yield (ton/rai)			
Model	No. of hidden neurons	Transfer function	Min. MAPE (%)
1 : irrigation cane	96	tansig	11.42
2 : late rained cane	164	logsig	11.80
3 : ratoon cane	261	logsig	10.68

Table 2 The MAPEs of C.C.S. prediction models

Output: C.C.S			
Model	No. of hidden neurons	Transfer function	Min. MAPE (%)
1 : irrigation cane	200	logsig	6.12
2 : late rained cane	98	tansig	6.79
3 : ratoon cane	52	tansig	7.66

3.2 Mathematical model

In this section, a mathematical model is formulated to determine the optimal harvesting schedules. The objective function of the model is to maximize revenues of all farmers. It is the product of sugarcane yield per area, the ratio of harvested area and the selling price. The price is based on the C.C.S. value. The model consists of six important assumptions, which are: 1) All sugarcanes must be available for cutting anytime, 2) The quantity of sugarcane cut could not be over than the sugar mill's capacity, 3) All planting areas have to be harvested, 4) Forecasted values of yield and C.C.S. must be known, 5) Harvesting labors are available throughout harvesting season, and 6) All sugarcanes should be processed within 24 hours after harvesting.

To describe the model, the following notations are used.

Indices:

i index of sugarcane field, $i = 1,2,\ldots,I$

j index of harvesting week, $j = 1,2,\ldots,J$

Parameters:

a_i planting area of the sugarcane field i (rai)

y_{ij} forecasted yield (ton/rai) of sugarcane field i in week j

p_{ij} price of selling sugarcane from field i in week j

Cap maximum capacity of sugar mill (ton/ week)

Decision variable:

x_{ij} harvested ratio of sugarcane field i in week j

The mathematical model is formulated as follow:

Maximize

$$\sum_{i=1}^{I}\sum_{j=1}^{J} x_{ij} y_{ij} a_i p_{ij} \quad (1)$$

Subject to

$$\sum_{i=1}^{I} x_{ij} y_{ij} a_i \le Cap \quad \text{for } \forall_j \quad (2)$$

$$\sum_{j=1}^{J} x_{ij} = 1 \quad \text{for } \forall_i \quad (3)$$

$$x_{ij} \ge 0 \quad \text{for } \forall_{ij} \quad (4)$$

The objective function (1) is to maximize all farmers' revenues. Constraint (2) describes that quantity of sugarcane harvested in each week could not exceed maximum capacity of sugarcane production. Constraint (3) guarantees that all fields have to be harvested. Finally, constraint (4) ensures that harvesting ratio of sugarcane field i in week j could not be a negative.

4. Results and discussion

The ANN models developed in previous section has been employed to forecast the sugarcane and C.C.S. of the case study mill. The predicted cane yield and C.C.S. of 9 sample sugarcane fields are as shown in Table 3, and Figure 2 presents the example curves of the predicted yield and C.C.S. of the field 1. The studied sugarcane cultivars are K 88-92, KK3 and LK 92-11 which have ages between 300 to 400 days. The maximum capacity of sugarcane production is 189 tons per week. In Figure 2, the results show that sugarcane yield would grow continuously until it reaches the maximum weight, then its growth rate would be slower in order to accumulate sucrose. Based on the yield and C.C.S. predictions, the best harvesting schedule for these 9 sugarcane fields could be obtained by applying the mathematical model presented in section 3.2. The example of optimal harvest schedule is described in Table 4.

Table 3 The predicted yields and C.C.S. of the example case

Sugarcane Field	Cultivars	Area (rai)	forecasting results	week 1	2	3	4	5	6	7	8
1	KK3	5.67	yield (ton/rai)	14.24893	14.44918	14.5008	14.75573	14.65407	14.45636	14.26883	14.10312
			C.C.S (%)	10.53313	10.68593	10.82416	10.93401	11.11116	11.28927	11.25193	11.14143
2	LK 92-11	12.3	yield (ton/rai)	16.32699	16.33758	16.34488	16.23924	16.17574	16.098	16.02479	15.91494
			C.C.S (%)	9.801514	10.07259	10.35124	10.46728	10.66281	10.95659	10.92359	10.87526
3	KK3	11.68	yield (ton/rai)	16.04396	16.05515	16.06427	16.11216	15.99035	15.96035	15.93237	15.87745
			C.C.S (%)	10.15797	10.23771	10.30216	10.3616	10.40807	10.44843	10.49503	10.42793
4	KK3	4.86	yield (ton/rai)	14.06643	14.07443	14.1229	14.25495	14.18434	14.09322	14.02655	13.91731
			C.C.S (%)	10.13946	10.46418	10.74393	10.82546	11.09887	11.35504	11.55616	11.46257
5	KK3	22.63	yield (ton/rai)	14.00237	14.16994	14.20672	14.38233	14.33233	14.22172	14.12449	13.95661
			C.C.S (%)	10.23591	10.27981	10.35988	10.43988	10.56374	10.69711	10.80632	10.9312
6	LK 92-11	15.43	yield (ton/rai)	14.15189	14.25434	14.39841	14.66892	14.57115	14.45779	14.36599	14.24697
			C.C.S (%)	10.916055	11.1468	11.24425	11.85362	11.94163	12.02364	12.00037	11.9164
7	LK 92-11	10.88	yield (ton/rai)	14.69606	14.8394	14.97134	14.65865	14.49987	14.34114	14.20492	14.06135
			C.C.S (%)	10.756889	10.87592	10.9559	11.92994	12.15258	12.04541	11.93417	11.81319
8	K 88-92	5.06	yield (ton/rai)	13.27978	13.25599	13.22908	13.17303	13.07748	12.96588	12.843	12.7072
			C.C.S (%)	11.91832	12.23321	12.85763	13.29704	13.33766	13.3133	13.3027	13.2157
9	KK3	11.68	yield (ton/rai)	16.02612	16.15342	16.2092	16.24144	16.21292	16.15467	16.12245	16.03312
			C.C.S (%)	10.90565	11.10198	11.33484	11.43064	11.4715	11.75084	12.00619	11.96184

Table 4 The optimal harvest schedule of the example case

Sugarcane Field	Percentage of Sugarcane Harvesting: Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week8	Revenue (Baht)
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	85,441.14
2	0.00%	0.00%	0.00%	0.00%	0.00%	91.40%	8.60%	0.00%	209,254.56
3	0.00%	0.00%	0.00%	0.00%	99.05%	0.95%	0.00%	0.00%	191,341.01
4	0.00%	0.00%	80.20%	0.00%	0.00%	0.00%	19.80%	0.00%	72,262.02
5	47.43%	0.00%	39.67%	0.00%	0.00%	0.00%	0.00%	12.90%	325,731.81
6	15.89%	84.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	234,329.65
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	172,485.03
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	76,704.30
9	0.00%	0.00%	1.28%	97.52%	0.00%	1.20%	0.00%	0.00%	205,994.60
								total	1,573,544.12

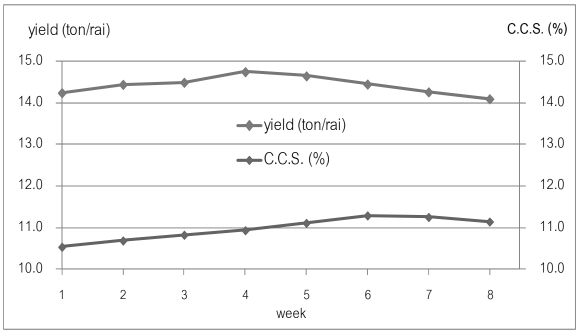

Figure 2 The predicted sugarcane yield and C.C.S. of the field no 1

The optimal harvest schedule of all 9 fields in the example case is as shown in Table 4. The harvesting schedule obtained provide the highest farmers' revenues 1,573,544.12 Baht under constraints that quantity of sugarcane harvested in each week could not exceed maximum capacity of sugarcane production and all fields had to be harvested. In this example case, all fields are cultivated at different period. The harvesting period is normally from the beginning of December to the end of March. The "Week" in Table 4 represents the harvesting week. For example, "Week1" may refer to the first week of December that the harvesting season starts. According to Table 4, all planting area in field no.1 must be harvested in week 8. Sugarcane in field no.2 will be harvested 91.40% of its planting area in week 6 and the rests 8.60% in week 7, whereas, the area of field no.3 should be 99.05% harvested in week 5 and another 0.95% in week 6. The rests of the Table could be described in the same manner. Comparing to the traditional harvest schedule which mainly considers only on cane yield, farmer revenues could be raised up 11,847.86 Baht by this proposed plan.

5. Conclusion

In this paper, the ANN approach is used as a tool for forecasting sugarcane yields and C.C.S. The yield and C.C.S. of each individual field could be obtained by developed ANN models. Then a mathematical model is developed to determine the optimal harvesting schedule in order to maximize farmers' revenue. However, this method considers revenues of all farmers as a group. It does not guarantee the optimal revenue for individual field. If those fields do not belong to one farmer or operate as a group, the solution may not be practical, since it may not be fair for all farmers. Future study could be expanded to consider the equality of farmers' benefits.

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