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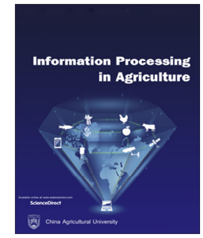

Production plan for perishable agricultural products with two types of harvesting

Jing Li[*], *Xinnan Gao, Biao Guo, Muyuan Wu*

Faculty of Engineering, Nanjing Agricultural University, Nanjing 210031, PR China

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ABSTRACT

Many crops in China have two or more harvesting methods; however, little research has focused on this phenomenon. The current study proposes an operational model that looks to maximize grower profits. This model considers a production plan for a perishable crop that has two harvesting methods: harvesting unripe produce at a lower operational cost but with a long lead time, and harvesting ripe crops at a higher operational cost but with quick turnaround. This study proposes a heuristic algorithm by which to pinpoint the optimal plan for the model; the model results indicate that for a crop with two harvesting methods, significant savings can be obtained by applying an optimal production plan. The current study's main contribution is a production model for crops that feature two harvesting methods and for which the market poses varying demands.

1. Introduction

Chinese growers of perishable crops (e.g., tomatoes, peaches, and cucumbers) often face planning problems, such as deciding how to combine different harvesting methods. Meanwhile, Customers' willingness to buy high-quality vegetables is enhanced at higher incomes [1]. Two types of tomatoes are sold in the Chinese market. The first type comes from harvesting unripe tomatoes that are subsequently exposed to ethrel to change their color. As tomatoes harvested in this way do not require a refrigerated supply chain, their transportation and stocking costs are lower than those associated with vine-ripened tomatoes. For this reason, the price of tomatoes harvested in this way is lower than that of vine-ripened tomatoes. However, the ethrel method requires a long lead time. The second harvesting method—namely, that involving vine-ripened tomatoes—requires a refrigerated supply chain, and so the cost (and therefore the price) of tomatoes harvested in this way is higher than that of tomatoes harvested early and ripened with ethrel. Unlike the two-product model studied by Deuermeyer [2] and Donohue [3], the model is the current study concerns these two harvesting methods for a single perishable product. The cost and lead time characteristics of each of these two methods are identical to those assumed by Donohue [3]. Additionally, the demands associated with the crops harvested in these two ways correlate negatively, and this finding aligns with that of Nagarajan and Rajagopalan [4]. To solve the problem modeled in the current study, we propose a heuristic algorithm similar to approaches found in many earlier studies. For instance, Sarker considers a crop-planning problem and proposes three different optimization approaches to its resolution [5]. In this context, the current study aims to assist growers by providing them with a decision model by which they can generate the optimal plan involving these two harvesting methods.

* Corresponding author.
E-mail address: phdlijing@njau.edu.cn (J. Li).

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There is a growing body of research literature on perishable products. These studies touch upon price-setting, replenishment strategies, distribution scheduling, and production planning [6–9]; all of these issues are of great significance to this study. For example, Cachon and Kok propose a decision model for perishable products where there is no opportunity to replenish inventory [10]. Other researchers propose some comprehensive models by which to price and order perishable products [11–13]. Research on replenishment strategies also relate to the current study [14,15]. Unlike with nonperishable products, the characteristics of perishable products are considered when formulating replenishment strategies. Rohmer et al. researched the two-echelon inventory-routing problem for perishable products [16]. Lu et al. considered a multi-period inventory system for a perishable product with unobservable sales losses [17]. Additionally, while considering heuristic replenishment policies, Deniz et al. propose inventory policies for a supply chain of perishable goods [18].

The current study considers two harvesting methods for a single crop. Several studies on multiple products relate to the current study [19–21]. Nagarajan and Rajagopalan, for example, studied inventory models for two substitutable products when the individual demands of the products negatively correlate [4]. Donohue examined production decisions in a two-mode production environment [3]. We, on the other hand, study two kinds of harvest models that differ from the supply contract of Donohue. Ishii and Nose propose an inventory model for a perishable product that has two customer types (i.e., high-priority customers buy only the newest commodity) [22]. Deuermeyer proposes a one-period model to determine the best production policy for a system comprising two production processes, types A and B; there are independent demand levels for the two perishable products produced via process types A and B [2]. Unlike Deuermeyer's study, the current study examines two harvesting methods for a single crop.

As crop production plans greatly influences grower revenue, recent studies have examined their optimization. Earlier researchers performed significant work in this field. Double-crop production systems have made Brazil one of the world's leading and most competitive grain-producing countries [23]. Cai and Chen et al. propose a model concerning a manufacturing problem for different product types made with a certain amount of perishable raw material; this model can be used to refine product types, machine-time allocations, and scheduling decisions [24]. Ekman considers the scheduling of field operations and machinery investments to study the linkages among various farm-level production decisions [25]. Because the prices of perishable products drop significantly after a period, Leung and Ng use the concept of postponement to divide the production process of perishable products into two phases [26]; their model considers direct production, master production, and final assembly. Given that the profitability of growers is highly contingent on short-term planning, Ahumada and Villalobos propose an operational model by which to make decisions vis-à-vis harvesting and distributing perishable agricultural products [27]. Given the intangible value of freshness, a model for integrated production and distribution planning was proposed to improve the production of perishable products [28]. Unlike the aforementioned studies, however, the current study examines the production plan of one crop that has two harvesting methods.

We propose a heuristic algorithm by which to determine the optimal result from the operational model. Past researchers have designed various heuristic algorithms to study agriculture [29,30]. Adeyemo and Otieno propose four strategies of a novel evolutionary algorithm to study a multi-objective crop planning model [31]. Based on a beam search, Borba and Ritt propose a heuristic algorithm by which to maximize the production rate of an assembly line [32]. Additionally, a heuristic algorithm was proposed to determine the best result in a multi-agent system [33].

It is clear from the literature that the optimization of production plans for perishable crops has attracted growing interest; nonetheless, there is a dearth of research on optimizing two harvesting methods for a single crop. The current study assumes that both demand and yield are stochastic and follow the same distribution parameters in the harvesting period, to ensure all yields can be sold on the market. The quality of perishable crops decreases as time passes, and the grower uses the harvesting plan to harvest crops in two ways and sell them to a retailer. That retailer then sells to customers two types of crops (i.e., those harvested by the two different methods), at different prices. We present an operational model for this problem and design a heuristic algorithm to analyze the model.

To demonstrate the applicability of the proposed model, we then propose a case study based on tomatoes. In China, tomatoes comprise a crop typically harvested by two different methods. Other reasons for choosing a tomato case study include their economic importance and modeling complexity. The optimal plan needs to preclude in-plot product deterioration, as well as retailer stockouts and crop discounting. Ultimately, we propose the optimal plan by which growers can maximize supply chain revenue.

2. Problem statement and model formulations

In this section, we provide a detailed description of an operational model that considers two methods of harvesting fresh produce. With the first harvesting method, defined herein as Schedule A, the grower harvests unripe products at a lower cost. Because the value of fresh ripe products is highly dependent on packaging, warehousing, and transportation, the cost of dealing with ripe products is higher than that of unripe products. With the second harvesting method—defined herein as Schedule B—ripe products are harvested at a higher cost. Because the freshness of the products harvested according to Schedules A and B differs, the lead time of Schedule A is longer than that of Schedule B.

From the grower perspective, both Schedules A and B can be used to harvest products every day. Ultimately, the goal is to determine the most profitable combination of Schedules A and B within the planning period. Fig. 1 graphically interprets the problem that the current study addresses. As seen in Fig. 1, Schedules A and B can be used on the same or different days. There is a trade-off between the product costs of the grower and the stockout costs of the retailer. The grower uses a harvesting plan (which consists of multiple iterations of Schedules A and B) to produce crops and sell them to the retailer.

The current study assumes that the product yield can remain stable during the planning period; meanwhile, the grower yield and the market demand have the same normal distribution. The revenue of the supply chain (i.e., the grower and the retailer) comes from selling of products at normal and discounted prices. The costs from the supply chain include product costs, stockout costs, the loss of freshness, and the cost associated with crop deterioration (i.e., due to untimely harvesting). The objective function of this problem is the profit of the supply chain in the planning period. The grower needs to find a plan (consisting of $X^A = \{x_1^A, x_2^A, \ldots x_n^A\}$ and $X^B = \{x_1^B, x_2^B, \ldots x_n^B\}$) that maximizes the supply chain profit. Because the notation herein is somewhat intense, we summarize below all the indices, parameters, and decision variables.

Indices	
$i \in \{1, 2, \ldots n\}$	planning period (days)
$p \in \{1, 2, \ldots P\}$	simulation time
Parameters	
Q_i	market demand on day i
μ_y	mean yield (kilograms per day)
σ_y	yield variance
p_i^A	selling price of tomatoes harvested by Schedule A on day i
q_i^A	demand for tomatoes harvested by Schedule A on day i
p_i^B	selling price of tomatoes harvested by Schedule B on day i
q_i^B	demand for tomatoes harvested by Schedule B on day i
T_A	lead time of Schedule A
T_B	lead time of Schedule B
s_{i-1}^{LA}	final inventory of tomatoes harvested by Schedule A on day $i-1$
s_{i-1}^{LB}	final inventory of tomatoes harvested by Schedule B on day $i-1$
α	discount rate of tomatoes harvested by Schedule A
β	discount rate of tomatoes harvested by Schedule B
λ	freshness parameter
h_i^A	initial day of the Schedule A proposed tomatoes on day i
h_i^B	initial day of the Schedule B proposed tomatoes on day i
s_i^A	initial inventory of tomatoes harvested by Schedule A on day $i-1$
s_i^B	initial inventory of tomatoes harvested by Schedule A on day $i-1$
c^A	harvesting cost (per kilogram) of tomatoes by Schedule A
c_{fixed}^A	fixed cost per Schedule A
c^B	harvesting cost (per kilogram) of tomatoes by Schedule B
c_{fixed}^B	fixed cost per Schedule B
y_i^1	yield of tomatoes with Breaker color on day i
y_i^2	yield of tomatoes with Turning color on day i
y_i^3	yield of tomatoes with Pink color on day i
y_i^4	yield of tomatoes with Light-red color on day i
y_i^5	yield of tomatoes with Red-ripe color on day i
η	preference of choosing Schedule A
Decision variables	
x_i^A	using Schedule A to harvest tomatoes on day i
x_i^B	using Schedule B to harvest tomatoes on day i

In this model, the grower yield is defined as $y_i^1 \sim N\left(\mu_y, \sigma_y\right)$, and the demand for crops $(Q_i = q_i^A + q_i^B)$ is proposed as $(q_i^A + q_i^B) \sim N\left(\mu_y, \sigma_y\right)$. It is assumed that the price of crops does not change during the harvesting period. The decision variables of x_i^A and x_i^B are defined in formulas (1) and (2), respectively.

$$x_i^A = \begin{cases} 1 & \textit{Harvest products with Schedule B on day i.} \\ 0 & \textit{Otherwise.} \end{cases} \tag{1}$$

$$x_i^B = \begin{cases} 1 & \textit{Harvest products with Schedule B on day i.} \\ 0 & \textit{Otherwise.} \end{cases} \tag{2}$$

The production plan for crops with two harvesting methods can be formulated as a 0–1 programming model $\max f(X^A, X^B)$, where $f(X^A, X^B)$ is defined as per formula (3).

$$f(X^A, X^B) = \sum_{i-1}^{n} \left[\begin{array}{c} q_i^A p_i^A + q_i^B p_i^B + \max\{i - T_A, 0\} s_{i-1}^{LA} p_i^A x_{i-T_A}^A \alpha \\ + \max\left\{i - T_B, 0\right\} s_{i-1}^{LB} p_i^B x_{i-T_B}^B \beta - \frac{1}{\lambda}\left(i - h_i^A\right) s_i^A - \frac{1}{\lambda}\left(i - h_i^B\right) s_i^B \\ - x_i^A c^A (y_i^1 + y_i^2 + y_i^3) - x_i^A c_{fixed}^A - x_i^B c^B (y_i^4 + y_i^5) - x_i^B c_{fixed}^B \\ - (1 - x_i^B)\left(y_i^5 p_i^B - y_i^5 c_i^B - c_{fixed}^B\right) \end{array} \right] \tag{3}$$

The grower's objective is to maximize formula (3) with $X^A = \{x_1^A, x_2^A, \ldots x_n^A\}$ and $X^B = \{x_1^B, x_2^B, \ldots x_n^B\}$. In formula (3), the revenue with normal prices is $q_i^A p_i^A + q_i^B p_i^B$, and that with discount prices is $\max\{i - T_A, 0\} s_{i-1}^{LA} p_i^A x_{i-T_A}^A \alpha +$ $\max\{i - T_B, 0\} s_{i-1}^{LB} p_i^B x_{i-T_B}^B \beta$.

We present a case study that features tomatoes, and use Ahumada and Villalobos's [27] color classification scheme. Tomato ripeness undergoes seven stages—namely, Mature green, Breaker, Turning, Pink, Light-red, Red-ripe, and Over-ripe. Mature green and Over-ripe tomatoes cannot be sold on the market. In this study, Schedule A is used to harvest Breaker (y_i^1), Turning (y_i^2), and Pink (y_i^3) tomatoes; Schedule B is used to harvest Light-red (y_i^4) and Red-ripe (y_i^5) tomatoes at higher costs. The product costs include $x_i^A c^A (y_i^1 + y_i^2 + y_i^3)$, $x_i^A c_{fixed}^A$, $x_i^B c^B (y_i^4 + y_i^5)$, and $x_i^B c_{fixed}^B$. $(1 - x_i^B)\left(y_i^5 p_i^B - y_i^5 c^B - c_{fixed}^B\right)$ is the opportunity cost associated with unharvested ripe tomatoes.

The literature defines crop freshness in two ways. The first is by a linear or exponential function, while the second is determined by estimating the change in color from the time of harvest until the time it reaches the customer. In line with the work of Ahumada and Villalobos [27], we use $\frac{1}{\lambda}\left(i - h_i^A\right) s_i^A$ and $\frac{1}{\lambda}\left(i - h_i^B\right) s_i^B$ to define the loss of tomato freshness, and like them, we too set $\lambda = 8$.

The constraints of the model can be defined as follows.

$$Q_i - Q_i - s_{i-1}^{LA} \quad \forall i \quad \text{and} \quad \max\{i - T_A, 0\} x_{i-T_A}^A = 1 \tag{4}$$

$$Q_i = Q_i - s_{i-1}^{LB} \quad \forall i \quad \text{and} \quad \max\{i - T_B, 0\} x_{i-T_B}^B = 1 \tag{5}$$

$$q_i^A = s_i^A \quad \text{and} \quad q_i^B = s_i^B \quad \forall i \quad \text{and} \quad s_i^A + s_i^B \leqslant Q_i \tag{6}$$

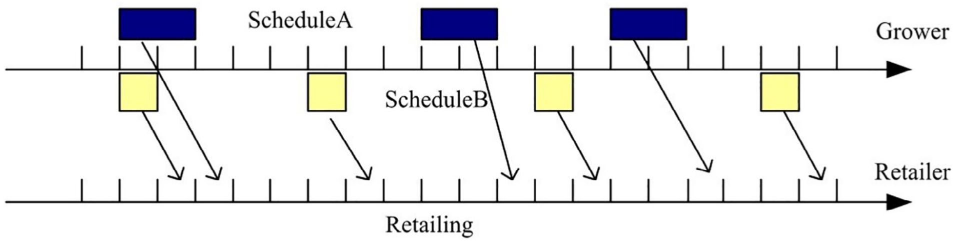

Fig. 1 – Harvesting plan for the grower and retailer.

$$q_i^A = \frac{3}{5}Q_i \quad \text{and} \quad q_i^B = \frac{2}{5}Q_i \quad \forall i \quad \text{and} \quad s_i^A + s_i^B > Q_i,$$
$$s_i^A \geqslant \frac{3}{5}Q_i, \quad s_i^B \geqslant \frac{2}{5}Q_i \tag{7}$$

$$q_i^A = Q_i - s_i^B \quad \text{and} \quad q_i^B = s_i^B \quad \forall i \quad \text{and} \quad s_i^A + s_i^B > Q_i,$$
$$s_i^A > \frac{3}{5}Q_i, \quad s_i^B < \frac{2}{5}Q_i \tag{8}$$

$$q_i^A = s_i^A \quad \text{and} \quad q_i^B = Q_i - s_i^A \quad \forall i \quad \text{and} \quad s_i^A + s_i^B > Q_i,$$
$$s_i^A < \frac{3}{5}Q_i, \quad s_i^B > \frac{2}{5}Q_i \tag{9}$$

$$p_i^B > p_i^A \quad \forall i \tag{10}$$

$$c^B > c^A \tag{11}$$

$$c_{fixed}^B > c_{fixed}^A \tag{12}$$

$$y_i^4 + y_i^5 > 0 \quad \forall i \quad \text{and} \quad x_i^B = 1 \tag{13}$$

$$y_i^1 + y_i^2 + y_i^3 > 0 \quad \forall i \quad \text{and} \quad x_i^A = 1 \tag{14}$$

$$y_i^2 = y_{i-1}^1 \quad \forall i > 1 \tag{15}$$

$$y_i^3 = y_{i-1}^2 \quad \forall i > 1 \tag{16}$$

$$y_i^4 = y_{i-1}^3 \quad \forall i > 1 \tag{17}$$

$$y_i^5 = y_{i-1}^4 \quad \forall i > 1 \tag{18}$$

Constraints (4) and (5) ensure that the residue stocks can be sold first (i.e., an "oldest first" policy). Constraint (6) introduces the demand for the two types of crops from different harvesting plans. Constraints (7), (8), and (9) describe the demand for the two types of crops when market demand is lower than the amount of stocks. Because Schedule A harvests crops y_i^1, y_i^2 and y_i^3, we use 3/5 in the constraints.

Constraints (10), (11), and (12) ensure that the prices and costs of Schedule B are higher than those of Schedule A. Constraints (13) and (14) mean that the grower can harvest on day *i* only if there are crops in the plots on day *i*. Constraints (15)–(18) ensure tomato yields of different colors; this means that tomatoes change color every day.

Given the characteristics of the variables in the proposed model, it is infeasible to pinpoint an optimal solution for large-scale instances of the problem. Because the two schedules are independent in the model, traditional algorithms—such as the ant colony algorithm or the genetic algorithm—cannot be easily used with this model. Based on the heuristic algorithms in the literature, we designed a new algorithm—as discussed in the next section—to obtain the optimal model solution.

3. Algorithm design for the model

Based on analysis of the model, we found that supply chain profits depend on three different components. The heaviest losses occur when some ripe tomatoes are unharvested: indeed, the cost of unharvested tomatoes has a significant effect on supply chain profits. The second is the opportunity cost associated with stockout, and planning needs to preclude its occurrence. The third component of profit losses is discounting. We designed four rules by which to preclude unharvested produce, stockouts, and discounts, as follows.

Rule 1: precluding unharvested produce

If $y_i^5 > 0$ and $x_i^B = 0$, then add Schedule A or Schedule B according to the probability of η (add Schedule A at period $i - T_A$) and $1 - \eta$ (add Schedule B at period $i - T_B$).

Rule 2: precluding stockout

If $s_i^A + s_i^B < q_i^A + q_i^B$, then add Schedule A or Schedule B according to the probability of η (add Schedule A at period $i - T_A$) and $1 - \eta$ (add Schedule B at period $i - T_B$).

Rule 3: precluding discounting

If $s_{i-1}^{LA} x_{i-T_A}^A > 0$, then delete Schedule A at period $i - T_A$; if $s_{i-1}^{LB} x_{i-T_B}^B > 0$, then delete Schedule B at period $i - T_B$.

Rule 4: recovery

If $f_{p+1}(X^A, X^B) < f_p(X^A, X^B)$, then $X_{p+1}^A = X_p^A$ and $X_{p+1}^B = X_p^B$; do not consider this period again. $f_{p+1}(X^A, X^B)$ is the profit of the next simulated planning period, and $f_p(X^A, X^B)$ is the profit of the current simulated planning period.

To preclude the situation in which ripe tomatoes are unharvested, *Rule 1* proposes the addition of Schedule A or B to the planning at period $i - T_A$ or $i - T_B$, respectively. η is

Table 1 – Parameter-setting in the model.

n	P	μ_y	σ_y	p_i^A	p_i^B	T_A	T_B	α	β	λ	c^A	c^A_{fixed}	c^B	c^B_{fixed}	η
30	40	500	50	6	12	2	1	0.5	0.5	8	2	500	4	1000	0.5

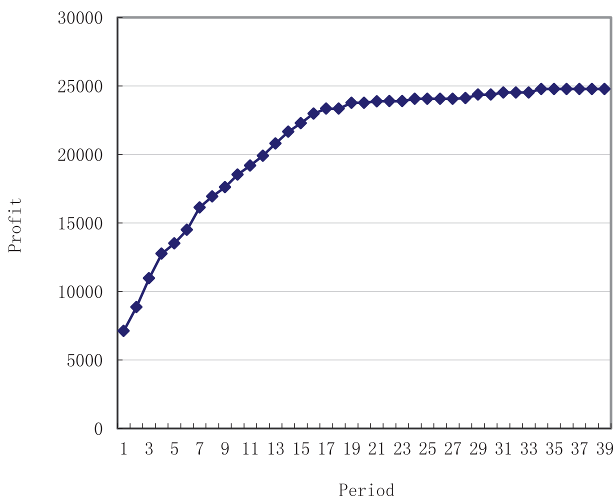

Fig. 2 – Average profits of each simulation period ($\eta = 0.5$).

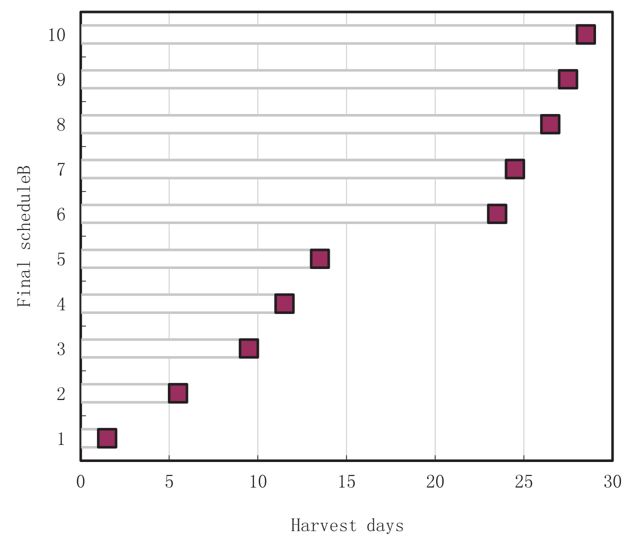

Fig. 4 – Gantt chart for the optimal Schedule B ($\eta = 0.5$).

the probability of choosing Schedule A, and its value depends on the characteristics of the market associated with the perishable product supply chain.

If the retailer stock cannot satisfy the demand in period i, *Rule 2* is used to add Schedule A or B to the planning in period $i - T_A$ or $i - T_B$, respectively. We suggest the application of *Rule 3* to delete Schedule A or B at period $i - T_A$ or $i - T_B$, respectively, in order to preclude discounting.

If the plan is changed by *Rule 1*, *Rule 2*, or *Rule 3* in the simulation period p and the profit in period $p + 1$ is less than that at p, the controller of the virtual supply chain will change the plan at period $p + 1$ to the plan at period p; this act embodies *Rule 4*. Based on the four rules, the steps of the heuristic algorithm are proposed in the following.

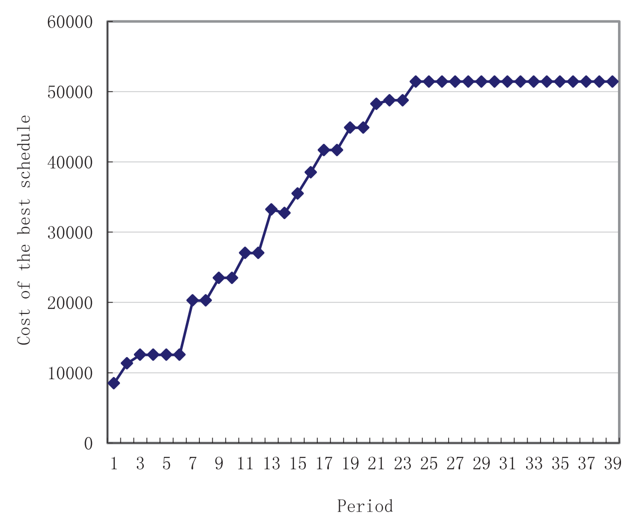

Fig. 5 – Costs incurred through the optimal plan ($\eta = 0.5$).

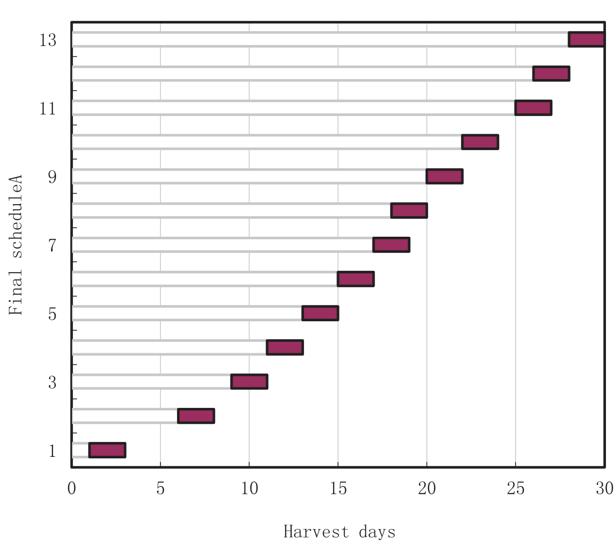

Fig. 3 – Gantt chart for the optimal Schedule A ($\eta = 0.5$).

Step 0:

Initialize all variables. Set $i = 1$ and $p = 1$. Go to the next step.

Step 1:

The virtual grower determines today's available tomatoes. Go to the next step.

Step 2:

The virtual grower reads Schedules A and B to determine today's yields and production costs. Go to the next step.

Step 3:

The virtual retailer checks the replenishment plan and updates current stocks. Go to the next step.

Step 4:

The virtual retailer calculates today's q_i^A and q_i^B according to formulas (6)–(9). Go to the next step.

Step 5:

The virtual retailer calculates today's profit $f(x_i^A, x_i^B)$. Go to the next step.

Step 6:

$i++$. If $i < n$, go back to *Step* 1; if $i = n$, calculate $f_p(X^A, X^B)$ and go to *Step 7*.

Step 7:

If some periods of y^5 are not harvested and these periods were not formerly considered by *Rule* 1, the virtual grower uses *Rule 1* to address the harvesting schedule and goes to *Step 10*; otherwise, go to *Step 8*.

Step 8:

If some periods have stockouts that were not formerly considered, and all periods suitable for *Rule 1* have been

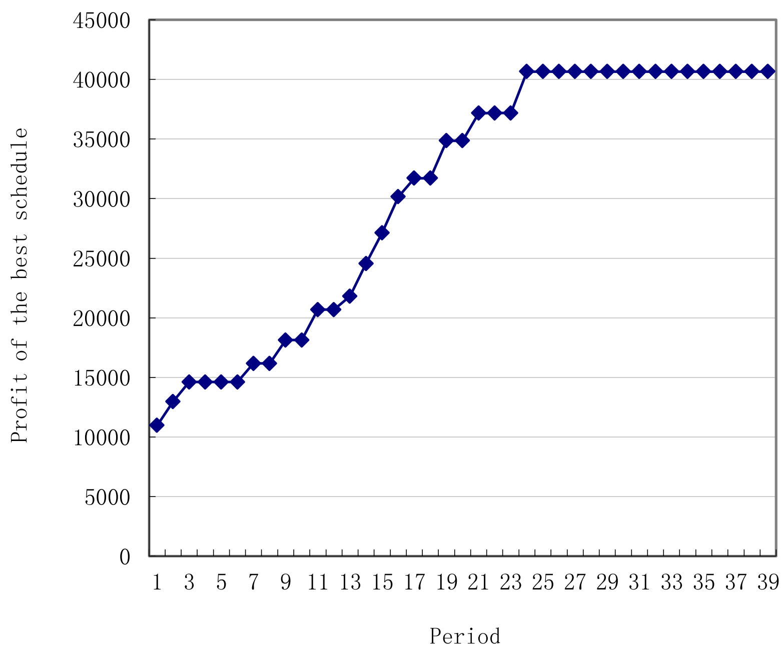

Fig. 6 – Profits made through the optimal plan ($\eta = 0.5$).

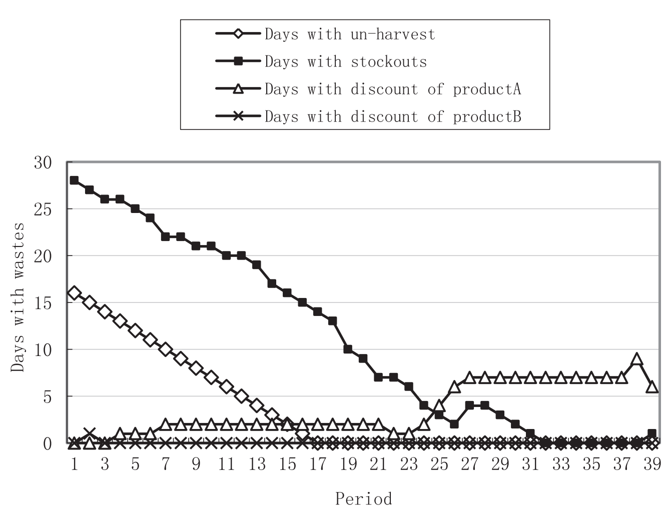

Fig. 7 – Changes to days with waste ($\eta = 0.5$).

considered, the virtual retailer uses *Rule 2* to address the harvesting schedule and then goes to *Step 10*. Otherwise, go to *Step 9*.

Step 9:

If all periods suitable for *Rule 1* and *Rule 2* have been considered and the retailer discounts tomatoes in some periods, the retailer uses *Rule 3* to address the harvesting schedule. Go to *Step 10*.

Step 10:

The controller of the virtual supply chain uses *Rule 4* to check the results of updating the schedules. Go to *Step 11*.

Step 11:

$p++$. If $p < P$ (P is the maximal simulation times), set $i = 1$ and go back to *Step 1*. If $p = P$, end this simulation.

Using this process, the algorithm finds the best result from formula (3). Schedules A and B will be added to or deleted from the algorithm for each simulation period. (For this process, we use JAVA to code the algorithm on the WinXP platform.) Three objects—namely, the virtual grower, virtual retailer, and controller—are coded into the programmer to simulate the grower, retailer, and manager of the simulation, respectively. All rules are designed as actions of the three objects, and variables are coded as attributes of the virtual grower, retailer, and controller. In the next section, we discuss the experiments used to demonstrate the validity of the algorithm, and this algorithm is used to craft the optimal production plan.

4. Case study

We use the proposed model and algorithm to resolve the planning problem for a hypothetical tomato grower, and in the process demonstrate their validity. As in the model formulation, the grower harvests tomatoes in two ways: Schedule A is used to harvest tomatoes of the colors Breaker (y_i^1), Turning (y_i^2), and Pink (y_i^3), while Schedule B is used to harvest tomatoes of the colors Light-red (y_i^4) and Red-ripe (y_i^5). The proposed parameter-setting for the model is shown in Table 1. The initial plan for Schedule A is to harvest at days 2, 9, and 16; the related Gantt chart is shown in Fig. 10(a). Meanwhile, the initial plan for Schedule B is to harvest at days 1, 7, 15, and 17; the related Gantt chart is shown in Fig. 11(a). The initial plans were set randomly.

For the first experiment, the market has no preference with respect to unripe versus ripe tomatoes ($\eta = 0.5$). We run the same experiment 100 times, and each iteration comprises 40 harvesting periods. Each harvesting period contains 30 harvesting days. Fig. 2 shows the average results of the experiments.

Because for the initial plan many tomatoes were not harvested, the algorithm adjusts Schedules A and B so as to improve profits. Fig. 2 demonstrates the validity of the model and the algorithm, for at the beginning of the simulation, the average profits increase substantially. Finally, in Fig. 2, the average profits approach a maximal value. Since the result can be optimized step-by-step to a stable value, Fig. 2 shows the validity of the proposed model and algorithm.

Because the algorithm process is highly uncertain, the iterative results of the 100 experiments differ. Figs. 3 and 4 show the optimal grower plans: the two Gantt charts show that, compared to the initial plans, many harvesting changes were made.

Figs. 5 and 6 show the final plan results. The process of deriving this result is illustrated in Figs. 5–7.

Figs. 5 and 6 show the evolution of the costs and profits, from the initial plan to the optimal plan. The algorithm has a significant effect on model calculations. In the final periods, the supply chain attains maximal profits, as Fig. 6 shows. Fig. 7 shows how, during the process of determining the optimal plan, the proposed changes were made to the days with waste (i.e., unharvested produce, stockouts, and discounts). In the

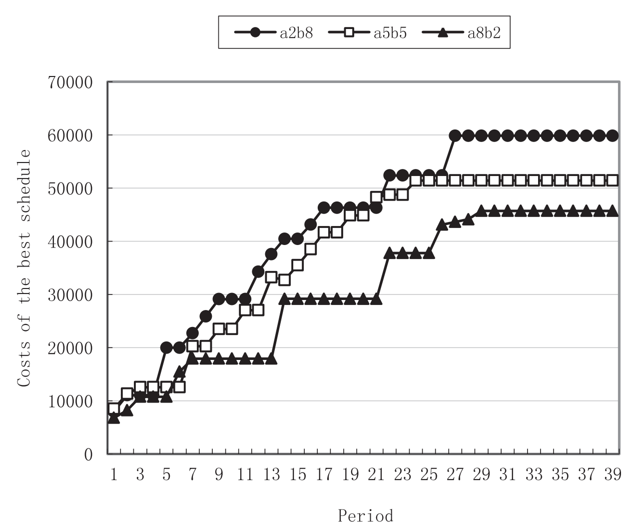

Fig. 8 – Cost comparison for the optimal plan among the three experiments.

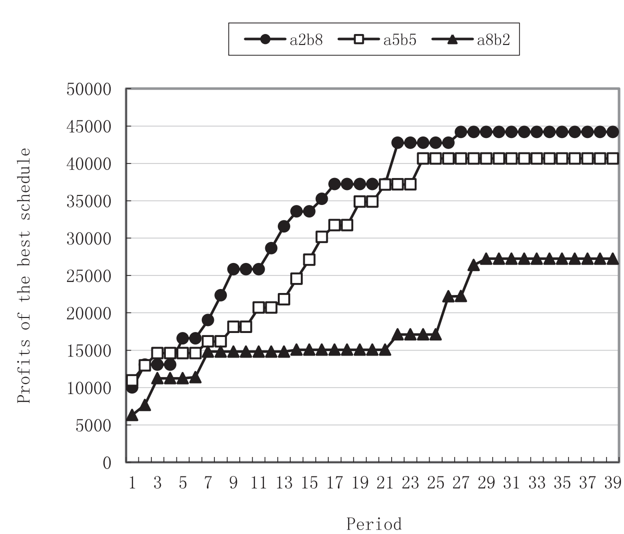

Fig. 9 – Profit comparison for the optimal plan among the three experiments.

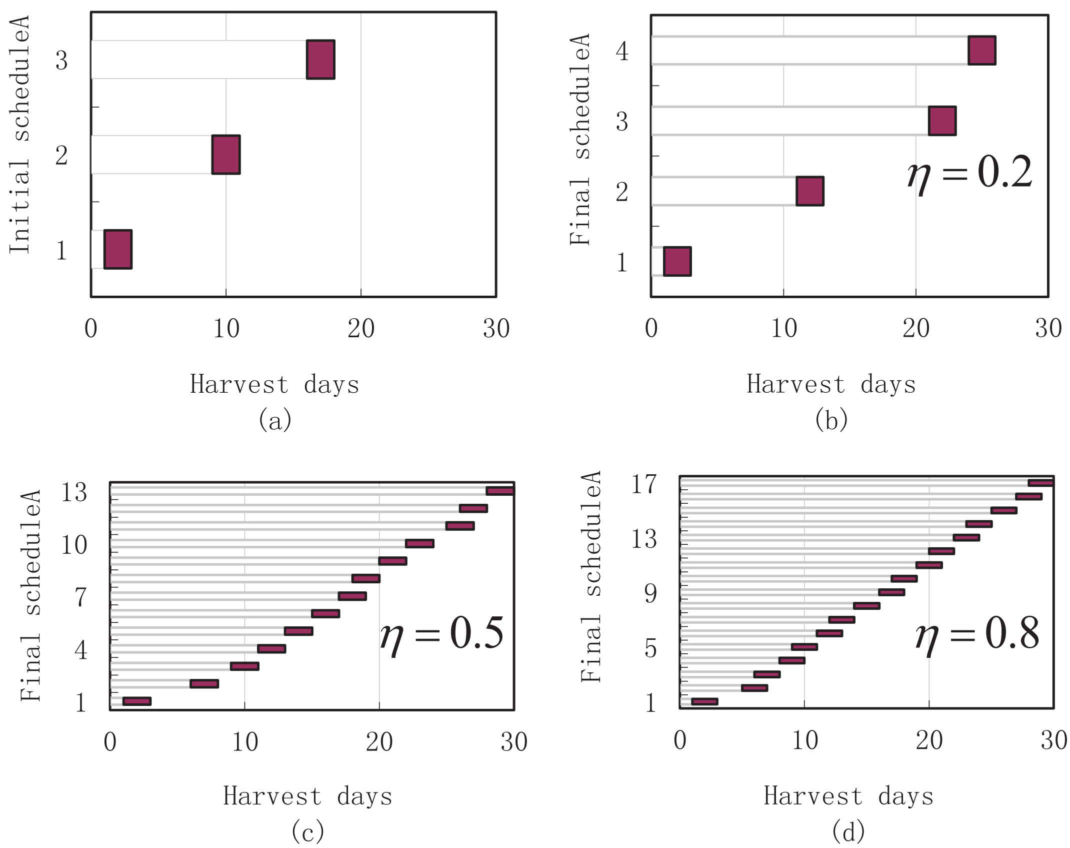

Fig. 10 – Comparison of Schedule As for the optimal plan for the three experiments.

initial plan, unharvest produce and stockouts occurred on many harvesting days; by using the algorithm, the plan could be adjusted so as to reduce the number of days with unharvested and stockouts to almost zero. Meanwhile, the number of days with discounts increased. By making such adjustments, the grower can derive the optimal production plan.

We put forward three experiments by which to demonstrate the validity of the model and the algorithm in different scenarios. In the first experiment, $\eta = 0.5$; hereafter, we refer to this experiment as *a5b5*. In this scenario, the market likes unripe tomatoes as much as ripe tomatoes. Another experiment, where $\eta = 0.2$, is called *a2b8*; in this scenario, the market prefers ripe tomatoes. Finally, the experiment with $\eta = 0.8$ is defined as *a8b2*, and in this scenario, the market prefers unripe tomatoes. The three experiments thus examine various market preferences.

Figs. 8 and 9 show the evolution of the optimal plan during the three experiments. The evolution of costs and profits is similar among the three experiments, suggesting that the proposed model and algorithm can be used to pinpoint optimal plans under various market-preference conditions. Figs. 10 and 11 show the differences in the optimal plans with respect to the three experiments.

Fig. 10(a) shows the initial Schedule A; (b), (c), and (d) show Schedule A of the optimal plan when the market preference is $\eta = 0.2$, $\eta = 0.5$, and $\eta = 0.8$, respectively. Fig. 10 shows that the algorithm can pinpoint optimal plans in line with different market preferences. Fig. 11(a) shows the initial Schedule B; the other parts of Fig. 11 show the changes in Schedule B among the optimal plans related to different market preferences.

The results vis-à-vis the harvesting of tomatoes suggest that the proposed model is effective in pinpointing optimal plans for different market preferences. The use of the proposed model and algorithm would be useful in maximizing the profits of growers who produce crops that have two harvesting methods.

5. Conclusions and future research

In this study, we presented an operational model by which one can plan a crop that features two harvesting methods; ultimately, the aim of this model is to maximize grower and retailer profits. We proposed a new heuristic algorithm by which to pinpoint the optimal model results, and we used as a case study tomatoes, a crop that features two harvesting methods. The results of three experiments showed that the model and algorithm are valid for both tomato-harvesting methods, and that they can be used to generate a harvesting plan by which grower and retailer profits can be maximized. Unlike earlier research, our model can be used to optimize the production of one crop with two harvesting types, and the products harvested by different methods have alternative demands. By using the model, growers can craft an optimized harvesting plan.

The research undertaken in the current study needs further development while taking into account real-world situations, where the demand and yield of crops can change

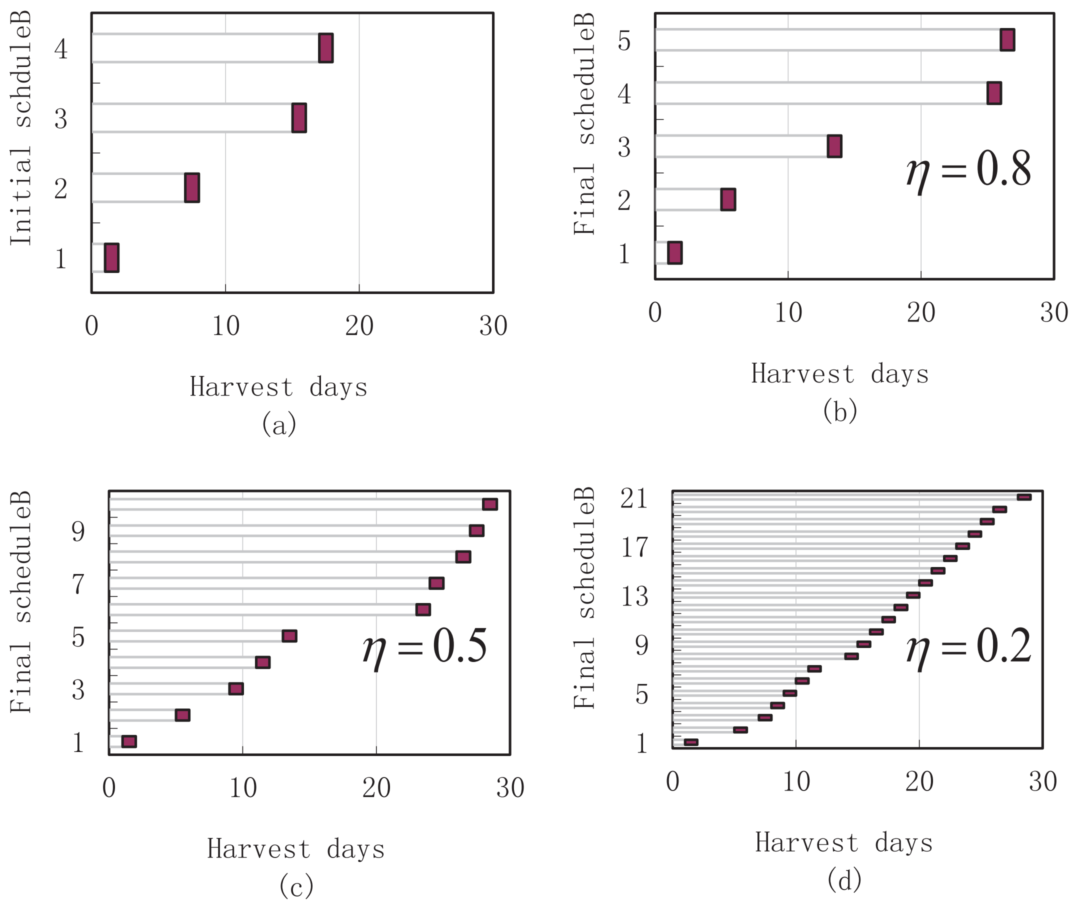

Fig. 11 – Comparison of Schedule Bs for the optimal plan for the three experiments.

dynamically. Future research should consider crops featuring more than two harvesting methods. Additionally, the derivation of optimal harvesting plans for multiple crops is an interesting topic, given current concerns with regard to food production and security. Ultimately, the current study serves as a sound first step in undertaking further developments in the area of crop production involving multiple crop-harvesting methods.

Declaration of Competing Interest

The authors declare that there is no conflicts of interest.

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