A Simulation-Based Metaheuristic Approach to Integrated Scheduling of Seedling Production

Jingyuan Feng, Xiangpei Hu, and Nan Kong, *Senior Member, IEEE*

***Abstract*—Seedling production is important to modern agriculture for its economic value in land utilization and yield promotion. Three crucial decisions for seedling production are new order acceptance, backlogged order fulfillment, and growth rate control. The first decision is made in an on-line fashion whenever a new order arrives, whereas the subsequent two decisions are made periodically. Given the interplay between the three operations and requirements on the heterogeneous frequency of the decisions, many analytical methods lack sufficient flexibility to deal with the problem and difficult to apply in practice. In this letter, we propose a simulation-based metaheuristic optimization approach to identify the appropriate policy for the above decisions, including a fine-grained simulation model for a representative seedling production process, heuristic decision rules on each of the decisions, and a particle swarm optimization algorithm embeds an optimal computing budget allocation scheme to explore the rules combination space efficiently. Through numerical experiments, we justify the viability of our metaheuristic algorithm; show the superiority of our backlog order fulfillment rules over two benchmark sequential dispatching rules; also demonstrate the economic benefit to periodically regulate the production rate rather than keep in invariant rate. Our work presents a novel application of simulation optimization to smart seedling production operations management.**

***Index Terms*—Optimization and optimal control, integrated planning and control, sustainable production and service automation, commercial seedling production, simulation-based metaheuristic.**

I. Introduction

THE agriculture sector is experiencing major changes in many countries with the growing pressure of land and labor shortage, a stringent requirement on food quality, and increasing promotion of sustainable development. Recently, we have witnessed the rapid development of industrial technologies for producing high value-added agriculture goods, including many novel ones in seedling production. Seedling production refers to the industrialized production process from seed (initial state) to seedling (ready to transplant state), which is a vital member of agricultural productive service for its ability of improving the health and yield of the plants to grow. For example, more than half of vegetable cultivation starts with seedling transplantation, which requires plenty of seedlings from seedling production factories.

Fig. 1. Key phases along the production process (photos taken from Panjin Xinye Agri-Tech CO., LTD., Liaoning, China).

Seedling production is a labor-intensive and time-consuming industrial process, typically consists of seed sowing, seedling growing, seedling packing and delivering (see Fig. 1). To offer better protection to delicate seedlings, the whole process is conducted in an environmentally controlled greenhouse, providing seedling factories the feasibility to regulate the production rate of its facilities and allocate nursery resources within the production capacity, in order to maximize its operational profit while maintaining continuous production and fulfilling a variety of customer orders.

From the operation management point of view, seedling production involves three crucial operational decisions. One, the new order acceptance decisions need to be made in real-time. More orders accepted bring higher revenue, but a higher order acceptance rate may lead to an increased backlog and prolonged delivery. Two, to reduce the sowing machine launching cost and for ease of workers gathering, the seedling production factories usually conduct seed sowing in fixed-time intervals, which prompts a periodic decision on which orders from the backlog list to be formed into batches and put into production together. Three, since seedling growing is conducted in an environmentally controlled greenhouse, the growth rate could be determined by precise greenhouse control. Several studies discuss seedling production rate control strategies. For example, Pucheta, *et al.* [1] proposed a neuro-dynamic programming-based optimal controller to regulate the growth of seedling. Gupta, *et al.* [2] developed a decision support system for greenhouse seedling production. Although efforts have been made to regulate the production rate to guide seedling growth to follow some economical trajectory, it still presents a significant opportunity to investigate the production rate control in multi-batch seedling production and the interplay between the production rate control with other seedling production operations.

In the multi-batch seedling production progress, above three decisions are interrelated. A higher proportion of order

Manuscript received November 6, 2021; accepted December 21, 2021. Date of publication January 4, 2022; date of current version January 20, 2022. This letter was recommended for publication by Associate Editor Hyun-Jung Kim and Editor Jingang Yi upon evaluation of the reviewers' comments. This work was supported in part by the National Key R&D Program of China under Grant 2019YFD1101103 and in part by the National Natural Science Foundation of China under Grant 72010107002. *(Corresponding author: Nan Kong.)*

Jingyuan Feng and Xiangpei Hu are with the School of Economics and Management, Dalian University of Technology, Dalian, Liaoning 116024, China (e-mail: jyfeng666@mail.dlut.edu.cn; drhxp@dlut.edu.cn).

Nan Kong is with the Weldon School of Biomedical Engineering, Purdue University, West Lafayette IN 47906 USA (e-mail: nkong@purdue.edu).

Digital Object Identifier 10.1109/LRA.2021.3140056

acceptance may increase backlog orders. Thus, to alleviate backlog pressure, it may be beneficial to set a high production rate to increase the throughput. While a higher rate corresponds to more intervention and increased control cost, the increased cost may be offset by increased revenue due to higher throughput. Meanwhile, appropriate selection of backlog orders could enhance the production capacity use, thus achieving a similar revenue increase. These outcomes being interrelated gives rise to joint decision optimization.

Since the impact of joint decisions on the seedling production process is quite complicated, we develop a fine-grained simulation framework for a representative process to perform process evaluation on several outcomes. Then we introduce an implementable heuristic policy, consisting of threshold-based switching rules for order admission and production rate control, and principle-based subset selection rules for backlog order fulfillment. Given the high computational expense from even one simulation run and a sizable rule-based policy parameter design space, we elect to combine particle swarm optimization (PSO) with an optimal computing budget allocation scheme (OCBA), to search for promising rules' configurations efficiently.

Our paper makes the following contributions. First, the work represents one of the pioneering studies in seedling production management engineering for modern agricultural productive service enterprise. As a result, our research is expected to elevate the process engineering capability in real-world seedling production factories for their production improvement. Second, we develop a representative simulation model with high granularity on this unique multi-batch production process from the literature, which accommodates the three-pronged nature of modern industrialized seedling production, namely make-to-order with real-time order acceptance, batch production with variable capacity, long processing time with controllable production rate.

The remainder of this paper is organized as follows. In Section II, we present a review of the related literature. In Section III, we establish a hybrid event-driven and fixed time-step simulation framework and construct decision rules for the three operations. In Section IV, we propose a PSO-OCBA algorithm to search for the optimal rules' configuration. In Section V, we report case studies to verify the algorithm efficiency and examine the joint system impact of the three decisions. We conclude the paper and outline future research directions in Section VI.

II. Literature Review

This section briefly reviews two categories of relevant literature: seedling production management and decision-making approaches for related operations.

For seedling production management, Ke, *et al.* [3] developed a production planning optimization strategy for industrial seedling production. Rantala [4] solved an integrated production-distribution problem in the seedling supply chain. Ding, *et al.* [5] analyzed the management process in a seedling enterprise and design a management information system. Ozer [6] tested the effect of heterogeneous seedling productions systems. Seedling production has been analyzed from a variety of perspectives in the above studies. However, integrated operation management, including new order acceptance, backlog order fulfillment, and production rate control, remains to be investigated.

Each of the above-mentioned operational decisions individually has been discussed extendedly in the literature. New order acceptance (also known as admission control) has always been a primary focus in capacity management research. For example, Örmeci [7] addressed dynamic admission control of a call center, Abedi and Zhu [8] developed a capable-to-promise based order acceptance model. A limited production capacity often results in backlog orders, brings the study of backlog production sequence or batch generation principle. Erramilli and Mason [9] grouped different backlog orders into jobs, then form the jobs to batches and schedule them on a single batch processing machine. Chen and Dong [10] conducted batch and real-time order fulfillment with allocation models for assemble-to-order system. Flexible production/service rate has shown to be very effective in relieving the adverse impact of customer arrival/demand variance. Zanoni, *et al.* [11] analyzed a system where energy consumption is strictly related to the production rate, find that a flexible production rate enables companies to achieve energy efficiency and economic benefits. Huang, *et al.* [12] investigated the strategy to assign the unstable customer orders to two channels and determine each channel's production rates to minimize the expected total cost.

To better incorporate the characteristics of practical issues, integrated decision-making problem emerged and attracted plenty of attention. To support manufacturing practice, Aouam and Brahimi [13] formulated three models: single production planning with backordering, integrated production and order acceptance, and the integrated model that allows flexible due dates, then show the superiority of the latter one. Ioannidis [13] presented a threshold-based policy for coordinating order admission and production decisions. Wang and Ye [15] formulated mixed-integer programming models for order acceptance and scheduling problem on unrelated parallel machines. Jauhari, *et al.* [16] determined the review period, production rate and delivery number in a production-inventory system, Glock [17] introduced production rate as an decision variable into batch sizing problem, Kim and Glock [18] extended the single machine setting in Glock [17] to multiple parallel machines, determining the lot sizes, production machines selection and their production rate simultaneously. Similar joint decisions could also be found in Logistics and service industries. For example, Noroozi, *et al.* [19] analyzed the tradeoff between revenue of accepted orders, costs of delivery, and penalties for tardiness incurred in an integrated production-distribution system. Qiu, *et al.* [20] proposed a multi-circle strategy for new order acceptance and dynamic vehicle routing. Adusumilli and Hasenbein [21] investigated a queueing system in which the controller can perform admission and service rate control. Yom-Tov and Chan [22] examined the trade-off between admission control and service rate speedup for ICU operation at hospitals, develop a distinct structure of a threshold policy. A summary of the joint operations management literatures is displayed in Table I.

The closest study to our work is Kim and Van Oyen [23], which holistically considered coordinating admission, production sequencing, and production rate control. They assumed the orders could be put into production anytime the system has spare capacity. However, seedling production factories usually conduct seed sowing in fixed-time intervals to save the batch seed sowing cost. This operation somewhat resembles that in many batch processes in manufacturing. However, our process has its uniqueness, namely batches processed together are not required to be complete simultaneously. Seedlings should be removed

TABLE I
BIBLIOGRAPHIC REVIEW FOR JOINT OPERATIONS MANAGEMENT

Articles	Decisions		
	Order Acceptance	Backlog fulfillment	Production Rate Control
Aouam and Brahimi [13], Ioannidis [14], Wang and Ye [15], Noroozi, et al. [19], Qiu, et al. [20]	√	√	
Jauhari, et al. [16], Glock [17], Kim and Glock [18]		√	√
Adusumilli and Hasenbein [21], Yom-Tov and Chan [22]	√		√
Kim and Van Oyen [23]	√	√	√

from the production immediately after achieving the required standard and making certain seedling beds idle, the generation of new batches with new size limits is determined dynamically.

The difficulty of addressing our problem is mainly manifested as various operations involved in the seedling production process are present at different decision scales, some are made at predefined time points while others are triggered by the occurrence of certain events. Moreover, the nature of agriculture production systems, such as long production time and limited shelf life, adds extra difficulty in integrating production plans [24], [25]. Analytical models and exact solution methods like stochastic programming (SP), dynamic programming (DP), or Markov decision process (MDP) lack sufficient level of fidelity and granularity when used to address the above problem. For example, with MDP, making sequential decisions of both event-driven and time-based in a stochastic dynamical environment would be extremely inconvenient from a modeling viewpoint and computationally challenging to solve the resultant optimization model. In response, we elect to employ simulation-based optimization [26], which can capture necessary complexity inherent in the system and evaluate more implementable solutions with the help of a flexible simulation framework.

III. SIMULATION FRAMEWORK AND DECISION RULES CONSTRUCTION

In a seedling production factory, the order acceptance decision should be made immediately after the order arrives, the admitted orders may be backlogged and wait to be sowed later. Each order takes a pre-specified number of seedling beds (i.e., production units). Once the sowed seedling tray is placed on seedling beds, the growth starts. Once the seedlings reach the predefined transplanting standard, they are packed in boxes, and the order is then delivered.

A. System Description

We abstract the production process as a continuously timed and periodically reviewed stochastic dynamic system. New orders arrive in the system continuously and periodic conduct operations take place at the beginning of each decision period. The main characteristics for the seedling production system are summarized below:

- Upon arrival, an order is either accepted or rejected. Since the new production action only takes place once in each decision period, the accepted orders cannot be put into production before the beginning of the next period.

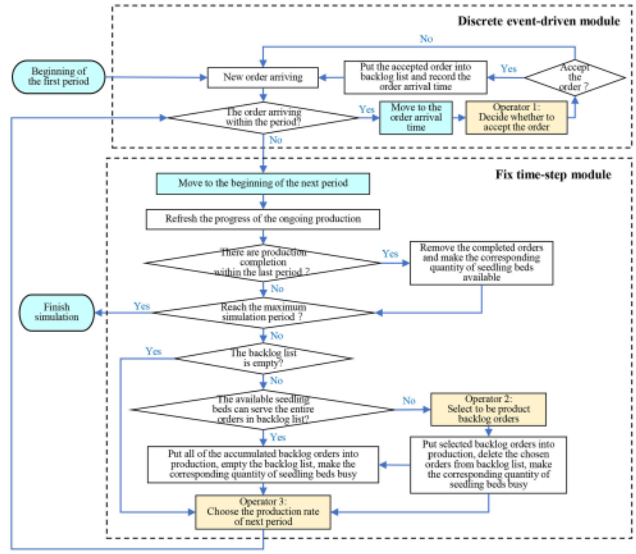

Fig. 2. Simulation Flowchart.

- The on-production status and on-hand demand status are checked at the beginning of every decision period. If the spare seedling beds cannot meet the production units required, only a subset of the backlog orders are put into production. For ease of delivery, each order must be put into production for its entirety.
- For the nature of plant growth, seedling production is assumed to be non-preemptive. That is, the production of a batch cannot stop once its sowing process is initiated. Subsequently, the production rate is regulated periodically.

B. Hybrid Simulation Framework

We develop a simulation framework (see Fig. 2), intending to (1) imitate the behavior of the seedling production system managed by operators, and (2) provide a high-fidelity performance evaluator for candidate rules configuration.

As shown in Fig. 2, the two interconnected parts in the simulation are a discrete event-driven module and a fix time-step module. Blocks with cyan background indicate potential simulation clock advances. Blocks with yellow background represent decision points activated under specific situations and managed by the three operators.

In the beginning, the simulation clock is advanced to the arrival time of the first order, and operator 1 is activated to make the order acceptance decision according to the new order acceptance rule. The next order's arrival time will decide whether to temporarily suspend the execution of the discrete event-driven module. If the new order's arrival time is not within the same period as the current order, the simulation clock is advanced to the beginning of the next period and the simulation enters the fix time-step module.

We implement logic judgment steps in the fix time-step module. First, the ongoing seedling production of every batch should be refreshed according to the production rate from the immediately previous period, and a check is invoked to determine whether any production completion should have occurred during the previous period. If so, completed orders are disposed from the system, leaving the corresponding seedling beds available for future production requests. This is followed by checking

TABLE II
SUMMARIZE OF THE DECISION RULES

Operations	Decision time	Characteristic of the rule
Order acceptance	New order arrives	Threshold-based rule on order acceptance/rejection
Backlog fulfillment	The beginning of each period	Optimality principle-based order subset selection
Production rate control	The beginning of each period	Threshold-based rule on the two-level production rate

the backlog. If it is not empty, another check is invoked to see whether the available seedling beds have the capacity to serve the entire backlog orders. If so, all the accumulated backlog orders will be put into production; otherwise, operator 2 is activated to choose a subset of orders to be put into production according to the backlog order fulfillment rule. Then, the simulation proceeds to adjust the production rate and the decision is made by operator 3 according to the production rate control rule. Finally, the simulator switches back to the discrete event-driven module and check the next order's arrival time. This decision cycle repeats until the last period of the simulation.

A good combination of rules should keep the production running smoothly while maintaining a decent level of profitability. The production process generates revenue whenever orders are complete; incurs sowing cost with seed sowing actions at the beginning of each period. Meanwhile, the cost due to production rate control is dependent on the control mode in each period; and orders' waiting cost are increasing and concave to the time between order acceptance and order completion. We assume that there is no penalty on order rejection. The overall system performance is evaluated by the average daily operational profit shown as:

$$Dop(S) = \left(\sum_{i \in I(|P| \times lp)} \left(R(i) - \sum_{t=at_i}^{dt_i} CW(i,t) \right) - \sum_{p \in P} \left(CB(p) + CR(p) \right) \right) \Big/ \left(|P| \times lp \right) \tag{1}$$

where Srepresents a combination of the decision rules, P is the set of decision periods for fix time-step decisions (i.e., backlog order fulfillment and production rate control decisions), $lp$is the lengths of one decision period, $I(t)$is the set of accepted orders up to time t, $at_i$and dt_i refer to the arrival time and completed time of the accepted order i. $R(i)$, $CW(i,t)$, $CB(p)$, $CR(p)$ represent the revenue generated by order admission, the penalty brought by backlog waiting, the cost spent for batch seed sowing, and the cost associated with production rate control, respectively.

C. Decision Rules Construction

Now, we construct decision rules for the three operations. A summary of the decision rules can be also found in Table II.

i) Regarding the new order acceptance, we consider a threshold rule based on the sum of backlog quantity and new order quantity (i.e., the size of backlog order pool or the length of order queue). If the quantity does not reach a certain threshold, it seems preferable to accept the incoming order to avoid the waste of production capacity. Otherwise, due to the backlog waiting penalty, it is desirable to reject an order when the acceptance action results in a large backlog.

ii) The periodic decision on the backlog order fulfillment is made myopically with a 0-1 knapsack problem. We consider two candidate rules as MUO (i.e., Maximum production unit occupancy) and MWS (i.e., Maximum backlog waiting-cost saving). MUO aims to increase capacity utilization as much as possible by selecting orders that can lead to large occupancy of available production units, while MWS gives priority to orders with higher waiting costs to avoid the backlog order waiting penalty.

iii) For the production rate control, we consider a threshold rule based on incomplete production quantity (i.e., total number of accepted but not delivered products), the indicator estimates the overall congestion of the system. If the incomplete production quantity reaches a certain threshold, a higher production rate is adopted; if there are incomplete productions but the quantity does not reach the threshold, a lower rate is adopted; otherwise, no intervention is needed.

It is intuitive to see that while the above decisions are made independently at different time points, they are interconnected and influence the production process jointly. We implement these decision rules in the simulation and obtain promising rule combinations via a simulation-based metaheuristic approach in the following sessions.

IV. SIMULATION-BASED METAHEURISTIC

We present a simulation-based metaheuristic method that utilizes PSO under the scheme of OCBA. We elect to apply PSO as the optimization engine for its strong spatial exploration ability. The momentum effects on particle movement provide fast convergence and diversity in searching trajectories [27]. However, stochasticity in the simulation, which could be regarded as noise factors to the optimization procedure, makes the particles easily misled by the inaccurate fitness evaluation. While one can reduce the noise effect by making simulation runs with multiple samples, it raises the concern of undesirable/uncontrollable computational burden. This promotes us to embed OCBA, a Bayesian ranking and selection procedure, into the PSO algorithm. Designed by Chen and Lee [28], OCBA uses sequential resampling to intelligently allocate additional computing budget on more promising candidates. Taking advantage of PSO and OCBA, the searching efficiency and accuracy are likely ensured simultaneously.

The PSO operations are presented in Algorithm 1. At iteration t, particle i has a position vector $\mathbf{X}_\mathrm{i}^\mathrm{t}$ that represents a potential solution to the problem, and a velocity vector $\mathbf{V}_\mathrm{i}^\mathrm{t}$ that in charge of the changing direction and range of $\mathbf{X}_\mathrm{i}^\mathrm{t}$. Moreover, record $\mathbf{Pb}_\mathrm{i}^\mathrm{t}$ as the personal best found by particle i so far, record $\mathbf{Gb}^\mathrm{t}$ as the global best found in the swarm so far. The velocity and location of particle i at iteration $t+1$ are updated by (2) and (3).

$$\begin{aligned} \mathbf{V}_\mathrm{i}^\mathrm{t+1} = {} & \omega \times \mathbf{V}_\mathrm{i}^\mathrm{t} \\ & + c_1 \times r_1 \times (\mathbf{Pb}_\mathrm{i}^\mathrm{t} - \mathbf{X}_\mathrm{i}^\mathrm{t}) \\ & + c_2 \times r_2 \times (\mathbf{Gb}^\mathrm{t} - \mathbf{X}_\mathrm{i}^\mathrm{t}) \end{aligned} \tag{2}$$

$$\mathbf{X}_\mathrm{i}^\mathrm{t+1} = \mathbf{X}_\mathrm{i}^\mathrm{t} + \mathbf{V}_\mathrm{i}^\mathrm{t+1} \tag{3}$$

Algorithm 1: *PSO*

Input: swarm size s, inertia coefficient ω, cognitive coefficient c_1, social coefficient c_2
Output: optimal rules configuration $\boldsymbol{Gb}$

PSO iteration $t \leftarrow 0$;
for *each particle* $i = 1$ *to* s **do**
  Uniformly generate particle location $\boldsymbol{X}_i^t$ and randomly generate velocities of each particles $\boldsymbol{V}_i^t$;
  $\boldsymbol{Pb}_i^t \leftarrow \boldsymbol{X}_i^t$;
while *not terminated* **do**
  call **OCBA** algorithm for sample mean $\bar{J}_i\ (i = 1, ..., s)$;
  for *each particle* $i = 1$ *to* s **do**
    $f(\boldsymbol{X}_i^t) = \bar{J}_i$;
  if t*=0* **then**
    for *each particle* $i = 1$ *to* s **do**
      $f(\boldsymbol{Pb}_i^t) \leftarrow f(\boldsymbol{X}_i^t)$
  else
    if $f(\boldsymbol{X}_i^t) > f(\boldsymbol{Pb}_i^{t-1})$ **then**
      $\boldsymbol{Pb}_i^t \leftarrow \boldsymbol{X}_i^t$;
    else
      $\boldsymbol{Pb}_i^t \leftarrow \boldsymbol{Pb}_i^{t-1}$;
  $\boldsymbol{Gb}^t \leftarrow arg\max f(\boldsymbol{Pb}_i^t)$;
  for *each particle* $i = 1$ *to* s **do**
    Update $\boldsymbol{V}_i^{t+1}$ and $\boldsymbol{X}_i^{t+1}$ according to Eq.(2) and Eq.(3);
  $t \leftarrow t + 1$;
$\boldsymbol{Gb} \leftarrow \boldsymbol{Gb}^t$

where c_1 and c_2 define how much a particle trusts its own search history and the whole set of particles.ω balances global and local search abilities and prevents the search from being trapped in local optima, r_1 and r_2 are two random variables between 0 and 1, which updated at each iteration. The fitness function $f$records the expected daily operational profit of specific rule configuration, equivalent to the mean output of multiple replications, as calculated by (1), and it is referred to as the sample mean in the following statement.

At every iteration of particle evolution, the OCBA algorithm is called upon to sequentially allocate the computing budget to candidate particles and obtain reliable performance estimates to help PSO identify elite particles. Algorithm 2 describes the operations of OCBA in detail. The algorithm proceeds by taking an initial sample $N_i^0 = n_0$ for each particle. Then the remaining budget $B - s \times n_0$ is divided into equal increment of computing budget Δ, and is allocated to particles that offer the greatest potential. Chen and Lee [28] prove that for incremental computing budget $\Delta = \sum_{i=1}^{s} N_i^{l+1}$, the approximate probability of correct selection is asymptotically maximized if:

$$N_i^{l+1} / N_j^{l+1} = (\sigma_i \times (\overline{J_b} - \overline{J_j}))^2 \Big/ (\sigma_j \times (\overline{J_b} - \overline{J_i}))^2,\ i \neq j \neq b \tag{4}$$

$$N_b^{l+1} = \sigma_b \sqrt{\sum\nolimits_{i=1, i\neq b}^{s} (N_i^{l+1}/\sigma_i)^2} \tag{5}$$

where N_i^{l+1} is the number of samples allocated to particle i in the next OCBA round, σ_i and $\overline{J_i}$ represent the sample mean and sample standard deviation for particle i, b stands for the best particle (the one with the highest sample mean).

V. Experiment Results and Analysis

A. Case Setting

We specify our simulation to capture a common seedling production system, which integrates representative features of our three partnering seedling production factories in China, including Panjin Xinye Agri-Tech CO., LTD (http://www.yinongjt.com/), Liaoning Yinong Agri-Tech CO., LTD (http://www.xynykj.com.cn/), and Haicheng Sanxing Ecological Agriculture CO., LTD (http://www.sxstny.com/).

Algorithm 2: *OCBA*

Input: particle location $\boldsymbol{X}_i^t$ $(i = 1, ...s)$, simulation budget B, initial simulation number n_0, one-time increment Δ
Output: sample mean $\bar{J}_i\ (i = 1, ..., s)$

OCBA round $l \leftarrow 0$;
for *each particle* $i = 1$ *to* s **do**
  perform n_0 simulation replications based on $\boldsymbol{X}_i^t$;
  particle simulation number $N_i^l \leftarrow n_0$;
Budget used $B^l \leftarrow m * n_0$;
while $B^l < B$ **do**
  for *each particle* $i = 1$ *to* s **do**
    Update sample mean $\bar{J}_i$ and standard deviation σ_i;
  Find optimal particle $b \leftarrow arg\max_i \bar{J}_i$;
  Calculate budget allocation proportion according to Eq.(4) and Eq.(5) ;
  for *each particle* $i = 1$ *to* s **do**
    Perform additional $\max(0, N_i^{l+1} - N_i^l)$ simulation replications for design i, satisfying $\sum_{i=1}^{s} \max(0, N_i^{l+1} - N_i^l) = \Delta$;
  Budget used $B^{l+1} \leftarrow B^l + \Delta$;
  $l \leftarrow l + 1$;

TABLE III
Parameters Value in the Case

Parameter	Value
Order completion revenue per unit	$r_1 = 2800,\ r_2 = 2400$
Batch sowing fixed cost per day	$cbf = 700$
Batch sowing variable cost per unit	$cbv = 700$
Production cost related to the two-level rate control for the whole facility per day	cs_1=4800, $cs_2 = 2000$
Time related backlog order waiting cost per unit	$\sum_{t=1}^{w(k)} 10^{-2} \times r_i \times (1+10^{-3})^t$ (*w(k)* is the waiting time (in days) of the accepted order *k*)
Length of each decision period	$lp = 5$ days

In the simulation, we generate seedling orders of two vegetable types (i.e., type 1: fruit vegetables; type 2: leafy vegetables), which leads to type-dependent order completion reward. The seedling production time can take any number of days between 14 and 40, determined by the seedling type and production rate. A seedling production rate is a percentage number measuring daily seedling progression towards completion. For fruit vegetables, the daily rate is 4.0% or 7.2% of the entire duration, whereas for leafy vegetables the daily rate is 2.5% or 5%. A higher production rate is achieved by intensive intervention in the greenhouse. We set the facility capacity to be 20 seedling beds and consider demand quantity of each order to be a multiple of bed number. The values of the basic parameters are reported in Table III. The measuring unit of cost and revenue is RMB.

B. Computational Results and Observations

The simulation and the PSO-OCBA algorithm are implemented in Matlab 2019b on desktop DELL Vostro 3668 (CPU: Intel Core i7-7700, RAM: 8GB DDR4 2.4GHz, Graphics: NVIDIA GTX1050). Through preliminary testing, the PSO algorithm parameters are fixed to be: swarm size $s = 20$, inertia

TABLE IV
COMPUTATIONAL RESULTS OF DIFFERENT ORDER ARRIVAL CHARACTERISTICS

No	Influential Factors		*Bp = MUO*					*Bp = MWS*				
			Optimal Thresholds		System Performance Metrics			Optimal Thresholds		System Performance Metrics		
	λ	$Q_{\max}$	*Ot*	*St*	*Wll*	*Oar*	***Dop***	*Ot*	*St*	*Wll*	*Oar*	***Dop***
1	level 1	low	17	19	0.88	92%	**491**	17	19	1.20	91%	**835**
2	level 2	low	16	18	1.17	92%	**2113**	15	14	1.43	87%	**2388**
3	level 3	low	13	12	1.80	87%	**3983**	12	10	2.21	73%	**3120**
4	level 4	low	12	9	2.84	76%	**4311**	10	8	2.36	68%	**3790**
5	level 1	medium	16	15	0.76	90%	**2771**	16	10	0.82	87%	**2998**
6	level 2	medium	14	9	1.55	84%	**3996**	14	8	1.82	71%	**3390**
7	level 3	medium	13	6	2.04	75%	**4221**	11	7	2.14	62%	**3561**
8	level 4	medium	11	6	3.01	51%	**4244**	10	7	2.47	61%	**3711**
9	level 1	high	15	8	0.82	83%	**2849**	16	10	0.51	91%	**2251**
10	level 2	high	13	6	1.37	75%	**3372**	10	8	1.25	64%	**3199**
11	level 3	high	11	6	2.45	58%	**4252**	10	7	2.03	57%	**3500**
12	level 4	high	11	6	3.84	51%	**4477**	10	7	2.62	44%	**3785**

Notes: λ = Order arrival rate; $Q_{\max}$ = Maximum allowed order quantity; *Bp* = Backlog production selection rule (*MUO* = Maximum production unit occupancy, *MWS* = Maximum backlog waiting-cost saving; *Ot* = Optimal order acceptance threshold; *St* = Optimal production rate control threshold; *Wll* = Average waiting list length; *Oar* = Average order acceptance rate; *Dop* = Average daily operational profit.

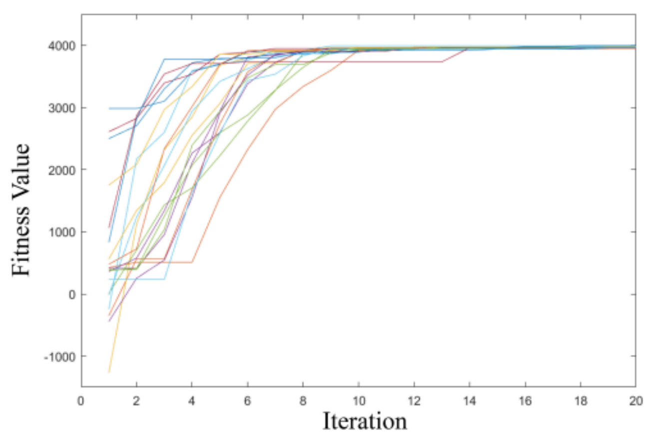

Fig. 3. Fitness values of each particle's Pb over iterations.

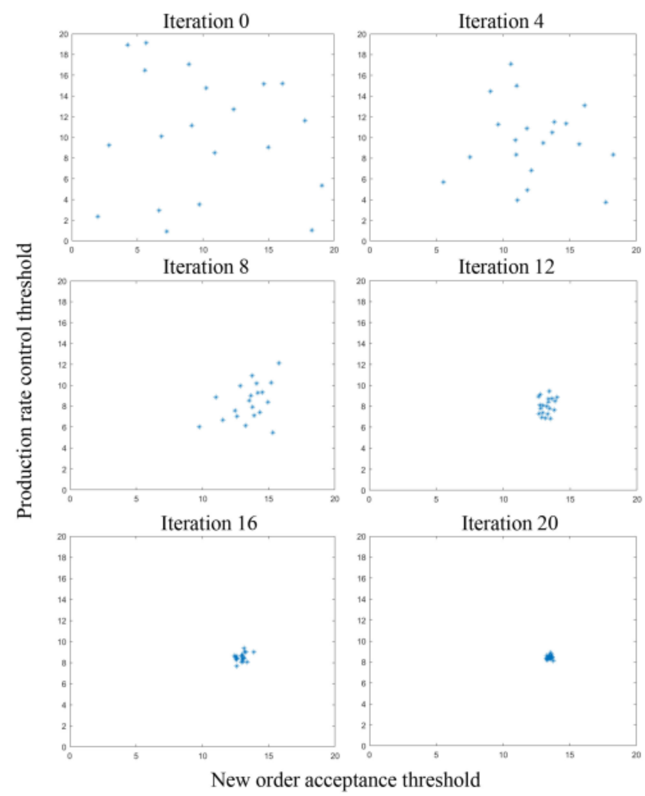

Fig. 4. Particles' location over the PSO iterations.

coefficient $\omega = 0.5$, cognitive coefficient $c_1 = 0.2$, social coefficient $c_2 = 0.2$. Following Chen and Lee [28], we set the initial sample size of each particle in OCBA to be $n_0 = 5$, computing budget in each resampling iteration to be $\Delta = s/10$, and length of each simulation are 500 days with a 20-day warm-up period. In each simulation process, the orders are generated following a Poisson process of constant arrival rate, and the capacity required per order follows a discrete uniform distribution. Through preliminary experiments, we find that the running time of each simulation replication varies from 2 to 5 seconds. Accordingly, we set a budget of 300 replications to be allocated sequentially to particles by OCBA for each PSO iteration, the experiment results show that the algorithm converges to a stable point within 20 PSO iterations. Overall, the total run-time of the PSO-OCBA algorithm is 3 to 8 hours.

In the baseline case, we choose key factors that are likely to influence the optimal rule configuration as: order arrival rate (i.e., the average number of daily arrivals) λ=0.3, maximum allowed order quantity (i.e., the maximum allowed seedling beds required by an order) $Q_{\max}$=7. Fig. 3 and Fig. 4 shows the evolution of each particle's personal best (i.e., Pb) and the particle location trajectory over iterations, the converge and clustering phenomenon suggests the viability of our solution method.

To examine how the identified rule-based solution is affected by changes in order arrival character, we consider 12 instance settings with 4 levels of order arrival rate λ (level 1 = 0.2, level 2 = 0.3, level 3 = 0.4, level 4 = 0.5), and 3 levels of maximum allowed order quantity $Q_{\max}$ (high = 9 units, medium = 7 units, low = 5 units). The results of the 12 instance settings are reported in Table IV.

Taking the average daily operational profit as the system performance evaluation metrics, our results suggest that only in the case of low order arrival rate and low maximum allowed order quantity (i.e., instance no. 1,2,5), the maximum backlog waiting-cost saving selection rule (*Bp* = *MWS*) is preferred than the maximum production unit occupancy criterion (*Bp* = *MUO*).

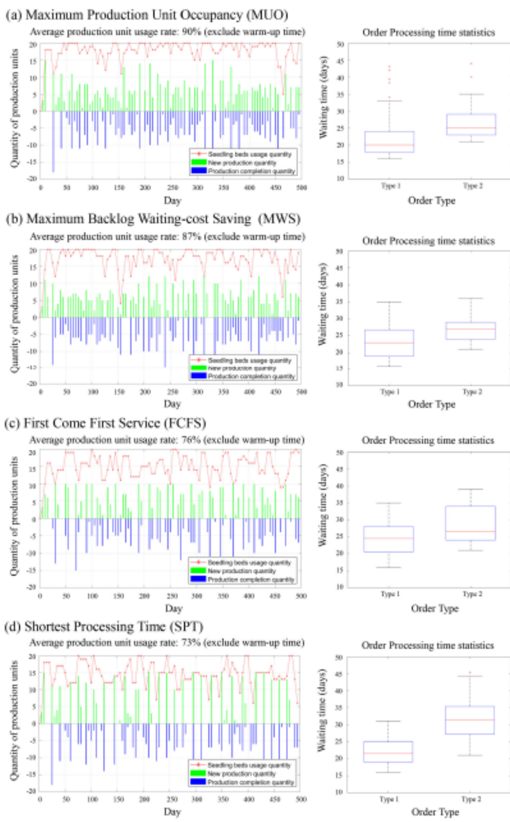

Fig. 5. Comparison of different backlog order fulfillment rules.

Another observation is made when increasing the order arrival rate. The optimal order acceptance threshold decreases to reduce the system congestion, and the optimal production rate control threshold decreases to increase the throughput and potential profit. Due to limited production capacity and high control cost for faster production, it stays almost constant with continuous increase of the order arrival rate.

C. Management Insights and Discussions

We also conduct numerical experiments to examine 1) the applicability of our proposed backlog selection rules in comparison with the well-known dynamic scheduling rules; 2) the superiority of periodic production rate regulation compared to production control with a time-invariant rate.

1) Applicability of Our Backlog Selection Rules: We test our backlog order fulfillment rules (i.e., MUO and MWS) against two well-known sequential dispatching rules, namely FCFS (First Come First Service) and SPT (Shortest Processing Time). When seedling beds become available, FCFS (widely used in current practice) puts in production the earliest backlogged orders that still remain, SPT selects orders with the shortest processing time (in our problem, although the processing time depends on production rate control during the following periods and cannot be fixed upon the start of production, the production rate of one order type is always higher than the other under the same greenhouse condition, thus SPT explicitly give priority to one order type). Fig. 5 record the experiment results.

In Fig. 5, the changes in seedling bed usage associated with new production quantity and production completion quality are tracked over time in the left charts. The order processing time summary statistics over accepted orders are displayed in the right charts. The result indicates that our proposed backlog order fulfillment rules (i.e., MUO and MWS) outperform the benchmark rules (i.e., FCFS and SPT) in terms of the unit utilization rate, and MUO realizes more consistent use of production capacity than MWS. In terms of order waiting time, MWS and FCFS offer more stable processing time for both order types. Few orders represent much longer waiting time with MUO, and type 2 is less preferred at the backlog selection with SPT, which leads to customer dissatisfaction. In conclusion, MUO and MWS are more suitable for the seedling production system studied. We summarize the performance comparison qualitatively in Table V.

TABLE V
SUMMARY OF DIFFERENT BACKLOG ORDER FULFILLMENT RULES

Backlog selection rule	Evaluation criterion	
	Capacity utilization	Order processing time
MUO	++	-
MWS	+	+
FCFS	-	+
SPT	-	-

Notes: '++' = 'Excellent', '+' = 'Good', '-' = 'So-so'

TABLE VI
COMPARISON OF DIFFERENT PRODUCTION RATE CONTROL STYLES

Control Style	Revenue and costs				
	Roc	*Cbs*	*Cbw*	*Crc*	***Dop***
Keeping low rate	4932	858 (17%)	1949 (40%)	1758 (36%)	**367 (7%)**
Periodic rate adjustment	9356	911 (10%)	3542 (38%)	2131 (23%)	**2771 (30%)**
Keeping high rate	9876	920 (9%)	3916 (40%)	2757 (28%)	**2282 (23%)**

$\lambda = level\ 4$ (highest)

Control Style	Revenue and costs				
	Roc	*Cbs*	*Cbw*	*Crc*	***Dop***
Keeping low rate	6704	952 (14%)	1941 (29%)	1955 (29%)	**1856 (28%)**
Periodic rate adjustment	12164	813 (7%)	3979 (33%)	3129 (25%)	**4244 (35%)**
Keeping high rate	11868	815 (7%)	3957 (33%)	3558 (30%)	**3538 (30%)**

Notes: λ= Order arrival rate; *Roc* = Average daily order completion revenue; *Cbs* = Average daily batch sowing cost; *Cbw* = Average daily backlog waiting cost; *Crc* = Average daily production rate control cost; *Dop* = Average daily operational profit.

2) Superiority of Periodic Production Rate Adjustment: To test the superiority of periodic production rate adjustment, we compare it against two baseline environment control styles (i.e., keeping in low rate or keeping in high rate. We consider two cases with the lowest and the highest order arrival rates, respectively; other parameters follow the baseline setting. The results in Table VI show that periodic production rate adjustment always makes sense.

VI. CONCLUSION

Industrial seedling production has become increasingly prominent in modern agriculture. Besides the use of advanced agricultural technologies, several operational level decisions are critical to a seedling production factory, such as selecting the most valuable orders from the new order stream; determining the order production sequence to improve production efficiency and reduce customer dissatisfaction; periodically regulating the production rate with consideration of seedling bed utilization and backlog order status. These operational decisions should be considered jointly to achieve profit maximization. However, analytical models and exact solution methods lack sufficient level of fidelity and granularity when used to address the problem. In this paper, we develop a simulation-based optimization approach, including a hybrid simulation framework for a representative of the seedling production system, several heuristic rules to control the dynamic production process, and a PSO-OCBA algorithm to search promising rule configurations efficiently. With our experiments, we justify the viability of the approach, examine the changes in optimal rule parameters with respect to order arrival rate and maximum order quantity. We also examine the superiority of proposed backlog fulfillment rules and periodic production rate regulation scheme. The practical implications of our work fall in two aspects. First, new backlog order fulfillment rules perform better than traditional sequential dispatching rules in seedling production application. Second, more economic benefit can be achieved if the production rate is dynamically regulated rather than fixed.

In the future, we plan to explore the following research items. First, it would be of much value to study the case where a seedling production factory coordinates price quotation and production scheduling for uncertain order inquiries. This adds another dimension to the decision and further complicates the ensuing analysis. Second, while we have made meaningful attempts to support practical decisions in seedling production system, the rule-based decision approach remains ad-hoc and myopic. In a follow-up study, we will take a more data-driven approach to identify the key decision(s) in collaboration with our industry partner and attempt to formulate a Markov decision process model with the more focused decision issue.

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