The Effect of Early Order Commitment in Order-Driven Supply Chain

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Abstract

In an order-driven supply chain (e.g. perishable product supply chain) consisting of a single manufacturer and multiple customers (i.e. downstream customer enterprises), the manufacturer determines its production capacity (e.g. number of workers) at a certain time based on the orders that have been already received and the predicted orders to come, and fulfills orders beyond the capacity by increasing it with higher production cost rate. In this paper, we introduce an early order commitment (EOC) strategy into the order-driven supply chain, wherein each customer enterprise places orders either before (i.e. early orders) or after (i.e. regular orders) the determination of manufacturer’s production capacity independently without knowing others’ order timings. Towards this end, we develop an analytical model for a grafted seedling supply chain as a case study to quantify the manufacturer’s production capacity and customer enterprise’s optimal order quantity, respectively. To estimate the production cost rate, a simulator was developed mimicking nursery and grafting operations together with related material handling activities. The experiment results indicate that EOC is beneficial to the entire supply chain but increases customer enterprise’s demand forecasting error, and each customer’s purchase cost rate is affected by both its own and others’ ordering times.

Keywords
Supply chain coordination, grafting propagation, discrete event simulation, ANOVA

1. Introduction

Order-driven production is commonly used in various supply chains, e.g. a perishable product supply chain, as the product perishability does not allow manufacturers as well as downstream supply chain members to build inventory before the demand is known. For this type of supply chain, the short delivery time and low product cost requirement together have posed great challenges on achieving a high service level. Therefore, independent members (e.g. manufacturers, wholesalers and retailers) within the same supply chain need to coordinate to provide low cost but high quality products for the market such that the entire supply chain remains competitive with their competing supply chains. Due to the advances in information system technologies (e.g. ERP) in recent years, market demand information can be shared through the entire supply chain almost in real-time. However, the information transparency has to be coupled with a corresponding well-designed production capacity to realize low production cost and quick response to the market dynamics. Normally, the manufacturer’s production capacity should be determined via demand forecasting, and be ready before orders from downstream are received. This applies to both traditional and order-driven supply chains. To respond to the unexpected demand, the production capacity can be further expanded or emergency supply can be purchased from other manufacturers [1], if the total demand goes beyond the current capacity. For a certain category of perishable products that require intensive manual operations and have seasonal demand (e.g. grafted vegetable seedlings), however, building up emergency production capacity in a short time is quite challenging and could increase the production cost rate dramatically. For example, a grafting enterprise (i.e. producer of grafted seedlings) has to build new chambers and hire temporary grafting workers at a higher cost (e.g. additional training cost) if its on-hand orders exceed available capacity. Such emergency capacity expansion may not even be realizable sometimes since temporary workforce may not be always available. Over-planned capacity, on the other hand, leads to low capacity utilization and thus higher amortized capacity construction cost and maintenance cost. Therefore, it is critical for the manufacturer to prepare the “right” capacity to achieve low product cost for the entire supply chain, especially when the demand is highly seasonal. Since the existing demand forecasting approaches are highly dependent on historical data (which may not be available or
applicable in many cases) and the accuracy of forecasting results is also scenario-dependent, an ideal way for the manufacturer to minimize the capacity design bias is to acquire the order information in advance. This accordingly requires the customer enterprises to commit their orders to the manufacturer prior to the determination of the production capacity, and this is referred to as early order commitment (EOC). However, placing early orders may increase customer enterprises’ risks of shortage or overage as a longer delivery lead time enlarges their demand forecasting windows. To motivate the customer enterprises to place early orders, supply chain coordination needs to be applied for sharing the potential benefits of implementing EOC between the manufacturer and its customer enterprises.

EOC has drawn many researchers’ attention in the past decade. For analytical studies, [2] quantified the benefits of implementing EOC for a steel distributor, and the price discount the distributor should provide for its customers. [3] proved that EOC is beneficial to both the supplier and buyers when the demand uncertainty is below a certain level. [4] studied a supply chain consisting of a manufacturer and a retailer who places periodic orders. They identified that the optimal EOC period for the retailer could be either the regular lead time or zero (meaning that early order is not beneficial). [5] extended the problem to a single manufacturer and multi-retailer case, and identified that the optimal EOC period derived in [4] still holds. Besides, computer simulation is also adopted to investigate the effect of EOC. For example, to compare the performance of EOC with demand forecasting models, a comprehensive simulation study was conducted by [6]. Recently, [7] identified the significant factors to the benefits from EOC for a supply chain with (S, s) inventory policy. Nevertheless, none of those findings apply to our supply chain configuration, that is, the manufacturer’s capacity is undetermined and affects each customer enterprise’s purchase cost. To the best of our knowledge, no study of EOC has been published for that supply chain configuration. In this paper, we consider an order-driven grafted seedling supply chain consisting of a single grafting enterprise (i.e. manufacturer) and ten vegetable growers (i.e. customer enterprises) who can place either regular orders or early orders. The grafting enterprise needs to determine its production capacity no later than a certain time point based on the existing order information (if receive any early orders) and demand forecasting. The vegetable growers forecast the demand from their downstream customers, and determine the grafted seedling quantities they should order from the grafting enterprise as well as the corresponding ordering times. This paper contributes to the literature in the following aspects. 1) We quantify the grafting enterprise’s production capacity and vegetable grower’s optimal order quantity; 2) we investigate the effect of EOC on the performance of each supply chain member in terms of profit and operational decisions (e.g. production capacity utilization and order fulfillment), as well as the significant factors to that effect via ANOVA; 3) a generic grafting propagation simulator, user interface and database are developed to estimate the grafting propagation cost rate under various scenarios via simulating the grafting propagation using real data.

The rest of paper is organized as follows. We describe the supply chain configuration in Section 2, and quantify the grafting enterprise’s production capacity and vegetable grower’s optimal order quantity in Section 3. Section 4 provides the details of supply chain simulation modeling. ANOVA is conducted in Section 5, and the effect of EOC on supply chain performance is analyzed in Section 6. Conclusions and future extensions are discussed in Section 7.

2. Supply Chain Description

Grafting is a horticultural technique used in crop management, wherein tissues from one plant (e.g. scion) are joined with another (e.g. rootstock) to obtain an integrated genotype. A typical grafted vegetable seedling supply chain is illustrated in Figure 1. The vegetable growers produce various vegetables (e.g. tomato) and supply to their downstream customers (e.g. supermarkets). They usually purchase vegetable seedlings from professional seedling producers (e.g. a grafting enterprise) instead of building their own propagation facility. Based on the demand forecasting, vegetable growers place seed orders (for both scions and rootstocks) to a seed supplier and grafted seedling orders to a grafting enterprise, and expect the delivery of grafted seedlings before the start of planting season (a3 in Figure 2). Note that we assume that seeds for grafting propagation are ordered directly by vegetable growers, which differs from traditional supply chains where manufacturers order raw materials. The uncertainty of seed delivery lead time is neglected in this paper as the seed supply is usually stable. After receiving the seeds from the seed supplier, the grafting enterprise starts grafting propagation based on the grafted seedling order deadline. The grafting propagation is conducted in both propagation nursery and grafting department, and consists of sequential stages and processes of seeding, germination, pre-sorting grow-on, sorting, pre-grafting grow-on, grafting, healing, and post-grafting grow-on. For detailed grafting propagation procedures, readers are referred to [8]. After the grafting propagation is completed, the grafted seedlings are shipped to vegetable growers for vegetable planting.
In this paper, we only focus on a two-echelon supply chain consisting of a single grafting enterprise and $N$ vegetable growers as highlighted by the dotted background in Figure 1.

Figure 1: Material and information flows within grafted seedling supply chain

Figure 2 shows a vegetable grower’s critical ordering and production time windows in days. A vegetable grower expects to receive the grafted seedlings no later than day $a_3$ to catch the planting season (normally one day after $a_3$). The minimum time for the grafting enterprise to deliver the grafted seedlings to a vegetable grower is thereby $a_3-a_2$, the seedling delivery lead time. This lead time includes the time for grafting propagation and seedling shipment. For the grafting enterprise, it needs to prepare its production capacity by building the propagation facility (e.g. healing chambers), purchasing materials (e.g. substrate materials), and employing grafting workers for the coming orders. The least time required for those preparation activities is $a_2-a_1$, meaning that the grafting enterprise needs to determine its production capacity and start preparation no later than day $a_1$ in order to meet the deadline of $a_3$. Since vegetable growers normally place their orders slightly earlier than day $a_2$ to minimize their demand forecasting error, we name the period between $a_1$ and $a_2$ as regular order window. Accordingly, the time before day $a_1$ is considered as early order window as the grafting enterprise has not determined its capacity yet.

Figure 2: Time windows for vegetable growers

In addition, we define the production capacity determined on day $a_1$ as $Cap$, and this capacity is referred to as the regular capacity. The production cost rate associated with this capacity is defined as $c_r$. If the orders that have been received exceed the regular capacity, emergency capacity can be built, for which the production cost rate is $c_e$ ($c_e > c_r$). Those production cost rates include amortized facility construction cost, utility cost, material cost and labor cost. The prices for grafted seedlings are defined as $p_s$ and $p_c$ ($p_s > p_r$, and $p_c-c_r < p_r-c_r$) for those propagated via regular and emergency capacities, respectively. This implies that the grafting enterprise would lose some marginal profit by using emergency capacity. The vegetable growers are assumed to be homogeneous in terms of vegetable production cost and sale price, which are defined as $c_v$ and $p_v$, respectively, regardless of the grafted seedling price. The transportation cost is neglected in this paper as it only accounts for a small portion of grafted seedling price. Without losing generality, all the cost and price parameters are assumed to be plant-based (in reality, the price of vegetable is weight-based). In addition, the overage cost and shortage penalty for vegetable growers are defined as $c_v$ and $p_v$, respectively. It is also assumed that the mean of a vegetable grower’s demand for grafted seedlings is a constant. But the standard deviation is a function of ordering time (see Section 3.1). The parameters for supply chain modeling are summarized in Table 1.
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Table 1: Parameters for supply chain modeling

<table>
<thead>
<tr>
<th>Notation</th>
<th>Explanation</th>
<th>Notation</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>Number of vegetable growers</td>
<td>$\mu_k$</td>
<td>Mean of demand for vegetable grower $k$ (plant)</td>
</tr>
<tr>
<td>$k$</td>
<td>Vegetable grower index</td>
<td>$c_v$</td>
<td>Vegetable production cost ($/plant)</td>
</tr>
<tr>
<td>$c_r$</td>
<td>Grafted seedling production cost rate for regular capacity ($/plant)</td>
<td>$p_v$</td>
<td>Vegetable sale price ($/plant)</td>
</tr>
<tr>
<td>$p_r$</td>
<td>Grafted seedling production cost rate for emergency capacity ($/plant)</td>
<td>$\sigma_k(T_k)$</td>
<td>Standard deviation of the demand for vegetable grower $k$ (plants)</td>
</tr>
<tr>
<td>$p_s$</td>
<td>Seedling price for emergency capacity ($/plant)</td>
<td>$T_k$</td>
<td>Vegetable grower $k$’s ordering time</td>
</tr>
<tr>
<td>$Cap$</td>
<td>Grafting enterprise’s regular capacity (plant)</td>
<td>$c_o$</td>
<td>Overage cost for vegetable growers ($/plant)</td>
</tr>
<tr>
<td>$D_k$</td>
<td>Actual demand for vegetable grower $k$ (plant)</td>
<td>$E(Q_{k}(...))$</td>
<td>Expectation of vegetable grower $k$’s order quantity (plant)</td>
</tr>
</tbody>
</table>

3. Quantification of Production Capacity and Order Quantity

3.1 Determination of Grafting Enterprise’s Regular Capacity

If a vegetable grower $k$ places an order at time $T_k$ ($T_k \leq a_2$), the grafting enterprise will have a regular capacity of:

$$\text{Cap} = \sum_{k=1}^{N} E(Q_{k}(T_k))$$ (1)

Since the grafting enterprise is facing a newsvendor problem, its regular capacity should be equivalent to the total “optimal” order quantities of vegetable growers. However, the grafting enterprise cannot estimate each vegetable grower’s real optimal order quantity without knowing their ordering times. Therefore, this “optimal” is for the condition that ordering time is unknown. In this case, the optimal capacity for vegetable grower $k$’s order should be $G^{-1}[(p_r+c_v)/p_v]$, where $G(\cdot)$ is a general cumulative density function with mean of $\mu_k$ and standard deviation of $\sigma_k(T_k)$. The standard deviation is a linear function of $T_k$, that is, $\sigma_k(T_k) = d_k(T_k - a_1) + c_k$ where $d_k$ and $c_k$ are the ordering time coefficient and noise factor, respectively. Note that one assumption here is that all vegetable growers share their demand mean and standard deviation with the grafting enterprise.

3.2 Determination of Vegetable Grower’s Optimal Order Quantity

For a vegetable grower $k$, it may have two vegetable cost rates: $p_r+c_v$ and $p_r+c_v$, depending on the grafting enterprise’s remaining regular capacity and the order quantity. To maximize its profit under stochastic demand from its downstream, it needs to decide the optimal order quantity at time $T_k$ by solving a newsvendor problem. In the classic newsvendor problem, the order quantity $Q = F^{-1}[(p-c)/p]$, where $p$ is the sale price, $c$ is the purchase cost and $F(\cdot)$ is a cumulative density function for demand. Since different purchase cost rates are involved in this paper, the optimal order quantity for vegetable grower $k$ is determined for two cases as follows:

Case 1: $Q_s \leq \text{Cap}$

$$\begin{align*}
R(Q_k, D_k) &= \begin{cases} 
p_v D_k - (p_r + c_v)Q_k, & Q_k \geq D_k 
(p_v - p_r - c_v)(2Q_k - D_k), & Q_k < D_k 
\end{cases} 
\end{align*}$$ (2)

$$E[R(Q_k, D_k)] = \int_{D_k=0}^{\infty} R(Q_k, D_k) f(D_k) dD_k$$

$$= p_v \int_{Q_k=0}^{D_k} D_k f(D_k) dD_k - (p_r + c_v) \int_{D_k=0}^{Q_k} Q_k f(D_k) dD_k + (p_v - p_r - c_v) \int_{D_k=Q_k}^{\infty} (2Q_k - D_k) f(D_k) dD_k$$ (3)

where $R(\cdot)$ is a profit function. Note that $\text{Cap}$ represents the grafting enterprise’s remaining regular capacity. It is obvious that this expression is similar to the classic newsvendor model. Therefore, the optimal order quantity is $Q_k = F^{-1}[2(p_r-p_r-c)/(2p_r-p_r-c)]$

Case 2: $Q_s > \text{Cap}$

\[ R(Q_k, D_k) = \begin{cases} (p_e - p_r - c_r) D_k - (p_e + c_r)(D_k - Q_k) - (p_e + c_r)(Q_k - Cap), & D_k \leq Cap \\ (p_e - p_r - c_r) Cap + (p_e - p_r - c_r)(D_k - Cap) - (p_e + c_r)(Q_k - D_k), & Cap \leq D_k \leq Q_k \\ (p_e - p_r - c_r) Cap + (p_e - p_r - c_r)(Q_k - Cap) - (p_e - p_r - c_r)(D_k - Q_k), & Q_k \leq D_k \end{cases} \]

After simplification, Equation (4) can be reformulated into:
\[ R(Q_k, D_k) = \begin{cases} p_e D_k + (p_e - p_r) Cap - (p_e + c_r) Q_k, & D_k \leq Q_k \\ - (p_e - p_r - c_r) D_k + (p_e - p_r) Cap + 2(p_e - p_r) Q_k, & Q_k \leq D_k \end{cases} \]

and its expectation is
\[ E[R(Q_k, D_k)] = \int_{D_k=0}^{Q_k} R(D_k, Q_k) f(D_k) dD_k \]
\[ = p_e H(Q_k) + (p_e - p_r) E[Cap] F(Q_k) - (p_e + c_r) Q_k F(Q_k) - (p_e - p_r) \mu_k + (p_e - p_r) H(Q_k) + (p_e + p_r) Cap - (p_e + p_r) E[Cap] F(Q_k) + 2(p_e - p_r) Q_k - 2(p_e - p_r - p_r) Q_k F(Q_k) \]

where \( H(\cdot) \) is defined as \( H(Q_k) = \int_{Q_k}^{Q_k} f(x) dx \). Then, Equation (6) can be further simplified into:
\[ E[R(Q_k, D_k)] = K_1 H(Q_k) - K_2 Q_k F(Q_k) + 2K_2 Q_k + K_3 \]

where \( K_1 = 2p_e - p_r - c_r \) is a constant, \( K_2 = p_e - p_r - c_r \) and \( K_3 = (p_e - p_r) Cap - (p_e - p_r - c_r) \mu_k \). Thus, the first derivative of \( E[R(Q_k, D_k)] \) with respect to \( Q_k \) is:
\[ \frac{dE[R(Q_k, D_k)]}{dQ_k} = -K_1 F(Q_k) + 2K_2 \]

By letting (8) equal zero, the maximizer of \( E[R(Q_k, D_k)] \), \( Q^*_k \), is found to be \( F^{-1}[2K_2/K_1] \). Also, it is easy to show that the second derivative of \( E[R(Q_k, D_k)] \) is always negative. Therefore, we can conclude that \( Q^*_k \) is the unique maximizer. Due to limited length of paper, detailed derivations are not provided here.

4. Supply Chain Simulation

4.1 Grafting Propagation Simulator

To estimate the grafted seedling production cost rate, a data-driven hierarchical (i.e. two-level) grafting propagation simulator has been developed in discrete event simulation software SimCad. The high level model, as shown in Figure 3, simulates the material flows through eight production departments, including seedling, germination, presorting grow-on, sorting, pre-grafting grow-on, grafting, healing, and post-grafting grow-on departments. Each department performances a specific operation, for example, the grafting department performs grafting operation. The low level model simulates detailed operational (e.g. cutting seedlings and joining scions with rootstocks) and material handling activities (e.g. delivering trays of seedlings) within each department. The simulator can be applied to simulating most widely adopted grafting propagations in terms of production scale, crop type, grafting automation level, machine model, and greenhouse technology.

In addition, a corresponding database has been developed for storing simulation inputs, where the real location-dependent inputs (e.g. labor cost rate) and crop-dependent inputs (e.g. germination days for tomato) are available. A user interface, as shown in Figure 4, is also designed for users to define the scenario of their interests and view simulation outputs (e.g. seedling production cost).
4.2 Random Demand Generator

For vegetable growers, the actual vegetable demand (from their downstream customers) should be randomly generated. In this paper, the demand is generated by the random demand generator given below:

\[ \text{demand}_k = BD \times [1 + \text{UNIF}(-0.2, 0.2)] + \text{Noise} \times S\text{Normal} \]  \hspace{1cm} (9)

where \( \text{demand}_k \) is the vegetable demand for vegetable grower \( k \), \( BD \) is the base demand, \( \text{UNIF} \) is a uniform random number generator, \( \text{Noise} \) is the noise factor, and \( S\text{Normal} \) is a standard normal random number generator.

4.3 Vegetable Grower’s Order Quantity

Vegetable growers need to predict the vegetable demand and make a corresponding decision on their seedling order quantity for the grafting enterprise. As the grafting enterprise does not share its detailed production information, we assume that a vegetable grower decides its seedling order quantity without knowing the grafting enterprise’s remaining regular capacity. Since each vegetable grower can place either a regular or early order, given the problem settings, vegetable grower \( k \)’s order quantity for regular order and early order are expressed in Equations (10) and (11), respectively:

\[ Q_k(t) = F^{-1}[2(p_v - p_r - c_v)/(2p_v - p_r - c_v)] \]  \hspace{1cm} (10)

\[ Q_k(t) = F^{-1}[2(p_v - p_e - c_v)/(2p_v - p_e - c_v)] \]  \hspace{1cm} (11)

where \( F(\cdot) \) is a cumulative density function of a normal distribution with mean (i.e. \( \mu_k \)) of \( \text{demand}_k \times (1 + \text{EB}) \) and standard deviation (i.e. \( \sigma_k(T_k) \)) of \( \text{ED} \times [1 + (a_2 - T_k)/(a_2 - a_1)] \). \( \text{EB} \) and \( \text{ED} \) are the demand forecasting error bias and deviation (see Table 3), respectively.
4.5 Grafting Enterprise’s Capacity
As discussed in Section 2, the grafting enterprise needs to determine its production capacity on day $a_1$ based on the orders that are already received (i.e. early orders) and predicted orders to come (i.e. regular orders). For regular orders, the grafting enterprise can use Equation (10) to determine the predicted regular order quantity by assuming all the ordering times are $(a_1+a_2)/2$. Note that we assume vegetable growers do not share their specific ordering times with the grafting enterprise before day $a_1$. For early orders, it is easy to know that the corresponding capacity to be prepared equals the actual order quantity (which is known), and the number of vegetable growers who place early order is an experimental parameter. Therefore, the grafting enterprise’s regular production capacity can be determined by Equation (12):

$$\text{Cap} = \sum EQk[(a_1 + a_2)/2] + \sum Qe(a_1)$$

(12)

5. ANOVA
In this section, we discuss ANOVA results that have been conducted to identify the significant factors to the effect of EOC on the supply chain in terms of profit. For the scenario, tomato seedling and Tucson city were selected, for which the default simulation inputs were collected. In addition, only one ordering/production period was considered for illustration purpose (the simulation model can be used for multi-period and multi-crop analysis). The times spent for the major propagation stages are listed in Table 2.

Table 2: Times spent for major propagation stages

<table>
<thead>
<tr>
<th>Germination days</th>
<th>Pre-sorting grow days</th>
<th>Pre-grafting grow days</th>
<th>Healing days</th>
<th>Post-grafting grow days</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>7</td>
<td>10</td>
<td>7</td>
<td></td>
</tr>
</tbody>
</table>

5.1 Independent Variables
In the experiment, there were six independent variables categorized into three classes: grafting enterprise parameters, demand forecasting parameters and supply chain parameters. Table 3 summarizes the values of the independent variables used for experimental design.

Table 3: Independent variable values for the simulation experiment

<table>
<thead>
<tr>
<th>Class</th>
<th>Parameter Type</th>
<th>Variable</th>
<th>Abbreviation</th>
<th>Levels</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grafting</td>
<td>enterprise parameters</td>
<td>Cost structure $(C_1/C_2)$</td>
<td>CS</td>
<td>3</td>
<td>1.19, 1.59, 1.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Regular order window</td>
<td>RW</td>
<td>2</td>
<td>14, 21 (days)</td>
</tr>
<tr>
<td>Demand</td>
<td>forecasting parameters</td>
<td>Error bias</td>
<td>EB</td>
<td>2</td>
<td>-5, 5 (%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Error deviation</td>
<td>ED</td>
<td>2</td>
<td>500, 1000 (plant)</td>
</tr>
<tr>
<td>Supply chain</td>
<td>parameter</td>
<td>Base demand</td>
<td>BD</td>
<td>2</td>
<td>10000, 50000 (plant)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vegetable grower ordering time</td>
<td>GT</td>
<td>4</td>
<td>Cases A, B, C, D (see Section 6)</td>
</tr>
</tbody>
</table>

Four cases with respect to vegetable growers’ ordering time (GT) are defined as follows:

- Case A: all vegetable growers place early orders;
- Case B: five vegetable growers place early orders, and the rest place regular orders at times evenly distributed through the regular order window;
- Case C: all vegetable growers place regular orders at times evenly distributed through the regular order window;
- Case D: all vegetable growers place regular orders at the end of the regular order window.

5.2 Performance Metrics
To quantify the effect of EOC on the performance of the supply chain as well as each individual supply chain member, three performance metrics are defined as follows.

- Total profit for the grafting enterprise (TPG): total revenue deducted by total grafting propagation production cost
- Total profit for vegetable growers (TPV): total revenue deducted by total seedling purchase cost, production cost, and shortage penalty.
- Total profit for the supply chain (TPS): summation of the grafting enterprise’s and vegetable growers’ profits.
5.3 ANOVA Results
For each combination of the six independent factors (i.e. CS, RW, EB, ED, BD, GT), ten simulation replications were run. Based on the simulation results, we then conducted two sets of ANOVA in Matlab. The first analysis included all the six independent factors, and we found that BD (i.e. base demand) is the only significant factor, which is consistent with our intuition. In the second analysis, we fixed BD to 10000, and the corresponding ANOVA results are presented in Table 4. We first found that CS, EB and ED are the main effects to TPG (total profit for the grafting enterprise). This is not difficult to follow because grafting enterprise’s cost structure (CS) influences its profit, and demand forecasting parameters (EB and ED) affect its regular capacity which further influences the capacity utilization and total profit. Interestingly, the vegetable grower’s ordering time (GT) can be also considered significant. The reason is that vegetable growers’ ordering times affect their order quantities and thus further influence the grafting enterprise’s total profit. For TPV (total profit for vegetable growers), we found that in addition to EB and ED, RW and GT are also significant factors. That is because when vegetable growers place orders early, which corresponding to larger RW and GT, they have to deal with higher demand forecasting error due to larger demand forecasting window. For the entire supply chain, its total profit (TPS) is mainly influenced by CS, EB, and ED. The significance of GT can also be identified and may increase in cases involving higher demand uncertainty.

<table>
<thead>
<tr>
<th>Source</th>
<th>TPG F-value</th>
<th>Pr&gt;F-</th>
<th>TPV F-value</th>
<th>Pr&gt;F-</th>
<th>TPS F-value</th>
<th>Pr&gt;F-</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS</td>
<td>19.74</td>
<td>&lt;.0001</td>
<td>.03</td>
<td>.9659</td>
<td>19.55</td>
<td>&lt;.0001</td>
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<tr>
<td>RW</td>
<td>.01</td>
<td>.9327</td>
<td>12.81</td>
<td>.0008</td>
<td>0</td>
<td>.9734</td>
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<td>EB</td>
<td>22.73</td>
<td>&lt;.0001</td>
<td>3400.52</td>
<td>&lt;.0001</td>
<td>7.98</td>
<td>.007</td>
</tr>
<tr>
<td>ED</td>
<td>19.2</td>
<td>&lt;.0001</td>
<td>33.48</td>
<td>&lt;.0001</td>
<td>20.77</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GT</td>
<td>2.87</td>
<td>.0472</td>
<td>4.13</td>
<td>.0226</td>
<td>3.07</td>
<td>.036</td>
</tr>
<tr>
<td>CS*RW</td>
<td>0</td>
<td>1</td>
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<td>&lt;.0001</td>
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<td>.9986</td>
<td>.17</td>
<td>.9527</td>
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<td>.889</td>
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<td>.8959</td>
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<td>.01</td>
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6. Effect of EOC on Supply Chain Performance
To identity the effect of EOC on the supply chain performance in terms of profit, simulation experiments were conducted with respect to vegetable grower’s ordering time (GT). The simulation parameters are specified in Table 5.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>RW (day)</th>
<th>EB (%)</th>
<th>ED (plant)</th>
<th>BD (plant)</th>
<th>p_r ($/plant)</th>
<th>c_r ($/plant)</th>
<th>p_c ($/plant)</th>
<th>c_c ($/plant)</th>
<th>p_f ($/plant)</th>
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<td>CS</td>
<td>1.19</td>
<td>14</td>
<td>-5</td>
<td>500</td>
<td>10000</td>
<td>0.19</td>
<td>0.21</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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</table>

Figures 5 (A)-(C) depict how vegetable grower’s ordering times influence the profits of the grafting enterprise, vegetable growers and the entire supply chain, respectively. As shown in Figure 5(A), the grafting enterprise gained the most profit when all the vegetable growers placed early orders (Case A), while its profit had no significant difference under the rest of scenarios. This finding is consistent with our intuition because early orders minimized the demand uncertainty from vegetable growers, and avoided either capacity idleness or emergency capacity. Figure 5(B) shows the total profits of ten vegetable growers. The results indicate that when vegetable growers postpone their ordering times, they gain more profit. That is because the later a vegetable grower places its order, the more precise its seedling order quantity (or its demand forecasting) will be to a smaller demand forecasting window. Therefore, the best ordering time for a vegetable grower is the end of the regular order window if there is no profit sharing incentive from the grafting enterprise. For the entire supply chain, Figure 5(C) shows that the supply chain
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achieved the most profit by implementing EOC (Case A), and Case D outperformed the other two cases. This finding implies that EOC can help the entire supply chain increase the total profit, which confirms with the results in [4].

![Total Profit for Grafting Enterprise](image)
![Total Profit for Vegetable Growers](image)
![Total Profit for Supply Chain](image)

(A) (B) (C)

Figures 5: Effect of EOC on supply chain performance

Furthermore, we wanted to investigate how EOC affects supply chain members at the operational level. Figure 6 shows the grafting enterprise’s regular capacity under four designed cases. When all the vegetable growers placed early orders (Case A), the demand uncertainty for the grafting enterprise was eliminated, which enabled the grafting enterprise to only keep the “right” capacity. As the number of early orders decreased, the grafting enterprise had to increase its capacity, as illustrated in Cases B and C, to meet the unexpected seedling demand. However, if a vegetable grower has decided to place regular order, its specific ordering time does not affect the grafting enterprise’s capacity as the grafting enterprise assumes that the expected ordering times are all in the middle of regular order window (i.e. PT/2).

For vegetable growers, they expect their orders to be fulfilled by regular capacity for the lower purchase rate (i.e. $p_r < p_e$). To investigate how a vegetable grower’s ordering time affects her order fulfillment, we extended the simulation experiment to five cases: ten, eight, five, two and zero early orders, respectively. The vegetable growers are indexed by their ordering time sequence, for example, vegetable grower 9 places its order earlier than vegetable grower 10. The experiment results indicate that the first nine vegetable growers’ orders were fulfilled by regular capacity for all five cases. But for vegetable grower 10, Figure 7 shows that its order was partially fulfilled by emergency capacity for all the cases except for the case involving ten early orders. The implication of this finding is that a vegetable grower’s ordering time affects its purchase cost rate when there are other vegetable growers (i.e. buyers) competing for the limited regular capacity. Each vegetable grower has to balance the tradeoff between the benefit of lower purchase rate and higher demand forecasting error by placing orders early. Although there was only one vegetable grower whose order was fulfilled by emergency capacity in our particular experiment settings, it is highly possible that there will be more vegetable growers whose orders have to be fulfilled by emergency capacity when the experiment settings change, especially when the grafting enterprise is conservative in its capacity design. Another interesting finding is that the quantity fulfilled by emergency capacity has a high variance, which implies that the demand uncertainty has a significant impact on the seedling purchase cost rate of vegetable growers who place orders later than others.
7. Conclusions
This paper studied the effect of EOC on the performance of an order-driven supply chain consisting of one manufacturer and multiple customer enterprises. A grafted seedling supply chain was adopted as the case study based on real data. Analytical solutions for the grafted enterprise’s (i.e. manufacturer) production capacity and vegetable grower’s (i.e. customer enterprise) order quantity have been derived. A data-driven grafting propagation simulator has been developed to estimate the grafting propagation cost rate. The obtained experimental results suggest that EOC is beneficial to the entire supply chain as a whole, but increases the customer enterprise’s demand forecasting error. In addition, ANOVA results indicate that manufacturer’s capacity cost structure, customer enterprises’ demand forecasting, ordering times and the demand for the supply chain are the significant factors to the effect of EOC. The sensitivity analysis results indicate that when multiple customer enterprises are involved, the purchase cost rate of each individual customer enterprise is affected by its own ordering time as well as those of others’. For future extension, analytical solutions for customer enterprise’s optimal ordering time will be derived, and the effect of information sharing (manufacturer’s remaining regular capacity) between a manufacturer and customer enterprises will be studied.

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References