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IMPROVING FOOD BANK GLEANING OPERATIONS: AN APPLICATION IN NEW YORK STATE

ERKUT SÖNMEZ, DEISHIN LEE, MIGUEL I. GÓMEZ, AND XIAOLI FAN

Gleaning is increasingly attracting the attention of food safety networks, including food banks, as a valuable tool that simultaneously reduces food loss and alleviates food insecurity. However, managing gleaning operations can be challenging because the arrival of gleaning opportunities and the attendance of gleaner volunteers are both stochastic. We develop a stochastic optimization model to characterize and optimize a gleaning operation. The food bank chooses the gleaning schedule, which affects the gleaner capacity and the number of gleaning opportunities scheduled. In a specific field study of the Food Bank of the Southern Tier in New York, we analyze the tradeoff between call and volume service levels to find the optimum schedule that maximizes the expected total volume gleaned. Moreover, we find that increasing the gleaning window and increasing slot availability can be used as substitute mechanisms for increasing the total volume gleaned. Additionally, we use our model to assess the impact of recruiting more volunteer gleaners.

Key words: Capacity planning, food bank operations, gleaning, stochastic optimization.

JEL codes: C61, C63, D24, Q18.

Although the per capita gross domestic product of the United States is one of the highest in the world, hunger continues to be a systemic problem. The USDA estimates that 14.3% of households were food-insecure in 2013 (i.e., 17.5 million households were at risk of not being able to acquire enough food for all household members because of insufficient money and/or other resources; Coleman-Jensen, Gregory, and Singh 2014).

Food-insecure and low-income households are especially vulnerable to weight-related health issues as a result of lack of access to healthy foods (FARC 2011). For example, according to Weinfield et al. (2014), many households receiving food assistance from Feeding America's food bank network face significant diet-related health challenges. Wilson et al. (2015) found that one out of three of these households includes someone who has diabetes, and nearly 60% include someone who has hypertension. Meanwhile, there is evidence that food-insecure households may experience micronutrient malnutrition due to inadequate diets associated with low consumption of fruits and vegetables (Davis and Tarasuk 1994; Tarasuk and Beaton 1999).

Although there are a significant number of food-insecure individuals, large amounts of food are wasted at different stages along food supply chains. The USDA Economic Research Service estimates that nearly one-third of the total edible food available for human consumption in the United State is lost each year (Coleman-Jensen, Gregory, and Singh 2014). Food loss or waste refers to the decrease in food quantity that arises because of a decrease in food quality along the supply chain that makes it unfit for human consumption (Gustavsson et al. 2011). Food losses occur at almost every stage

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of the supply chain, including production, post-harvest, processing, distribution, and consumption (Lipinski et al. 2013). Food waste is higher among perishable products, including fresh fruits and vegetables, which could contribute to improving the nutritional status of food-insecure individuals. An important part of perishable product waste occurs at the production stage. In particular, a significant amount of unharvested crops that is fit for human consumption is left in fields. This may be because of mechanical harvesting that leaves behind some product, or there could be poor market conditions for the crop (e.g., because of cosmetic blemishes on the crop), making it not worthwhile for the farmer to harvest. Kantor et al. (1997) estimates that each year about 6–7% of U.S. planted acreage for human consumption is not harvested.

The loss of these nutritious products, particularly fruits and vegetables, could be mitigated by gleaning, which is an ancient practice dating from biblical times where farmers and large landowners allow the poor to gather crops in the field after the harvest. In contemporary times, gleaning is generally performed by organizations (often using volunteers) that donate the goods to food banks or pantries that serve the needy. Gleaning in modern times may also refer to farm-food donations out of farmers' packing lines and storage houses.

Food safety networks, including food banks, are increasingly turning to gleaning as a mechanism for simultaneously reducing food loss and alleviating food insecurity (NRDC 2012). A number of gleaning programs, in many cases supported by local and state governments, have been created in recent years as a result. In 2010, New York farmers donated nearly 3.6 million pounds of products to food banks through gleaning (Schuelke, Hoffmann, and Gómez 2011). In 2012, the California Association of Food Banks' gleaning program, Farm to Family, distributed 127 million pounds of fresh produce to 41 food banks around the state (California Association of Food Banks 2011). Similar gleaning programs operate in Arizona, Texas, and Ohio (18.5 million, 13 million, and 26 million pounds of fruits and vegetables distributed in 2011, respectively). Other states such as Arkansas, Colorado, and Kentucky have smaller, but rapidly growing, gleaning programs (Vitiello et al. 2014). As gleaning programs garner support nationwide and continue to grow, food banks need to think systematically about how to efficiently manage their gleaning operations.

In spite of the increasing interest in gleaning fruits and vegetables, very little research has been conducted to help food banks and policy makers develop effective gleaning programs. To address this gap in the literature, we develop a stochastic optimization model to characterize and optimize a gleaning operation. In our model, gleaning opportunities from farms in a given geographic area arrive randomly to the food bank. The processing capacity available for each gleaning opportunity is also stochastic, and depends on the schedule employed by the food bank (i.e., the number of gleaning slots available per week), the number of volunteer gleaners, and the gleaner productivity function.

Our analysis reveals the tradeoff between call and volume service levels, which are the fraction of gleaning opportunity calls from farmers that are scheduled and the fraction of volume opportunity that is gleaned by the food bank, respectively. The food bank's gleaning schedule affects gleaner capacity and the number of gleaning opportunities scheduled. Although call service level increases as the slot availability increases, beyond a threshold level the volume service level decreases in slot availability. This is due to decreasing effective gleaner capacity (because of gleaner burn-outs and wasted gleaner capacity). Gleaners attend trips early in the season (on trips that are likely to be over-capacity), and then do not return for trips late in the season (that are likely to be under-capacity). Thus, there is an optimal level of slot availability, that is not too high or too low, that maximizes the total volume gleaned. Moreover, as more gleaning trips are scheduled, the volume gleaned per trip decreases. This negatively affects farmers because gleaning can also be thought of as a service to farmers. If the volume service level is too low, farmers may not find it worthwhile to participate in the gleaning network.

We also show that increasing the gleaning opportunity window (i.e., the number of days the food bank has to harvest before the donated crop perishes on field) and increasing slot availability (i.e., the number of days in a week that the food bank will organize a gleaning trip if there is a gleaning opportunity) are substitute mechanisms for increasing the total volume. This is a manifestation of the value of information in an operation. By increasing the gleaning window, we have better information on gleaning opportunities and can thus accommodate them better. Similarly, increasing the gleaner pool size can also increase total volume, but at a decreasing rate. This is because the stochastic nature of the process results in wasted gleaner capacity.

We apply our model to the apple gleaning program of the Food Bank of the Southern Tier (FBST) in New York State. The FBST recently launched a major gleaning initiative to increase its offering of healthy fruits and vegetables to its food assistance recipients. The FBST services six counties covering nearly 4,000 square miles. In this area, one out of four residents receives food assistance at some point during the year. The FBST partners with over 160 agencies to ensure that food donations reach the needy, including food pantries, soup kitchens, shelters, after-school programs, and senior housing sites, among others. In 2013, FBST distributed over 9.7 million pounds of food with a value of $16.1 million.

Our results show that the optimal number of slots for FBST is 5 slots per week (i.e., the schedule that maximizes expected total volume gleaned), but diminishing returns to additional slots suggest that the cost-efficient schedule should be less than 3 slots per week. We also show that if the gleaning window were to increase from 7 days to 9 days, the total volume gleaned would increase by 3% when using a 1-slot per week schedule. Thus, better (i.e., more timely) information, enabled by a longer gleaning window, can improve performance without adding resources. Additionally, the food bank can use our model to assess the volume impact of recruiting more gleaners.

The manuscript is organized as follows. The next section reviews the literature on food bank supply chain operations. Next, we present the model and the calibration to apply the model to FBST's gleaning operation. Subsequently, we discuss the results and present concluding remarks.

Literature Review

A number of studies focusing on food assistance programs, hunger relief, and food donations have underscored the critical role of food banks in reducing food losses and enhancing food security (e.g., Riches 2002; Weinfield et al. 2014). However, researchers have also pointed out that food banks have succeeded in distributing mainly processed food products (Poppendieck 1999). The fact that food banks have focused on processed foods has been associated with the rise of malnutrition problems (obesity and micronutrient deficiencies) among food-insecure individuals who are food bank assistance recipients (Campbell, Ross, and Webb 2013; Handforth, Hennink, and Schwartz 2013). Such emerging malnutrition problems have prompted researchers to study the nutrition quality of the products distributed by food bank networks and the adequacy of diets among recipients of food assistance (Starkey, Gray-Donald, and Kuhnlein 1999; Teron and Tarasuk 1999; Irwin et al. 2007). Food banks are responding by reconsidering their food sourcing strategies to improve the dietary quality of the foods distributed to their partner organizations (Handforth, Hennink, and Schwartz 2013).

One important strategy that food banks are increasingly employing to improve the diets of food assistance recipients is to increase their sourcing and distribution of fresh fruits and vegetables through gleaning programs (Vitiello et al. 2014). Hoisington et al. (2001) posits that emerging gleaning programs (often supported by local and state governments) operated by food banks can reduce food insecurity and malnutrition by improving the diets of recipients. Extant literature has emphasized the impact of gleaning programs on the quality of dietary intake of recipients as well as their food preferences (e.g., Teron and Tarasuk 1999; Irwin et al. 2007). Several case studies have examined how food banks operate gleaning programs and their role in relieving hunger and enhancing food security (Badio 2009; Drage 2003; Hoisington et al. 2001; Kuhl, Tuttle, and Villarreal 2014). Freeman (2007) conducted a spatial analysis to address obstacles to building a regional food gleaning network. Vitiello et al. (2014) examined the role of gleaning programs in promoting community food security and food justice.

Although gleaning programs are being promoted by academics and practitioners, they are being challenged by numerous operational issues, including appropriate scheduling of procurement and distribution, volunteer group management, and operational capacity under uncertainty, among others. Davis et al. (2013) argue that gleaning programs need to be operated effectively and efficiently to succeed in distributing healthy fruits and vegetables among food-insecure individuals. Researchers have not specifically addressed the efficiency of gleaning programs, but there is a growing body of literature that focuses on overall food bank operations. For example, the operations management literature has studied the pickup and delivery vehicle routing problem (VRP). Davis et al. (2014) modeled a food bank's operation as a VRP with backhauls and can incorporate both the collecting and delivering customer in a network. Lien, Iravani, and Smilowitz (2014) and Gunes, Hoeve, and Tayur (2010) formulated resource allocation problems for food banks as VRPs using an objective function that minimizes food waste and ensures equitable and effective service (in contrast to the traditional VRPs' profit- or cost-based objective functions). Mohan, Gopalakrishnan, and Mizzi (2013) developed a VRP to show that improving food bank warehouse operations can result in larger food volumes distributed among food-insecure individuals. Davis et al. (2013) focused on improving forecasting methods for the foods donated to food banks to improve operational efficiency.

The models developed to improve the efficiency of food bank operations are not directly applicable to the challenge of improving the operation of gleaning programs. In particular, gleaning activities are primarily staffed by volunteers; therefore, managing volunteer capacity is crucial to gleaning operations (Badio 2009). A related problem, volunteer scheduling, has been studied in the context of humanitarian organizations (Falasca and Zobel 2012), disaster management (Oloruntoba 2005), and other sectors where volunteer participation is required (Gordon and Erkut 2004; Sampson 2006; Kaspari 2010). In the food bank context, Davis et al. (2014) studied food bank collections and deliveries as a scheduling problem, but they did not consider the volunteer scheduling problem. Phillips et al. (2013) show that food bank scheduling improvements can help reduce food waste and mitigate hunger. The authors focused on dry foods and not on fresh fruits and vegetables, which are more perishable and thus more complex to model in the context of a gleaning program.

We contribute to the emerging literature by developing a stochastic optimization model that characterizes a food bank gleaning operation. We use the model to identify operating policies that optimize various performance metrics including volume gleaned, and call and volume service levels. Our paper contributes to the literature on food supply chain operations by explicitly modeling the gleaning process (i.e., the stochastic arrival of gleaning opportunities and gleaner attendance); the existing literature has focused primarily on the vehicle routing problem. In addition, our model has practical implications for managers of food bank networks, as they implement programs to improve the dietary quality of food assistance recipients. Whereas the food bank operations literature has focused mostly on reducing food losses, our model can help food banks identify strategies to simultaneously increase the quantity and nutritional quality of food distributed through their networks.

Model

We develop a stochastic optimization model that represents a food bank's gleaning operation. In our setting, there are three parties: (*a*) farmers who call the food bank to offer gleaning opportunities, (*b*) volunteer gleaners who attend gleaning trips to harvest donated produce, and (*c*) the food bank (FB) that organizes gleaning trips to match gleaners to gleaning opportunities.

The FB organizes gleaning trips during a gleaning season that starts on day 1 and ends on day t_e. The set of discrete days in the gleaning season is represented by $\mathcal{T} := \{1, 2, \ldots, t_e\}$. Throughout the planning horizon $\mathcal{T}$, the FB operates schedule j, which represents the days of the week on which the FB will organize a gleaning trip if there is a gleaning opportunity. For example, one possible schedule is $j := \{\text{Monday, Wednesday, Saturday}\}$—where gleaning trips can be organized on Mondays, Wednesdays, and Saturdays of each week. We refer to each day in the schedule as a slot that can be filled by scheduling a gleaning trip on that day. Thus, the schedule $j := \{\text{Monday, Wednesday, Saturday}\}$ has 3 slots per week. We represent the set of possible gleaning schedules by $\mathcal{J} := \{\{\text{M}\}, \{\text{W}\}, \{\text{Sa}\}, \{\text{M, W}\}, \{\text{M, Sa}\}, \ldots\}$.

The gleaning season $\mathcal{T}$ is the union of an active and a late season, denoted by $\mathcal{T}^a$

and $\mathcal{T}^l$, during which gleaning opportunities arrive more and less frequently, respectively. Farmers call the FB offering gleaning opportunities with average rate λ^a during $\mathcal{T}^a$, and average rate λ^l during $\mathcal{T}^l$ (typically, $\lambda^a > \lambda^l$).

Each gleaning opportunity has a potential gleanable volume of produce (measured in bushels, which we convert into pounds), which we represent with random variable v. The gleaning opportunity window is the number of days the FB has to harvest before the donated crop perishes on field, and is denoted by x. Following the farmer's call, the FB checks its schedule j to see if there is an available slot within the gleaning opportunity window. If a slot is available within the window, the gleaning opportunity is scheduled on the first available slot, otherwise, the opportunity is lost. To keep track of the scheduled gleaning opportunities, we define the binary (Bernoulli) random variable $I_t(j)$ as follows:

$$I_t(j) = \begin{cases} 1 & \text{If a donation is scheduled for gleaning on day } t \text{ under schedule } j, \\ 0 & \text{Otherwise.} \end{cases}$$

Once a gleaning opportunity is scheduled, the FB announces the trip to the volunteer gleaner pool via email lists or the FB website. We represent the number of active gleaners in the gleaner pool at the beginning of day t under schedule j with $Q_t(j)$. We denote by $p_d(j)$ the probability that a given gleaner in the pool will attend a scheduled trip on day d, $d \in \mathcal{D} :=$ {Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday}. Let $g(t)$ be the day $d \in \mathcal{D}$ corresponding to $t \in \mathcal{T}$. We then represent the number of gleaners who will attend a gleaning trip scheduled on $t \in \mathcal{T}$ under schedule j with binomial random variable $A_t(j) \sim \text{Binomial}(Q_t(j), p_{g(t)})$.

We denote by α the productivity of a gleaner during a trip, that is, the volume harvested by a gleaner during a standard three-hour gleaning trip (expressed in pounds). Then, the total volume gleaned on a trip is the minimum of the potential gleanable volume and the sum of the productivity of the gleaners who attend the trip. Each gleaner attending a trip will remain inactive for a random number of days, denoted by w (a rest period). Once the inactive period of a gleaner is over, s/he returns to be an active member of the gleaner pool. To keep track of the active gleaner pool size at the beginning of each day t under schedule j, $Q_t(j)$, we define $r_t(j)$ as the random variable representing the number of gleaners returning back to the active pool at the beginning of day t under schedule j. To keep track of inactive gleaners, we define the binary random variable $\Phi_{ktw}(j)$:

$$\Phi_{ktw}(j) = \begin{cases} 1 & \text{If the } k^{th} \text{ gleaner who attends a trip on day } t \text{ stays } w \text{ days inactive under schedule } j, \\ 0 & \text{Otherwise.} \end{cases}$$

Following the setup and notation given above, our model is:

$$\text{(1)} \quad \max_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} E[I_t(j) \cdot \min(v, A_t(j) \cdot \alpha)]$$

s.t.,

$$\text{(2)} \quad I_t(j) \leq 1 \quad \forall t \in \mathcal{T},$$

$$\text{(3)} \quad Q_{t+1}(j) = Q_t(j) - A_t(j) \cdot I_t(j) + r_{t+1}(j) \quad \forall t \in \mathcal{T}, \quad \text{and}$$

$$\text{(4)} \quad r_t(j) = \sum_{\tau=1}^{t-1} \sum_{k=1}^{I_\tau(j) \cdot A_\tau(j)} \Phi_{k\tau(t-\tau)} \forall t \in \mathcal{T}.$$

The objective function (1) selects the gleaning schedule j that maximizes the expected total gleaned volume over the gleaning season $\mathcal{T}$.[1] Constraint (2) ensures that, at most, one gleaning trip is scheduled for each day t.[2] Constraints (3) and (4) are the flow balance equations updating the size of the gleaner pool and the number of gleaners returning to the pool after their inactive period, respectively. Our model assumes that the marginal value of gleaned product is constant. This is

[1] We focus on an operational model to maximize expected total volume gleaned because the food bank's goal for the gleaning operation is to increase the amount of healthy fresh food distributed to its clients (vs. profit maximization or cost minimization). The cash operation costs of a gleaning program consist of administration of the program and transport associated with a gleaning trip. These are typically fixed costs per trip and relatively modest. In the Results section on page 15, we perform a break-even cost analysis that takes into account the cash operation costs of a trip.

[2] The application site of our study, the Food Bank of the Southern Tier (FBST), currently has resource (truck, attending staff, etc.) capacity of one gleaning trip per day. However, our model can also accommodate the possibility of multiple trips per day with some minor modifications.

because the demand for gleaned product in the FB network is sufficiently large so that all product gleaned is productively used. Our model also assumes that waste in the gleaning operation is negligible. This is representative of practice because the supply chain of a gleaning operation is short, and all product gleaned is distributed, regardless of the grade.

We solve our model using a simulation-optimization approach. To do so, we first develop a discrete-event simulation model of our setting using the Arena© simulation software to estimate the probability density functions of the binary random variables utilized for tracking gleaning opportunities scheduled and the evolution of the gleaner pool size over the planning horizon (code available in a supplementary online appendix). We run our simulation model for each candidate schedule $j \in \mathcal{J}$ and obtain the associated performance metrics of interest. Each simulation scenario is replicated 1,000 times and the half-width of a 95% confidence interval on the estimate of each metric calculated is at most 0.05% of the mean. We then compare the alternative schedules $j \in \mathcal{J}$ with respect to the performance metrics of interest. These include the following: (*a*) expected total gleaned volume over the gleaning season, defined in function (1), (*b*) call service level, $\sum_{t\in\mathcal{T}} E[I_t(j)]/\left(\lambda^a \cdot |\mathcal{T}^a| + \lambda^l \cdot |\mathcal{T}^l|\right)$, where $|\cdot|$ denotes the cardinality of a set, (*c*) volume arrived service level, $\sum_{t\in\mathcal{T}} E[I_t(j) \cdot \min(v, A_t(j) \cdot \alpha)] / \left([\lambda^a \cdot |\mathcal{T}^a| + \lambda^l \cdot |\mathcal{T}^l|] \cdot E[v]\right)$, and (*d*) volume scheduled service level, $\sum_{t\in\mathcal{T}} E[I_t(j) \cdot \min(v, A_t(j) \cdot \alpha)] / \sum_{t\in\mathcal{T}} E[I_t(j) \cdot v]$. A flowchart of our simulation model is given in appendix A.

Application of Model to the Food Bank of the Southern Tier

We apply our model to assess the gleaning operations of the FBST, a food bank that serves six counties in southern New York state. Our study focuses on the gleaning of apples, as FBST has already established gleaning operations for this crop and there is significant potential for increasing apple gleaning in New York's Southern Tier area. The parameter values used in our study were based on current FBST gleaning operations, data from Boston Area Gleaners (BAG), a non-profit gleaning organization that operates in the Boston metropolitan area, and data from the 2012 U.S. Census of Agriculture. The parameter values used in our base case analysis are listed in table 1. We analyze a set of schedules that includes all possible number of slots per week (i.e., from 1 to 7 slots per week). For each slot number, we choose the schedule most likely to be adopted by the food bank (e.g., the most likely schedule for 2 slots per week is {M, W}).

In addition to our analysis using the base case parameters given in table 1, we also study the sensitivity of our results with respect to the parameters of interest. Our sensitivity analysis includes the following parameters: (*a*) the number of participating farms $\in \{4, 8, 12, 16\}$, (*b*) the gleaning opportunity window $\in \{5, 7, 9\}$ days, and (*c*) initial gleaner pool size $\in \{100, 150, 200\}$.

Results

In this section, we present the results of our field study for the FBST apple gleaning program. First, we present our findings using our base case setting (see table 1) on gleaned volume, and call and volume service levels. We then discuss how our results change when we vary the gleaning opportunity window and initial gleaner pool size under our sensitivity analysis.

Volume Gleaned

Figure 1 shows the expected total volume of apples gleaned over the harvest season as a function of alternative gleaning schedules (represented on the x-axis as the number of slots per week). The number of farms in the base case is 8 farms; however, we show how the results change for a range of number of farms (i.e., for 4, 8, 12, and 16 farms). This figure suggests that the expected total volume gleaned first increases (at a decreasing rate), then flattens out, and may eventually decrease as the number of slots in the schedule increases. This non-monotonic behavior is driven by the opposing effects that increasing the number of slots can have on the number of scheduled calls and the number of gleaners attending each gleaning trip.

On one hand, as the number of slots in the schedule increases, more calls will be scheduled. However, due to stochastic call arrivals and the finite gleaning opportunity window, a doubling in the number of slots results in less than doubling of the calls scheduled. Thus,

Table 1. Parameter Values for Base Case Analysis

Parameter Value	Description
$\mathcal{T} := \{1,2,\ldots,60\}$	For apples, the active harvest season is Sept. 1 to Oct. 25 and the late season is Oct. 25 to Oct. 31 for a total of 60 days.
$\lambda^a = 0.562$ calls/day	In our base case, there are 8 farms participating with the gleaning program of the FB. Each farm calls 4 times per season with gleaning opportunities. We choose successive inter-arrival times to be exponentially distributed after conducting Chi-square and Kolmogorov-Smirnov tests on the inter-arrival times data of BAG.
$\lambda^l = 0.2807$ calls/day	Late season call arrival rate is half that of the active season.
$\alpha = 235.13$ pounds/trip	Gleaner productivity.
$x = 7$ days	Gleaning opportunity window.
$v = \begin{cases} 888.8 & p = 0.37 \\ 1536.29 & p = 0.28 \\ 3052.41 & p = 0.23 \\ 4000.67 & p = 0.12 \end{cases}$	Probability density function of potential gleanable volume (in pounds).
$Q_1(j) = 150$ gleaners	Initial gleaner pool size.
$p_d = \begin{cases} 0.1 & \text{for weekdays} \\ 0.12 & \text{for Sa or Su} \end{cases}$	Probability of a gleaner attending a scheduled trip.
$w = \begin{cases} 6.29 & p = 0.0051 \\ 8.98 & p = 0.0101 \\ 12.94 & p = 0.0152 \\ 18.33 & p = 0.0303 \\ 31.43 & p = 0.1566 \\ 73.33 & p = 0.2929 \\ \infty & p = 0.4899 \end{cases}$	Probability density function of gleaner inactive days (rest period).
$\mathcal{J} = \{\{M\},\{M,W\},\{M,W,F\},\{M,Tu,W,F\},\{M,Tu,W,Th,F\},\{M,Tu,W,Th,F,Sa\},\{M,Tu,W,Th,F,Sa,Su\}\}$	Set of possible gleaning schedules, ranging from 1 slot per week to 7 slots per week.
Number of farms $= 8$	Number of farms in the gleaning network.

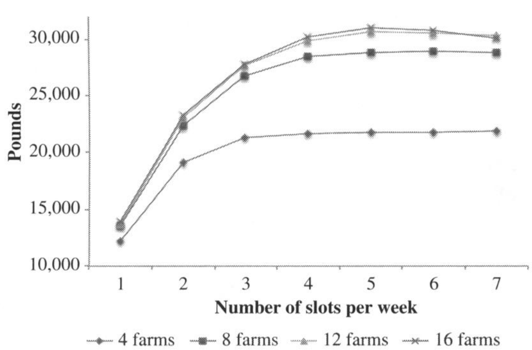

Figure 1. Expected total volume gleaned as a function of the gleaning schedule (number of slots per week)

at most, total volume gleaned can increase at a decreasing rate as the number of slots per week increases. On the other hand, as more calls are scheduled, fewer gleaners will attend per trip, thus the volume of apples gleaned per trip decreases. Moreover, as slots per week increase, there is more opportunity for gleaners to "burn out"—that is, a gleaner can attend a gleaning trip, and then decide not to come back for the rest of the season. Our results indicate that, with more slots per week, more burn-outs will occur earlier in the harvest season. This decreases the volume gleaned later in the season, which then further decreases the total volume gleaned.

Figure 1 also shows that for a given schedule (i.e., number of slots per week), total volume gleaned increases at a decreasing rate as the number of farms increases. The exception is at 7 slots per week—when the number of farms increases from 12 to 16, the total volume gleaned slightly *decreases*. This is due to decreasing gleaner capacity over the harvesting season because of gleaner burnout—with 16 farms, more calls are scheduled early on, leading to higher burn out. For the base case of 8 farms, we see that the optimal schedule that maximizes total volume gleaned is 5 slots per week. However, given the diminishing benefit of each marginal slot in the schedule, FBST may want to limit the schedule to 3 or fewer slots per week.

Figure 2 shows the average volume gleaned per trip as a function of the number of slots per week. As discussed before, the average volume gleaned per trip decreases as the number of slots per week increases because the number of gleaners per trip decreases. Figure 2, combined with gleaning cost data obtained from FBST, allows us to calculate the breakeven number of slots per week that will make gleaning trips worthwhile, on average. The cost of a gleaning trip expressed in terms of the apple volume gleaned is 714.3 pounds.[3] Using this metric, figure 2 suggests that in the base case with 8 farms, the average volume gleaned under all possible schedules is greater than the cost of the gleaning trip. However, if the number of participating farms increases to 12 or 16 farms, schedules that include 4 or more slots per week may not be worthwhile.

When FBST schedules a gleaning trip, it broadcasts a message to the pool of volunteer gleaners with the time and location of the gleaning trip. Gleaners decide whether to attend the trip or not, and manage their own transportation. Thus, FBST does not control the number of gleaners that eventually attend a gleaning trip. On some trips, more gleaners than needed may show up—in this case, there would be excess gleaners.[4] Figure 3 shows

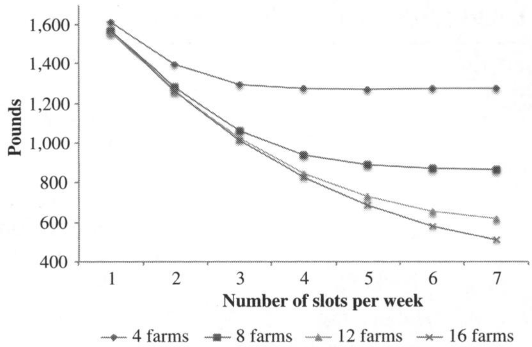

Figure 2. Average volume gleaned per trip as a function of the gleaning schedule (number of slots per week)

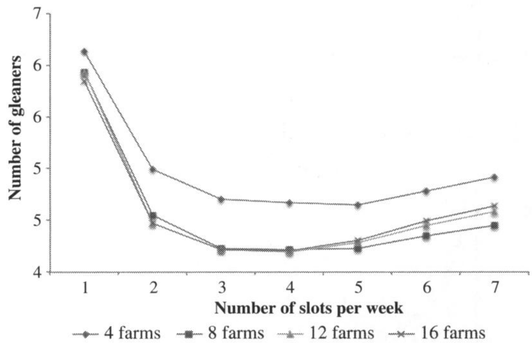

Figure 3. Average number of excess gleaners on over-capacity trips as a function of the gleaning schedule (number of slots per week)

the average number of excess gleaners on the trips that exhibit gleaning overcapacity (i.e., trips that have more gleaners than necessary) as a function of the number of slots per week. As weekly slot availability increases, the excess number of gleaners first decreases due to spreading gleaners among more gleaning trips. However, as slot availability increases even more, the spreading out of gleaners has the effect of taking productive gleaners from trips later in the harvest season (causing those trips to exhibit gleaner undercapacity), and putting them on trips earlier in the season (which already exhibit gleaner overcapacity). Therefore, gleaners will tend to attend the earlier trips, thus increasing the excess gleaning capacity on earlier trips and driving up the average number of excess gleaners on those trips. Although fewer trips

[3] According to FBST, the cost of a gleaning trip is estimated to be \$150, calculated as follows: 1) transport \$22 (average round trip is 40 miles at \$0.55 per mile); and 2) administrative costs (salaries and fringe benefits) of \$128 (4 hours at \$32 per hour). This amount can be expressed as 714.3 pounds of apples gleaned (\$150 cost of a gleaning trip divided by \$0.21, the average per pound farm gate price of lower quality apples in 2014).

[4] The number of excess gleaners is the difference between the total number of gleaners that attend a given gleaning trip and the minimum number required to glean the available volume on that trip, that is, the number of excess gleaners is equal to $\max\{A_t(j) - v/\alpha, 0\}$.

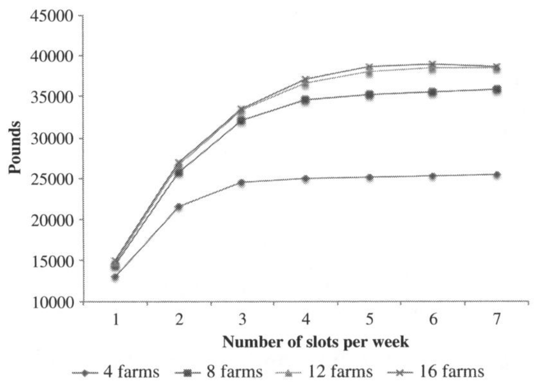

Figure 4. Expected total volume gleaned when the number of gleaners per trip is capped as a function of the gleaning schedule (number of slots per week)

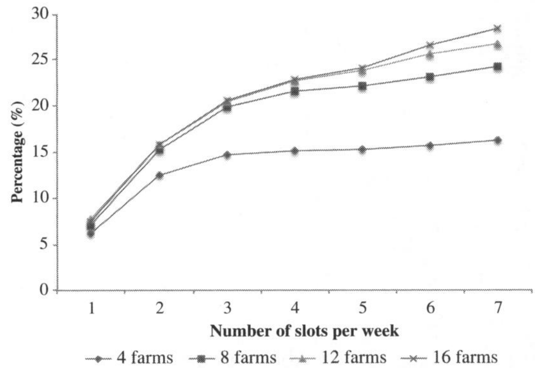

Figure 5. The percentage increase in expected total volume gleaned when the number of gleaners per trip is capped as a function of the gleaning schedule (number of slots per week)

have excess gleaners, the ones that exhibit overcapacity tend to have more excess gleaners, exacerbating gleaner capacity waste. This is consistent with the net loss of gleaned apple volume when the number of slots per week exceeds a certain threshold (depending on the number of farms; see figure 1). We note that gleaner capacity is wasted on a significant percentage of gleaning trips, especially when the farm number is low. For our base case, the percentage of trips with excess gleaner capacity ranges from 28% (7 slots per week) to 68% (1 slot per week).

The FBST could implement a coordination mechanism that would enable them to cap the number of gleaners that attend a given gleaning trip. The number of gleaners required to glean the available volume on a given trip is v/α (rounded up to the nearest integer). The FBST could implement, for example, a sign-up sheet for each gleaning trip, allowing gleaners to sign up until the cap of v/α gleaners is reached. Figure 4 presents the expected total volume gleaned when the number of gleaners is capped. We observe that our insights pertaining to the model without the gleaner cap (figure 1) remains qualitatively the same when the number of attending gleaners is capped, that is, the expected total volume gleaned increases at a decreasing rate as slot availability increases. Even though excess gleaners are eliminated, the benefit of adding more slots still diminishes because the stochastic arrival and gleaner burnout effects persist (see discussion for figure 1). However, capping the number of gleaners does improve performance. Figure 5 shows the percentage increase in expected total volume gleaned when the number of gleaners per trip is capped. It is intuitive that the effect of capping increases in slot availability and number of farms—the avoided excess gleaners can be put to more productive use when there are more slots and more farms.

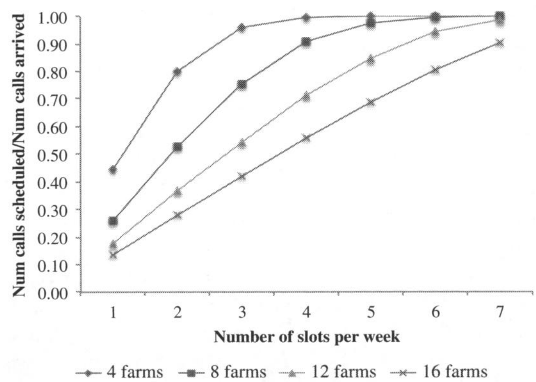

Figure 6. Call service level as a function of the gleaning schedule (number of slots per week)

Call and Volume Service Levels

We define the call service level as the fraction of arriving gleaning calls (gleaning opportunities) that are scheduled by the food bank. Figure 6 shows that the call service level increases as the number of slots per week increases, but at a diminishing rate. For the base case with 8 farms in the network, the service level increases substantially until slots per week reaches 4 and eventually reaches

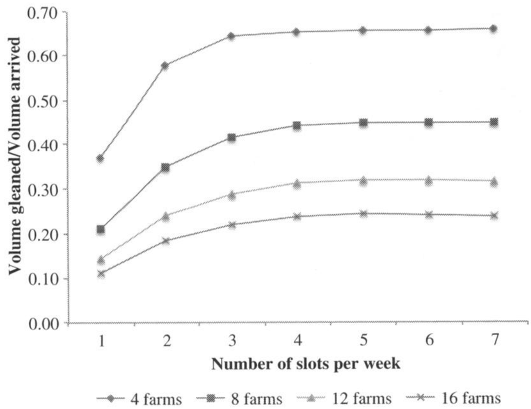

Figure 7. Volume arrived service level as a function of the gleaning schedule (number of slots per week)

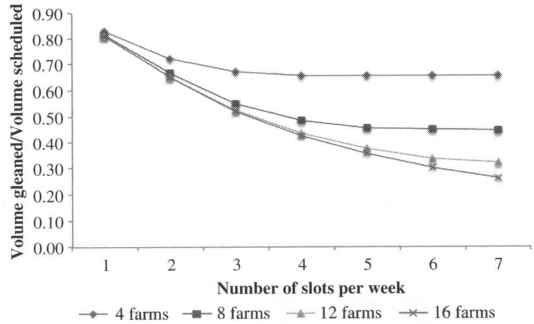

Figure 8. Volume scheduled service level as a function of the gleaning schedule (number of slots per week)

100% service level at 6 slots per week. The call service level is sensitive to the number of farms in the gleaning network. If there are 4 farms in the network, the effect of increasing the number of slots on call service level decreases dramatically after 3 slots per week (since 96% of the calls are already scheduled at 3 slots per week). As the number of farms increases to 16 farms, increasing the number of slots per week has almost a linear effect on call service level. This is because the call arrival rate is very high and very few slots are left unused. For example, for 16 farms, even at 7 slots per week, the number of unused slots over the entire season is less than 5.

Another performance metric is the volume service level, which represents the fraction of the volume opportunity that is actually gleaned. There are two types of volume opportunities: (*a*) the volume arrived opportunity offered by farmers, and (*b*) the volume opportunity that is scheduled by FB. As seen in figure 7, the volume arrived service level first increases as more slots per week are allocated, but then flattens out and may even decrease. For example, for the base case of 8 farms in the network, scheduling 1 slot per week yields a service level of about 20%; the service level increases to 45% at 4 slots per week; the service level stays practically the same for more than 4 slots per week. The figure also indicates that the service level decreases as the number of farms in the network rises. The flattening out of the volume arrived service level curves indicate that gleaner capacity is constraining the total volume, not the number of slots per week.

Figure 8 indicates that service level for the gleaning volume scheduled decreases in the number of slots per week. For the base case of 8 farms, scheduling 1 slot per week yields a service level of about 80%, and it decreases at a decreasing rate to reach a service level of about 45% with 7 slots per week. The reason is that, as the number of slots increase, fewer gleaners attend each trip and each trip nets a lower volume gleaned as a result. This suggests that too many slots per week makes gleaning less useful for the farmers in the network. Gleaning can also be thought of as a service to farmers and if each gleaning trip captures only a small percentage of the donated volume, a farmer may not find it worthwhile to participate in the network (e.g., in terms of tax benefits associated with donations, etc.).

Our results show that there can be a tradeoff between call service level and volume service level. Increasing slot availability will always increase the call service level, but beyond a threshold number of slots, the volume service level decreases in slot availability. Thus, the food bank must manage the schedule to avoid under-scheduling and over-scheduling.

Sensitivity Analysis

Changing the Gleaning Opportunity Window. Changing the gleaning opportunity window can change the total volume gleaned without changing the number of weekly gleaning slots. As seen in figure 9, increasing the gleaning window from 7 to 9 days increases the total volume gleaned, whereas reducing the gleaning window from 7 to 5 days has the opposite effect. Figure 9 indicates that the effect of changing the gleaning

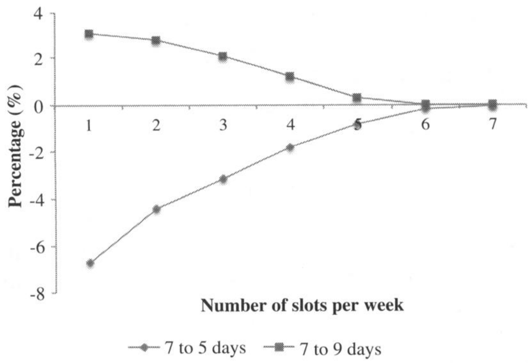

Figure 9. Percentage change in volume gleaned by changing the gleaning opportunity window, as a function of the gleaning schedule (number of slots per week)

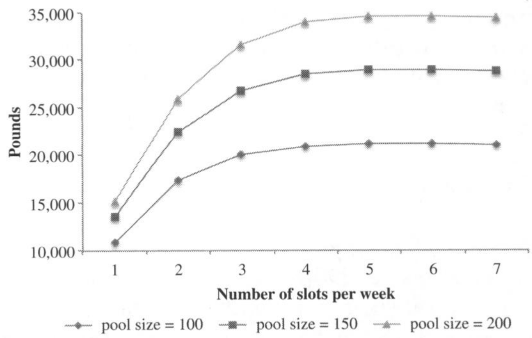

Figure 10. Expected total volume gleaned as a function of the gleaning schedule (number of slots per week), for varying initial gleaner pool size

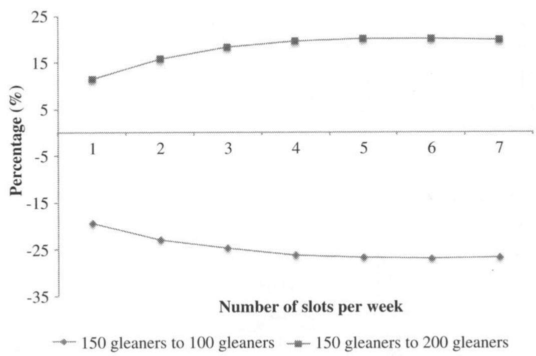

Figure 11. Percentage change in volume gleaned by changing the initial gleaner pool size, as a function of the gleaning schedule (number of slots per week)

window is most pronounced when slot availability is low. For example, at 2 slots per week, increasing the gleaning window from 7 to 9 days increases the volume gleaned by about 3%. Conversely, decreasing the gleaning window from 7 to 5 days reduces the volume gleaned by over 4%. As weekly slot availability increases, there are already so many calls scheduled that increasing the gleaning opportunity window does not affect the volume gleaned. These results suggest that the gleaning opportunity window and slot availability are substitute mechanisms for increasing volume gleaned. Essentially, increasing the gleaning window gives better (i.e., more timely) information on gleaning opportunities, which increases the number of slots that can potentially serve an arriving gleaning opportunity. Therefore, we can compensate for lower capacity (i.e., fewer slots) by having better information (i.e., a longer gleaning window). This illustrates the value of information in a gleaning operation.

Changing the Volunteer Gleaner Pool Size

Another lever the food bank can use to increase the volume gleaned is to recruit more volunteer gleaners, thereby increasing the initial gleaner pool size. Clearly, more gleaners will lead to more volume gleaned. In figure 10, consistent with figure 1, the expected total volume increases at a decreasing rate as the number of slots per week increases. Additionally, for each schedule, larger pool size leads to higher volume. However, figure 11 shows that the effect of increasing the pool size does not increase the volume gleaned in the same proportion. For example, a 33% increase in pool size—from 150 to 200 gleaners—does not result in a 33% increase in volume, even at the highest frequency schedule (the increase in volume gleaned ranges from 10–20%). This is because with stochastic gleaner attendance and call arrivals, some of the additional gleaner capacity will be added to trips that already exhibit gleaner overcapacity. Figure 11 shows that a decrease in pool size of 33% has a larger (negative) effect on total volume than the equivalent percentage increase in pool size (the reduction in gleaned volume ranges from 18–27%). This is because fewer trips will have gleaner overcapacity, and therefore each marginal gleaner removed from the pool has a higher likelihood of volunteering on trips that are under-capacity. Thus, adding gleaners has a positive effect, but losing gleaners has an even greater negative effect on total volume gleaned.

Concluding Remarks

Gleaning is appealing on many levels; it reduces waste, helps provide adequate diets for food-insecure individuals, and it gives opportunities for well-intentioned volunteers to be involved in an activity that benefits their community. However, because farm donations and processing capacity are both voluntary, managing such an operation can be challenging. This study used a stochastic optimization model to characterize and optimize a gleaning operation. We used our model to derive general operational insights and applied the model to make specific operating policy recommendations to the Food Bank of the Southern Tier in New York.

Our model revealed the tradeoff between call and volume service levels. The food bank chooses the gleaning schedule, which affects the effective gleaner capacity and the number of gleaning opportunities scheduled. Increasing the number of slots per week can increase both call and volume service levels when slot availability is low. However, beyond a certain threshold, further increasing the number of slots can decrease the volume service level due to decreasing effective gleaner capacity (because of gleaner burn-outs and wasted gleaner capacity). This threshold is lower when there are more farms in the network. This tradeoff indicates that there is an optimal slot availability that maximizes the total volume gleaned for a given parameter set. Too few slots will result in missed gleaning trips that would have adequate gleaner capacity, and too many slots will reduce effective gleaner capacity resulting in lower total gleaned volume. Moreover, low volume service level also negatively affects farmers because gleaning can also be thought of as a service to farmers. Farmers may not find it worthwhile to participate in the network if each gleaning trip only captures a small percentage of the donated volume.

For the parameters that best represent the operating conditions of FBST (the base case), our model showed that the optimal slot availability that maximizes the total volume gleaned is 5 slots per week. Moreover, using cost data from FBST, we can determine the cost-efficient threshold slot availability that would make gleaning trips worthwhile, on average. For the base case (8-farm network), all schedules are within the cost-efficient threshold. However, given the diminishing returns on the marginal gleaning slot, restricting the slot availability to fewer than 3 slots per week seems to be most prudent for FBST.

We also identified that increasing the gleaning window and increasing slot availability are substitute mechanisms for increasing the total volume gleaned. Increasing the gleaning window gives the food bank more information, and that can substitute for additional capacity (number of slots per week). For example, if the gleaning window were to increase from 7 days to 9 days, our model predicts that the total volume gleaned would increase by 3% when using a 1-slot per week schedule. Therefore, encouraging farmers to call earlier with gleaning opportunities could increase the gleaned volume without adding extra resources.

Increasing the gleaner pool size can also increase the total volume gleaned. However, because of the stochastic nature of gleaner attendance and limited available volume per gleaning opportunity, increasing the gleaner pool size does not increase the volume gleaned proportionally, that is, some of the additional gleaner capacity can be wasted. Our model can quantify the expected increase in volume under each schedule, for changes in the gleaner pool size. Thus, the food bank can use this measure to assess whether it is worthwhile to use resources to recruit gleaners.

Our findings are valuable to food banks that are interested in improving their growing gleaning operations. Nevertheless, our model has several limitations that should be addressed in future research. For example, our model considers only one product (apples). Future research should extend our model to include a variety of fruits and vegetables, given that variety is essential for improving the dietary quality of individuals receiving food assistance from food banks. In addition, our model can be extended to consider the spatial location of farms in the gleaning network. By doing so, the model can address issues of cost-minimizing truck routes for further improving the efficiency of gleaning operations.

Supplementary Material

Supplementary material is available at http://oxfordjournals.our_journals/ajae/online.

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Appendix A

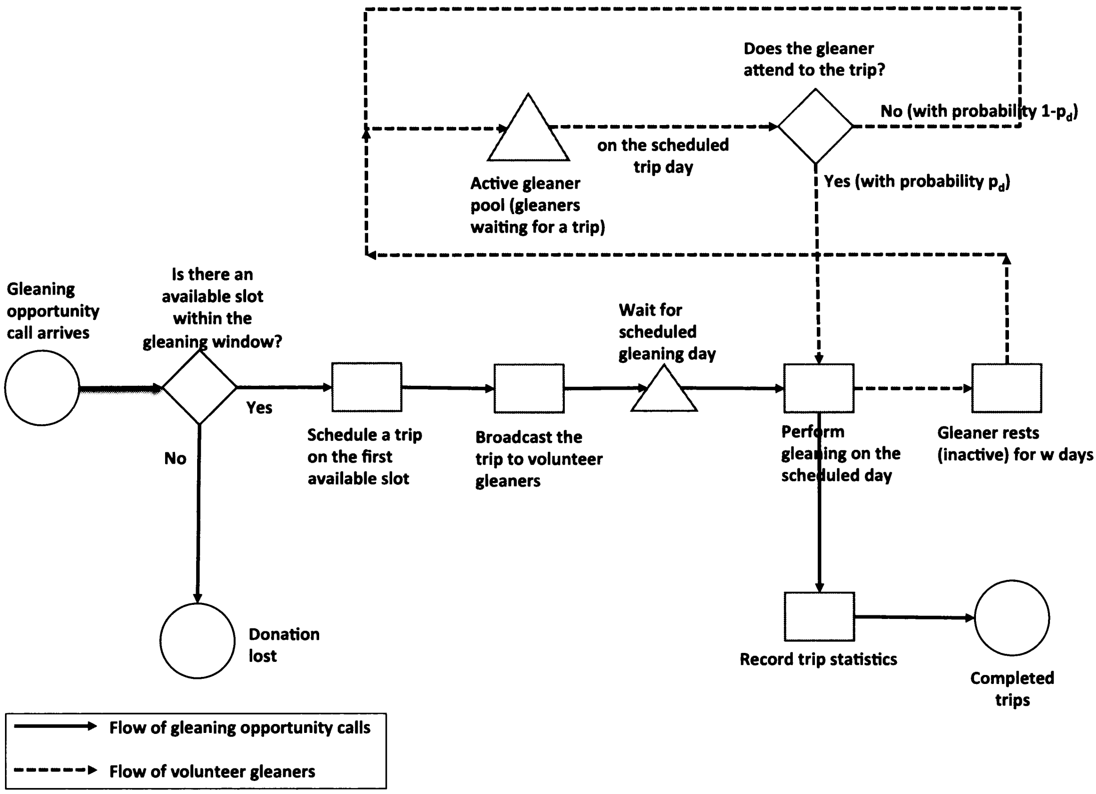

Figure A1. Simulation flowchart