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Tactical planning of the production and distribution of fresh agricultural products under uncertainty

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ABSTRACT

We present a stochastic tactical planning model for the production and distribution of fresh agricultural products. The model incorporates the uncertainties encountered in the fresh produce industry when developing growing and distribution plans due to the variability of weather and demand. The main motivation for building this model is to make tools available for producers to develop robust growing plans, while allowing the flexibility to choose different levels of exposure to risk.

The modeling approach selected is a two-stage stochastic program in which the decisions in a first stage are designed to meet the uncertain outcomes in a second stage. The model developed is applied to a case study of growers of fresh produce in Mexico and in a simulation of various scenarios to test the robustness of the planning decisions. The results show that significant improvements are obtained in the planning recommendations when using the proposed stochastic approach as compared to those rendered by deterministic models. For instance, for the same level of risk experimented by the producer, planning based on the proposed stochastic models rendered increases of expected profit of over 50%. At the same time when risk aversion policies were implemented, the expected losses decreased significantly over those recommended by deterministic planning models.

1. Introduction

Growers of perishable agricultural products, such as fresh fruits and vegetables, very often face complex planning problems such as deciding how much of a particular crop to plant, the timing of planting, and harvesting. The complexity of this problem and its importance for securing the food supply chain has prompted several applications. For instance, Ahumada and Villalobos (2011) presented a deterministic tactical model for planning the production and distribution of fresh agricultural products. Given that experience indicates that some parameters used in deterministic planning models are highly dependent on weather and market conditions (Lowe and Preckel, 2004), it is necessary to develop models that capture this variability. In particular, it is necessary to capture the uncertainty on price and yield which are very important for those growers that operate under open-market conditions. For these growers, the prices of their products vary along the harvesting season due to the combined effects of supply and demand and the lack of storage opportunities because of the perishability of these crops. For this reason, models that capture these uncertainties are needed to find more robust tactical solutions that are adaptable to the situations experienced by the different types of growers and their tolerance to risk.

In this paper, we develop a model that deals with the uncertainties mentioned above for the fresh produce industry. The model builds on the work introduced by Ahumada and Villalobos (2011), by adding random variables, to better reflect the variability experienced by producers. The main motivation for building this model is to develop planting and distribution plans that are robust to the uncertain effects of markets and weather. From the perspective of the growers, the model should help them achieve their goals in the fresh produce supply chain, whether these goals include maximizing the expected income of growers, also known as risk neutral approach, or at reducing the probability of experimenting a loss, which is also known as the risk-averse approach. For the development of this project, growers were involved on providing data and validating the results found.

The present work follows a similar approach to the one presented in Ahumada and Villalobos (2011), which consisted of designing a model with tactical decisions such as planting, labor planning, harvesting and distribution decisions that could be applied to any fresh agricultural problem, and then demonstrating its applicability by applying this methodology to a real case study of fresh produce growers located in Mexico.

The approach selected for improving the deterministic model is to use a two-stage stochastic program (Birge and Louveaux, 1997)

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in which the decisions in the first stage are made to meet the uncertain outcomes in the second stage. The use of a two-stage planning model comes natural to agricultural planning given the time elapsed from the time of planting to harvest (10–15 weeks). Most of the time, the long lead time between the time of planting and the time of harvest require that all planting decisions are made before there is a single crop harvested. These physical constraints prevent the tactical plan from being reevaluated, thus reducing the planning decisions to a single stage. At the beginning of the planting season, the farmer should decide on how much of each product will be planted without having certain information of future weather and market conditions.

In accordance with the two-stage approach, the information available to the farmer at the time that tactical decisions are made is divided in two sets. The first stage set incorporates the planting constraints and the costs associated with the planting decisions, such as labor cost and availability. In the second stage the information available is the random distribution of crops' prices and crops' yields. Also in the second stage, there are transportation, harvesting and distribution costs. Other relevant features in the second stage include demand requirements that must be met, such as pre-existing contracts, market demand, and transportation available during the harvesting period. The solution for the two-stage problem is then dependent on the first stage decisions (planting), the random realizations (Crop yield and prices) and the second stage decisions (harvesting and distribution).

As mentioned before, the benefit of using stochastic programs (SPs) is that, unlike the deterministic solutions, which are based in expectations, the stochastic approach can be used to consider specific scenarios that occur according to the realizations of the different random variables explicitly considered in the model (Darby-Dowman et al., 2000). Moreover with the information provided by the solution of each scenario it is possible to implement more meaningful risk metrics that are both relevant and better understood by the growers. In this paper besides developing the methodology for a SP application for agricultural planning, we apply risk measures that can help farmers to make more robust planning decisions.

One of the main benefits of the work to be presented is that it would provide the farmer with a tool to make decisions based on his/her tolerance to risk and to explore what are the expected worst case scenarios.

2. Background, related works and proposed model

Planning models dealing with perishable products very often fail to incorporate realistic stochastic features present in the different echelons of the fresh produce supply chain (Ahumada and Villalobos, 2009). This may be due to the added complexity of finding solutions for the resulting models. In the few cases available in the literature that reality-based stochastic features were introduced into the models the results justified the added complexity of the model (Jones et al., 2003; Allen and Schuster, 2004). For instance, Kazaz (2004) presents an SP model for a Turkish company producing olive oil. The company has the option of leasing the olive trees to grow the olives or to buy the olives in the open market at a higher price. The planning model consists of two-stages, where the decisions at each stage depend on the stochastic distribution of demand and the uncertain yield of the olive trees. In the first stage the company determines the amount of trees to lease, and in the second stage, based on the yield and the prices of olives in the open market, the company determines the amount of olive oil to produce and olives to buy from the farmers. The objective of the model is to maximize the expected profit subject to demand and the sales price of the olive oil.

Our case is similar to that of Kazaz (2004) in the use of a two-stage SP. The traditional formulation of the two-stage SP has the following structure (Birge and Louveaux, 1997):

$$Max\{cx + E_pQ\{x, \xi(w)\}|Ax = b, \quad x \geqslant 0\} \tag{1}$$

where

$$Q\{x, \xi(w)\} = Max\{q(w)y|Wy = h(w) - T(w)x, y \geqslant 0\}$$

In this notation the vector x is the first-stage decision variable and y is the second-stage decision vector with feasible sets $\{x|Ax - b, x \geqslant 0\}$ and $\{y|Wy = h(w)x, y \geqslant 0\}$ respectively. W is the matrix for the parameters of the second stage variables, $h(w)$ are the random vectors associated with random realizations of w and $T(w)$ is the random matrix effected by the first stage decisions variables vector (x). The objective of this problem is to maximize the revenue of the first stage cost and revenues (cx) with the expectation of the second stage solutions ($q(w)y$). In the case of a discrete distribution, for example, when scenarios approximate the distribution, the formulation then becomes a linear program. The deterministic equivalent for the two–stage SP has the following structure:

$$Max\left\{cx + \sum_s p_s q_s y | Ax = b, \quad x \geqslant 0\right\} \tag{2}$$

s.t.

$$T_s x + W_s y = h_s, y \geqslant 0, \quad s = 1 \dots S$$

It can be observed in (2) that in the deterministic equivalent the random realizations w are approximated by the scenarios S.

The previous model allows the introduction of specific scenarios of importance to the farmer. For instance, scenarios with low probability of occurrence but high impact on the potential profit, such as climate or market dislocations, could be captured into the model. This is an advantage of stochastic over deterministic models that very often are based on expected value that do not capture very well events in the tails of the distributions that could have a dramatic impact on the economic performance of the farm. For instance, some farmers may want to absolutely minimize the observation of catastrophic events at the expense of higher expected profits.

In our case, the first stage decisions for the stochastic model of the grower of fresh produce are formed by the planting decisions. It is assumed, in accordance with the two-stage approach, that costs and resources in the first stage are deterministic, thus leaving the second stage or recourse variables as the only random functions. In the second-stage of the problem it is assumed that the stochastic parameters are the crops' yield ($y_{tjt'}$) and the market prices (p_{tki}) for product k at shipping period t, and customer i, which are represented by the scenarios S developed in Section 4. Then the model for the first stage problem is developed in the following way:

$$\max\left[\sum_s pr^s \sum_{ts} Q_t^s - \lambda \sum_{ts} pr^s (T - Q_t^s)_+ - \sum_{tjl} Plant_{tjl} \cdot Cplant - \sum_{tl} Opl_{tl} \cdot Clabor - \sum_{tl} Hire_{tl} \cdot Chire - \sum_{tl} Opt_{tl} \cdot Ctemp\right] \tag{3}$$

s.t.

$$\sum_j \sum_p Plant_{pjl} \leqslant LA_l \cdot \quad \text{all } l \text{ where } l \in L, \; p \in TP(j,l), \quad \text{and } j \in J \tag{4}$$

$$\sum_j \sum_p \sum_l Plant_{pjl} \cdot Cplant_{jl} \leqslant Inv \tag{5}$$