OPTIMIZING PRODUCTION AND INVENTORY DECISIONS AT ALL-YOU-CARE-TO-EAT FACILITIES

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

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AT ALL-YOU-CARE-TO-EAT FACILITIES

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DEDICATION

This dissertation is dedicated to my love, Salih, and my wonderful parents Ayse and Yasar for their unconditional support, encouragement, and love.

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ABSTRACT

Food service, feeding people outside of their home, is one of the largest industries in the world (Hartel and Klawitter, 2008). Restaurants, hospitals, military services, schools and universities are among those organizations providing these services. Management of a food service system requires operations management skill to operate successfully. A key element of food service is food production. Forecasting, demand, managing inventory and preparing menu items are key tasks in the food production process. In this research a series of three studies are presented to improve the food production system policies at an all you care to eat (AYCTE) facility.

The first study examines two objectives, limiting its focus to foods for which all overproduction must be discarded (that is, leftovers cannot be saved and used in future periods). The first objective of this research is to present a novel method for estimating shortfall cost in a setting with no marginal revenue per satisfied unit of demand. Our methodology for estimating shortfall cost obtains results that are consistent with CDS management's stated aversion to shortfall, we estimate shortfall values are between 1.6 and 2.7 times larger than the procurement cost and between 30 and over 100 times larger than disposal costs. The second objective is to identify how optimal food production policies at an AYCTE facility would change were life cycle cost estimates of embodied greenhouse gas (GHG) emissions, including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), included in the disposal costs associated with overproduction. We found that optimal production levels are decreased significantly (18–25%) for food items with high environmental impacts (such as beef), and reduced less for foods with less embodied CO_2.

The second study considers a broader set of food types, including both foods that cannot be saved and stored as leftovers (as in the first study), and also foods for which overproduction can potentially be saved and served in the future as leftovers. Food service operations in an AYCTE environment need to consider two conflicting objectives: a desire to reduce overproduction food waste (and its corresponding environmental impacts), and an aversion to shortfalls. Similar to the first study, a challenge in analyzing such buffet-style operations is the absence of any lost marginal revenue associated with lost sales that can be used to measure the shortfall cost, complicating any attempt to determine a minimum-cost solution. This research presents optimal production adjustments relative to demand forecasts, demand thresholds for utilization of leftovers, and percentages of demand to be satisfied by leftovers, considering two alternative metrics for overproduction waste: mass; and GHG emissions. A statistical analysis of the changes in decision variable values across each of the efficient frontiers can then be performed to identify the key variables that could be modified to reduce the amount of wasted food at minimal increase in shortfalls.

The last study's aim is to minimize overproduction and unmet demand under the situation where demand is unknown. It also addresses correlations across demands for certain item (e.g., hamburgers are often demanded with french fries). As in the second study, we again utilize a Hooke-Jeeves optimization method to solve this production planning problem. In order to model a more realistic representation of this problem, demand uncertainty is incorporated in this study's optimization model, using a kernel density estimation approach. We illustrate our approach in all three studies with an application to empirical data from Campus Dining Services operations at the University of Missouri.

Chapter 1

Introduction

This chapter provides an overview of this dissertation, along with motivation for this research. This research proposes to prescribe changes in food production system policies at an all you care to eat (AYCTE) facility. Three completed studies are presented: one in which we estimate shortfall cost for unsatisfied demand and environmental effects on production decision when overproduced items must be discarded immediately, a second in which overproduction can potentially be served as leftovers in the future, assuming known and fixed demand, and a third study whose setting is similar to the second study, but now with unknown demand that is stochastic and correlated. Research questions and sub research questions are presented for each study to provide readers an understanding of the aspects of food waste that will be addressed in each study.

1.1 Overview

Food waste is a significant issue around the world. Moreover, the impact of food waste is increasing as the world's population rises. Considering that the United Nations predicts that the world population will reach 9.6 billion by 2050 (United Nations, 2013), food waste presents an important issued to be solved for the future well-being of mankind.

Considering the economic and environmental aspects of food waste in the USA, the estimated annual value of food waste in American households is greater than $43 billion annually (Jones, 2004). Another analysis (Venkat, 2011) shows that avoidable food waste in the US exceeds 55 million metric tons per year which produces life-cycle greenhouse gas emission of at least 113 million metric tons of carbon dioxide equivalents CO_2e annually, equivalent to 2% of national emissions.

1.1.1 What is the issue?

In recent years, a number of studies have led to increasing societal awareness of the environmental effects of food waste (Kantor *et al.*, 1997; Griffin *et al.*, 2008; Buzby and Hyman, 2012; FAO, 2013b). The FAO (2013b) study, for example, estimated that one-third of all food produced for human consumption in the world is lost or wasted. While there is no consistently applied definition of the term *food waste*, the framework developed by the FAO (2013b) provides a supply-chain perspective divided into six phases: agricultural production, post-harvest handling and storage, processing, distribution, consumption, and end of life. Although waste occurs at all phases of the food supply chain, the largest losses in developed nations occur at the consumption stage; e.g., 39 percent (%) of waste is estimated to occur at the consumption stage for North America and Oceania (FAO, 2013b).

The Food and Agriculture Organization (FAO) of the United Nations generates estimates of agricultural production and use. Recent FAO data suggest 36% of agricultural production in North America is wasted, equaling more than 20 pounds of food per person per month. FAO also estimates the fraction of waste that occurs at each phase of supply chain. Figure 1.1 illustrates the percentage of food wastage of North America and Oceania along the food supply chain. The consumption stage, at 39%, is responsible for the greatest amount of total food wastage. From the perspective of the food processing facility, upstream wastage volumes, including agriculture, post-harvest handling and storage, represent 43% of total wastage, while downstream wastage volumes, including processing, distribution and consumption, is 57% (FAO, 2013b).

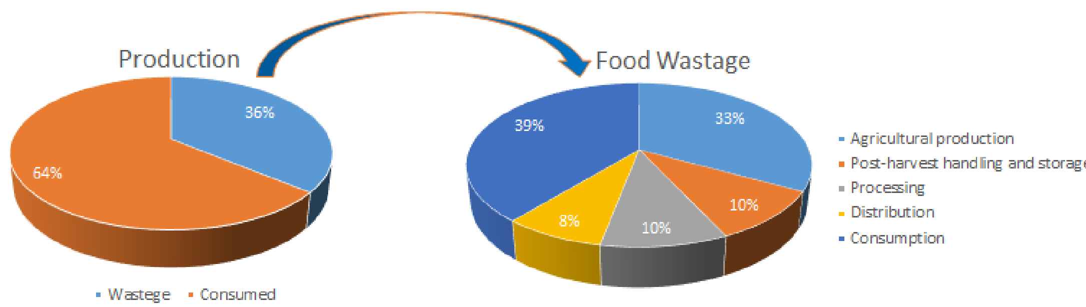


Figure 1.1: Food waste in North America and Oceania

Since food waste is more easily defined and less ambiguous at the consumption stage, this stage has been more thoroughly investigated than other stages (Buzby and Guthrie, 2002; Engström and Carlsson-Kanyama, 2004; Parfitt *et al.*, 2010). Food waste at the consumption stage can be further categorized as either *pre-consumer* or *post-consumer* waste. Pre-consumer waste is generated from such sources as storage loss, preparation loss, and serving loss, whereas plate waste and overproduction comprise post-consumer waste.

Although different institutions try to reduce their food waste, such as military institutions (Lenahan and Karwan, 2001), hospitals (Williams and Walton, 2011), food waste is of particular interest to university administrators because the disposal cost of waste has increased in recent years and is expected to continue to increase (Merrow *et al.*, 2012). Saphire (1998) shows that more than 3,000 higher learning institutions in the United States generate approximately 3.6 million tons of waste, which is about 2 percent of the country's solid waste stream.

Costello *et al.* (2016) described food waste generation at the University of Missouri (MU) Campus Dining Service (CDS). Pre-and post-consumer food waste were collected from four AYCTE facilities during three months in 2014. During the study period, approximately 246.3 tons of food reached the retail level, while only 206 tons of food was consumed by customers. 26.5 tons of wastage occurred in the post-consumer stage, this waste was further divided into edible (21.2 tons) and inedible (5.3 tons) fractions. The remaining 13.8 of tons wastage occurred in pre-consumer stage (10.1 tons edible, 3.7 tons inedible). Figure 1.2 presents the total pre- and post-consumer waste during this study period.

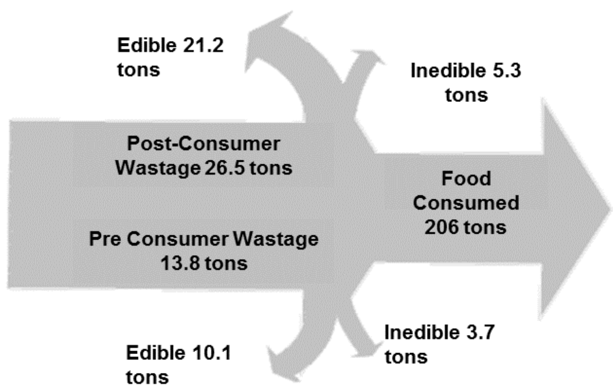


Figure 1.2: Food waste in University of Missouri during February 17 to May 16, 2014, Costello et al.(2016)

In addition to describing pre- and post-consumer waste amount, the study also estimated the greenhouse gas emissions (GHGs) that were embodied in 11.1 CO_2e tons in pre-consumer, 56.1 CO_2e tons in post-consumer food waste.

1.1.2 What is the thesis about?

Within this dissertation, three different studies are presented, each appearing in a separate chapter. The first study in this thesis examines the environmental impact of overproduction food waste (i.e., discarded leftovers), in an aim to study production planning possibilities in a situation that places increased emphasis on the environmental impacts of overproduction. In particular, we examine the influence of overproduction on the optimal production level for food items served at MU CDS. This setting is of particular interest because CDS operates AYCTE facilities, for which there is no value for lost revenue that can be utilized as an estimate of shortfall (inventory stockout) costs. Given the absence of existing literature detailing how one might compute shortfall costs in such an environment, the second objective of this research is to present a novel method for estimating shortfall costs in an AYCTE setting, inferring the value that current management places on shortfalls as a consequence of its historical production decisions. We limit our attention to single-period food products (i.e., overproduction cannot be stored and later served as leftovers, but must be discarded). These items are produced from frozen inventories, and can effectively be thought of as having no storage loss. Because these are single period items, there is no holding cost value; rather, a disposal cost is incurred for each overproduced item. The most straightforward interpretation of disposal cost is simply the landfill cost incurred when this item enters the solid waste stream. However, recognizing that wasted food also wastes upstream resources associated with food production, we extend disposal costs to include estimates of the greenhouse gas emission in units of carbon dioxide equivalent (CO_2e) emissions embodied in wasted food, to identify the extent to which inclusion of these environmental costs impacts optimal production levels. We demonstrate our analytic approach using empirical data from a set of food items commonly produced by CDS.

The second study examines optimal production strategies, including policies for the usage of leftovers, in an aim to balance two conflicting objectives: a desire to reduce overproduction food waste (and its corresponding environmental impacts), alongside an aversion to stockouts (in which some customer demands go unsatisfied). In particular, we define production adjustments relative to demand forecasts, demand thresholds for utilization of leftovers, and percentages of demand to be satisfied by leftovers, and again illustrate our approach with an application to empirical data from food service operations at MU CDS. We consider two alternative metrics for overproduction waste: mass (in kg); and greenhouse gas (GHG) emissions (in kg), to account for the embodied chemical usage during farming, transportation, and landfill decomposing of overproduced food waste.

The third study examines leftover usage and environmental impact of overproduced food waste when demand is uncertain and correlated. Assuming deterministic demand is not a practical way to minimize waste and shortfall amount in real-life applications. Therefore, this study applies a similar process to that presented in the second study, now extending the models to address correlated and uncertain demand.

Given the absence of existing literature examining pre-consumer overproduction waste in AYCTE facilities, this dissertation contributes to knowledge by providing optimization models for production planning in such an environment, presenting a novel method to estimate shortfall costs, and investigating the influence of CO2e considerations on production planning both when overproduction can and cannot be reutilized as leftovers. The specific aims of these studies are detailed below.

Aim 1: Investigate the environmental impact of overproduction food waste for single period items and present a novel method for estimating shortfall costs in an AYCTE setting.

Aim 2: Investigate leftovers usage and the environmental impact of overproduced food waste when overproduction can potentially be served as leftovers in the future, assuming known demand.

Aim 3: Investigate leftovers usage and the environmental impact of overproduced food waste where overproduction can be potentially served as leftovers in a future when demand is stochastic and correlated.

In the second chapter, a detailed literature review is presented to clarify previous work in this area, providing the motivation for this research, and outlining current gaps in the literature, in order to justify this dissertation's research. Chapters 3, 4 and 5 present the methodology and research design addressing the first, second and third research questions, respectively. Concluding remarks and suggestions for future research are then presented in Chapter 6.

Chapter 2

Literature Review

2.1 Food service:

A number of studies have considered optimal production decisions in a food service environment. Ryu and Sanchez (2003) developed demand forecasting approaches to address overproduction and shortfall at institutional food service operations by identifying the most appropriate method for forecasting meal counts based on accuracy and simplicity at Texas Tech University. Goto *et al.* (2004) used Markov decision processes to identify minimum cost strategies for airline flight catering, investigating the tradeoff between having overage and shortage meals on a flight. Result of applying this optimal policy yields cost saving of 17%, 1%, and -14% in the long-, medium-, and short-duration groups, respectively. Rivera and Azapagic (2016)) contrasted the life cycle costs and environmental impact of the production and consumption of ready-made meals, when contrasted with similar meals prepared at the consumer's home. As a result of comparison between home-made meal and ready-made option, the home-made is the best option on the life cycle cost and environmental impacts. Extending the scope beyond food service operations, many studies have examined the related field of perishable inventory. Nahmias (1982) provides a review of the early literature in this area, much of which is related to food items. Non-food related applications are also numerous, such as Eppen Gary D and Iyer (1997), which examines ordering decisions for fashion inventory.

A food service operation has distinctive characteristic that makes it unique compared to production of other products (USDA, 2002), such as food safety concerns, requiring special handling both during and after preparation, or the labor-intensive nature of food production and service, requiring a broad mix of both skilled and unskilled labor.

One important characteristic differentiating among food service providers is the population to be served. In this analysis, we will focus on institutional food service providers, such as those supporting universities, schools, correctional facilities, or military installations. Many such facilities provide all-you-care-to-eat (AYCTE) service. In such an environment, menu planning is an activity with a significant effect on daily production operations. One way to address demand uncertainty in food service production planning is through the use of a cycle menu. A cycle menu offers selected items on a regular basis (e.g., daily, weekly, biweekly), such that the entire menu is repeated over some time horizon. According to Spears and Gregorie (2006), a cycle menu offers a variety of choices to customers with some degree of control over purchasing, production and cost.

Food service operators face a variant of the standard production planning problem. For some food items, when overproduction occurs, relative to demand, the excess production cannot be retained for future use. Common examples of such food items are fried foods, such as french fries or fried chicken patties. Since such food items constitute a single-period production system, optimal production policies can be identified using a variant of the newsvendor model (Hadley and Whitin, 1963). The aim of the newsvendor problem is to define an optimal inventory level in the event of uncertain demand, balancing the effects of holding costs (when production exceeds demand) with those of shortfall costs (when demand exceeds production).

2.2 Food waste:

Most studies for food waste reduction in a university or school are only focused on plate waste (Saphire, 1998; Al-Domi *et al.*, 2011; Merrow *et al.*, 2012; Thiagarajah and Getty, 2013). Their results are suggestions to reduce food waste, such as increase awareness of students to food waste by announcing the previous week's food waste amount (Saphire, 1998). Thiagarajah and Getty (2013) tried switch from a tray to trayless delivery system to reduce plate waste. A significant decreases in solid waste by switching tray to trayless system, on the other hand, breakage of dishware and needs for wipe down tables increase. Al-Domi *et al.* (2011) also determine the proportions of food plate waste in University of Jordan and show that 13% of purchased food items is wasted. In the meantime, other studies evaluate food waste generally in the universities. Costello *et al.* (2016),for example, focused on pre-and post-consumer food waste at University of Missouri and provides pre-and post-consumer food waste by weight and GHG emission. The distinction between weight and GHG emission of wasted food is related when considering alternative management options for food waste. Lam (2010) defined reasons such as poor food quality, serving portion, buffet serving for food waste in the UC Berkeley.

A few studies have considered minimization of overproduction food waste. Darlington and Rahimifard (2007) provided a hybrid two-stage planning technique for reduction of overproduction waste by utilizing dynamic and static approaches to production scheduling for a ready-meal manufacturer. The result of the application is that static approach reduces overproduction waste and improve utilization of resources for food manufacture. Garrone *et al.* (2014) presented a model of surplus food generation and management to understand

and quantify surplus food, “recoverable” surplus food and food waste. Papargyropoulou *et al.* (2014) proposed a food waste framework to identify and to give priority to the option for minimization and management of food surplus and waste.

2.3 Shortfall Cost:

A particular characteristic of AYCTE food service operations that complicates the identification of optimal production policies is the lack of revenue associated with each individual item served. In this context, there is no per-item lost sales value that is incurred when demand for a particular food item exceeds the available supply. Thus, in this study, shortfall cost represents only “loss of goodwill”. In interviews, CDS management stated a strong aversion to shortfalls at their AYCTE facilities, although they were not able to provide an estimate of the cost value placed on shortfalls. Therefore, we will utilize a newsvendor model to infer a range of shortfall costs implied by CDS’ current production practices, using these estimates to reflect their implied (but unstated) valuation of shortfalls.

Although shortfall costs are one of the most important parameters necessary to utilize a newsvendor model of production, there has been limited research published on approaches to estimating a shortfall cost when there is no direct link to lost revenue. Ishii and Konno (1998) considered a newsvendor model in which the shortfall cost was assumed to be given by a fuzzy number. Wu *et al.* (2013) considered a model with uncertainty in demand along with uncertainty in shortage cost using a Conditional Value-at-Risk (CVaR) approach. However, neither of these studies addresses how one might estimate a baseline shortfall cost from an actual production environment.

Moreover, classical references for inventory management (Zipkin, 2000; Teunter *et al.*, 2009; Axsäter, 2015) do not contain any discussion for how one might obtain a shortfall cost; rather, these authors provide approaches for utilizing a given shortfall cost. This is problematic, since, as noted by Axsäter (p.45):

Because shortage costs are so difficult to estimate, it is very common to replace them by a suitable service constraint. Of course it is also difficult to determine an adequate service level, but yet this is regarded to be somewhat simpler in many practical situations.

Zipkin makes a similar observation (pp.25-26):

One can measure a holding cost (subject to the caveats above), but it is harder to imagine measuring the cost of a stockout to a customer. In any case, accounting systems typically do not touch such costs. Faced with this difficulty, many people simply give up. As we shall see, it is possible to formulate an inventory model without stockout-cost parameters, using constraints instead, ... My own view, however, is that this just translates the problem to different terms. The basic problem remains to understand what stockouts mean to customers.

2.4 Environmental costs of wasted food

When a food item is wasted all upstream resources that went into production processing and distribution that food is wasted. In other word, considerable amount of chemical, fuel, fertilizer, and 25% of all fresh water in US is used to produce food is wasted (Hall *et al.*, 2009). In addition that all uneaten food rots in landfill and generates methane emission which is a powerful greenhouse gas that is 72 times more potent global warning potential than CO2 (IPCC) for 20-yr time horizon. While GHG emissions from the agricultural sector include gasses aside from CO_2 (notably, N_2O and CH_4 for livestock products, [(de Vries and de Boer, 2010)], and N_2O due to fertilizer application and manure management. [(Mweetwa *et al.*, 2012)]), in this study we will consider all three gasses in terms of their CO_2 equivalents.

Life cycle estimates of GHG emissions associated with agricultural production differentiate among food items based on the total energy use required to produce and deliver an end item to customers (including the emissions embodied in the enabling resources, such as diesel fuel or fertilizers). Numerous studies have attempted to estimate CO_2 emissions embodied in agricultural products, and different authors have produced different estimates for similar products. For example, de Vries and de Boer (2010) estimated that production of 1 kg of poultry resulted in 3.9- 4.9 kg CO_2-equivalent (CO_2-eq), while Lesschena *et al.* (2011) found poultry production to cause 3.6 kg CO_2-eq per kg poultry. Nonetheless, one consistent finding is that plant-based foods generate less CO_2-eq per kg of food than do meats such as poultry or pork, while beef generates significantly more CO_2-eq per kg of food than do other meats. Table 1 below presents CO_2-eq emissions estimates for three commonly-used foods at CDS: potatoes, chicken, and beef.

Food item	**CO_2-eq per kg food**
potatoes (fried)	0.23-2.9 kg (Mweetwa *et al*., 2012)
chicken	3.9-4.9 kg (de Vries and de Boer, 2010)
beef	14-32 kg (de Vries and de Boer, 2010)

Table 2.1: Life cycle CO_2 emission estimates for selected food items

Given these estimates of the CO_2 embodied in different food items, we can obtain a dollar cost equivalent for each kg of wasted food utilizing the Social Cost of Carbon (SCC) estimates provided by the US Environmental Protection Agency (EPA, 2013). The EPA states that these estimates represent

the value of damages avoided for a small emission reduction (i.e., the benefit of a CO2 reduction)

Assuming a 2015-emission year and a 3 percent discount rate, these EPA estimates range between \$0.039/kg CO2 and \$0.116/kg CO2, based on the average SCC and the 95th percentile SCC, respectively.

2.5 Uncertain and correlated demand

The main subject of the last chapter of this dissertation is the uncertain and correlated demand and their effect on both pre- and post-inventory management strategies. Although CDS uses CBORD which has statistical technique to forecast number of production, eventually adjusted that forecast based on the expert judgement, because of special considerations such as game day or weather conditions. Another problem associated with forecasting demands in such a multi-product system is correlation. In a food production environment, the demands of two products might be correlated because of customer eating behavior. Since demand decision are correlated (e.g. french fries served with hamburgers), their production decisions need to account for this correlation.

Problems with random production and demand are common in many industries (Hsu and Bassok, 1999). Ferguson and Dantzig (1956) presented a linear programming application for solving the problem of allocation of aircraft to routes in order to maximize expected profits when costumer demand is uncertain. Rastogi *et al.* (2011) analyzed variability in demands to buy/make decision and investigated the effect of correlation between demands of different products in supply network. Another industry is health care, Gaynor and Anderson (1995) investigated the result of uncertainty in hospitals and strongly reject the hypothesis that uncertainty does not affect hospital cost.

For sure, the exact quantity of production demanded cannot be predicted in advance, however by using previous experience, historical data, some useful information can be obtained. One of the useful information is the probability distribution. Probability distribution can be estimated by using previous observations of any random event (Nahmias and Olsen, 2015). Since we know demand variability from historical data, we can represent these as statistical models with an associated probability density function. The probability density function can be represented two ways: the first one is parametrically which specify approximate statistical distribution by using some techniques such that maximum likelihood estimation (MLE) or Bayesian estimation (BE), the second one is nonparametric approach (Elgammal *et al.*, 2002).

Most of those studies assume that demand distribution is precisely known as Poisson (Xu, 1999) or Normal distribution (Tyworth and O'Neill, 1997). In real world it is not practical. On the other hand, if demand comes from a sample data then distribution can be defined by using best fit algorithm. In that case another problem arise which is lack of desirable statistical properties such as consistency or asymptotic normality(Carrizosa *et al.*, 2016) . In order to deal with these problems some distribution free approaches have been studied in the literature. This study of distribution-free approached is started with Scarf (1958). Scraf (1958) maximized the minimum profit for all demand distribution with known mean and standard deviation. Gallego and Moon (1993) expended Scarf's approach and stimulate new research on robust inventory policies. Another remarkable distribution-free works Yue *et al.* (2006) in which aims at a robust solution by bounding the cost space.

This system becomes much more complex when there are multi product items and also some correlation on demand of those items. In the literature most of the multi-product inventory systems studies assume that demand of each product is independent, there is no correlation (Feng *et al.*, 2015). For efficiency reason, it is important to take these correlations into account in demand modeling. In daily life example, demand of electronic products such as ipad, iphone etc. and their accessories such as case cover are positively correlated (Feng *et al.*, 2015). Liu L and Yuan (2000) determine Markovian model of coordinated replenishments with correlated demand. Shahabi *et al.* (2014) also studied three level location inventory problem with correlated demand across retailers. There exists some literature for correlated demand cases. Eppen Gary D. (1979) shows that amount of savings depends on the correlation of multivariate of normal product demands in single period of stochastic problem. Corbett and Rajaram (2006) generalized Eppen's (1979) normality to near-arbitrary multivariate demand distributions.

Chapter 3

Optimal Production Planning in a No-Leftovers Environment

3.1 Research design-methods

3.1.1 Estimating implied shortfall cost

The University of Missouri CDS provided access to their installation of the CBORD software system (www.cbord.com), which CDS uses to track production, sales, and inventory management data. For sales, CBORD presents information at the *menu item* level (e.g., "french fries" are a menu item in the data); we extracted the number of portions served for each menu item for each specific meal and day over the Fall 2013 and Spring 2014 semesters. As an illustration, Figure 3.1 presents the demand information for menu item *french fries* served at one AYCTE dining facility (Mark Twain dining hall) over this time interval, showing the empirical probability density function (PDF) and cumulative density function (CDF) for the number of items (portions) served at each meal when french fries were offered (there were 462 such meals in our data set). Note that in the event that demand exceeds supply for some menu item, CDS replaces the item whose supply is exhausted with a suitable substitute, and tracks the portions served for this substitute as demands for the exhausted item (this data is recorded, and utilized by managers to modify future demand projections).

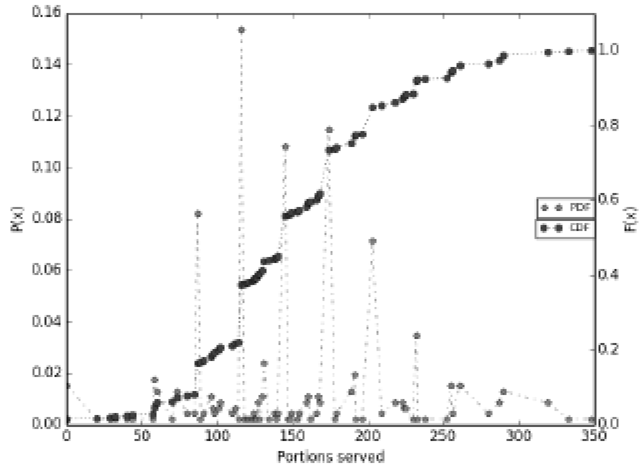


Figure 3.1: PDF and CDF of demand for french fries at one dining facility

In order to infer an estimate of the shortfall cost that is consistent with CDS' historical production decisions, we will assume that current CDS management makes near-optimal decisions, given their existing incentives (which do not address the environmental impacts of overproduction). Currently, each CDS facility obtains a proposed production level for each menu item from the CBORD data system, facility managers then have discretion to modify this value based on their expert judgment. Our underlying assumption here is that the managers at CDS facilities who make production decisions are responding to incentives (both explicit and unstated) from upper CDS management regarding how the facility should be run. Those facility managers who remain in their job (as is the case with the dining hall examined here) are responding in a manner that is satisfactory to upper management, and thus, can be viewed as near-optimal with respect to these incentives.

For the example illustrated in Figure 3.1 (french fries at Mark Twain dining hall), we will assume that the optimal decision under the current incentives lies near CDS' actual production level for french fries over this time interval; specifically, we assume that the optimum lies in an interval defined by the historical production level's CDF values of 0.4 and 0.6, which correspond to 127 and 167 units of production, respectively.

Were CDS making optimal decisions, their optimal production level would correspond to the newsvendor problem solution, which minimizes total expected cost according to the formula

$$\Phi = p - c/p + h$$

where p=shortfall cost; c=procurement cost; h= holding (disposal) cost; and Φ= percent of the time that all demand is satisfied.

There are four costs associated with inventory in a newsvendor model: (1) ordering cost (2) setup cost (3) holding cost and (4) shortage cost (Malakooti, 2013). In the context of our food production problem, view the ordering cost as the cost necessary to produce a food item, including the procurement of the necessary ingredients, and the setup cost as negligible. Since it is assumed that all overproduction of such food items goes directly into the solid waste stream, we do not have a holding cost *per se*. However, since there is a disposal cost associated with these overproduced items, we will initially consider this disposal cost as defining our holding cost in the model.

3.1.2 Determining impact of including environmental costs on optimal production levels.

To determine the environmental cost associated with each wasted food item, it is necessary to identify the ingredients for each menu item, this information was also collected from CBORD. We then utilized the data from Table 2.1 to estimate the life cycle g CO2 embodied in each portion (considering only the food items in Table 2.1, not all ingredients in the menu item), and multiplied these values by the SCC estimates to obtain a lower estimate and an upper estimate on the environmental cost per portion;

these values appear in Table 3.1. We will utilize these costs as our estimates of the environmental cost per overprepared (discarded) portion. Adding these environmental costs to the aforementioned disposal cost allows us to generate an overproduction cost that accounts for environmental considerations.

Menu item	**g CO2 per portion**		**Environmental cost per portion**	
	Lower estimate	Upper estimate	Lower estimate	Upper estimate
French fries	16.55	206	$0.000645	$0.02389
Chicken sandwich	375.9	472.3	$0.01466	$0.05478
Beef ravioli	1,144	2,616	$0.04463	$0.30341

Table 3.1:Life cycle CO2 and environmental cost per portion for selected menu items

We are now in a position to identify how the optimal production levels would change as the environmental costs of overproduction are included. We assume here that management's implied shortfall cost remains constant when environmental costs are added to disposal costs. Note also that the environmental cost is only applied to discarded over preparation, we are not including these estimates of the embodied life cycle CO2 emissions costs in the item procurement costs. One could potentially include environmental costs in the procurement costs for menu items (to the extent that these environmental costs are not currently included), which would add further inducement to avoiding overproduction of high-environmental-cost menu items.

3.2 Results

3.2.1Estimating implied shortfall cost

From CBORD, we obtained a procurement cost of $c = \$0.11$ per french fry portion. We analyzed data from the University's solid waste disposal contract with the City of Columbia and computed an average disposal cost of \$0.08538 per kg from dining hall trash receptacles. Given CBORD data showing a weight of 71.16 g per french fry portion, this implies a disposal cost of $h = \$0.006075$ per french fry portion. The Φ values corresponding to 127 and 167 portions then generate implied shortfall value estimates of $p = \$0.1847$ and $p = \$0.2935$, respectively, per french fry portion. Comparing the relative magnitudes, we observe that the shortfall values are between 1.6 and 2.7 times larger than the procurement cost and between 30 and 49 times larger than the disposal cost, consistent with CDS management's stated aversion to shortfalls. Figure 3.2 presents the total expected cost for a range of production levels under each of the low- and high-estimates of shortfall cost. Observe that total expected cost is minimized at a production level of 127 for the low estimate of shortfall cost, while the high estimate of shortfall cost generates an optimal production level of 167, as expected.

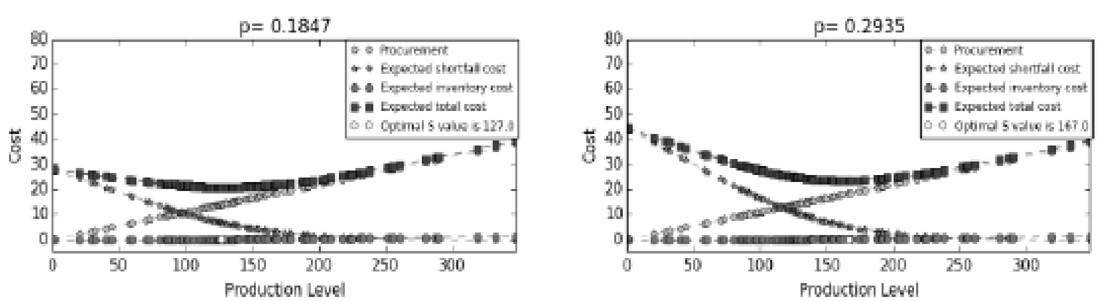


Figure 3.2: Total expected costs as a function of production level for french fries, for lowest and high-estimate of shortfall costs

In order to understand the impact of our assumption that the optimum response in the current environment (which does not consider environmental costs) lies in an interval defined by the historical production level's CDF values of 0.4 and 0.6, we repeated this analysis across a broader interval of CDF values (0.2 and 0.8), which correspond to 102 and 203 units of production, respectively. The Φ values corresponding to 102 and 203 portions generate implied shortfall value estimates of $p = \$0.1390$ and $p = \$0.5743$, respectively, per french fry portion.

Figure 3.3 presents the total expected costs under this assumption.

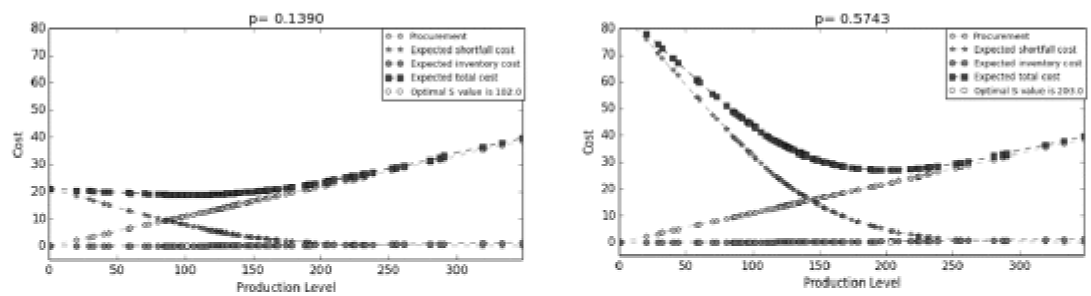


Figure 3.3: Total expected costs as a function of production level for french fries, for lowest and highest-estimate of shortfall costs

Consider two other single-period (i.e., no use of leftovers) menu items commonly produced by CDS: *chicken sandwich*, and *beef ravioli*. Using the method presented above for *french fries*, under the current assumption that item disposal cost comprises the only holding cost, we identified optimal production levels for these menu items (again assuming historical production approximates optimal decisions under the current management incentives) and the resultant implied shortfall costs.

Figure 3.4 presents the demand information for menu item *chicken sandwich* served at one AYCTE dining facility (Mark Twain dining hall) over this time interval, showing the empirical probability density function (PDF) and cumulative density function (CDF) for the number of items (portions) served at each meal when french fries were offered (there were 70 such meals in the data set).

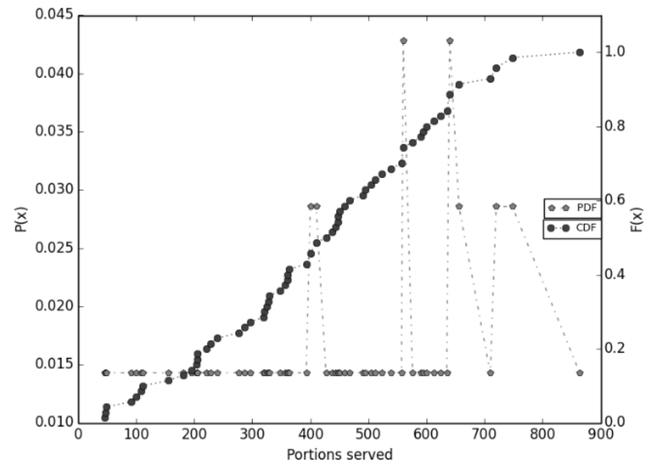


Figure 3.4: PDF and CDF of demand for chicken sandwich at one dining facility

From CBORD, we obtain procurement cost $c = \$0.65$ and the weight of a portion chicken sandwich 96.39 g, and we compute a disposal cost of $h = \$0.008230$ per portion. Figure 3.5 presents the total expected cost for a range of production levels under each of the low- and high-estimates of shortfall cost. Observe that total expected cost is minimized at a production level of 364 for the low estimate of shortfall cost, while the high estimate of shortfall cost generates an optimal production level of 463, as expected.

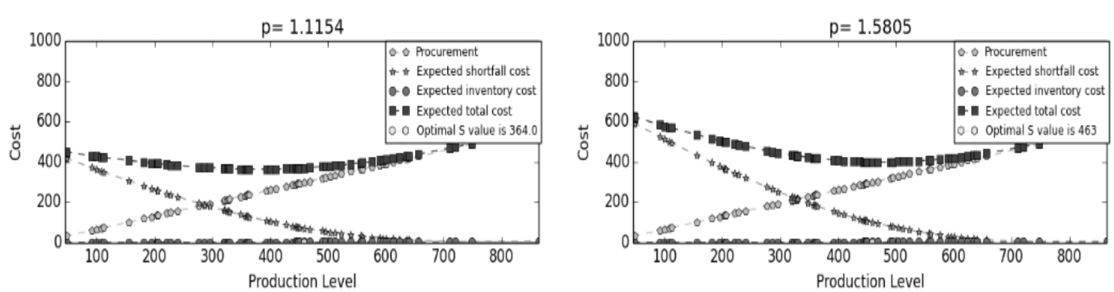


Figure 3.5: Total expected costs as a function of production level for chicken sandwich, for lowest and high-estimate of shortfall costs

Under the assumption that the optimal production level lies between historical production levels, we estimate implied shortfall costs ranging between $p = \$1.1154$ and $p = \$1.5805$ per portion.

The last single period item is beef ravioli. Figure 3.6 presents the demand information for menu item *beef ravioli* served at one AYCTE dining facility (Mark Twain dining hall) over this time interval, showing the empirical probability density function (PDF) and cumulative density function (CDF) for the number of items (portions) served at each meal when french fries were offered (there were 32 such meals in the data set).

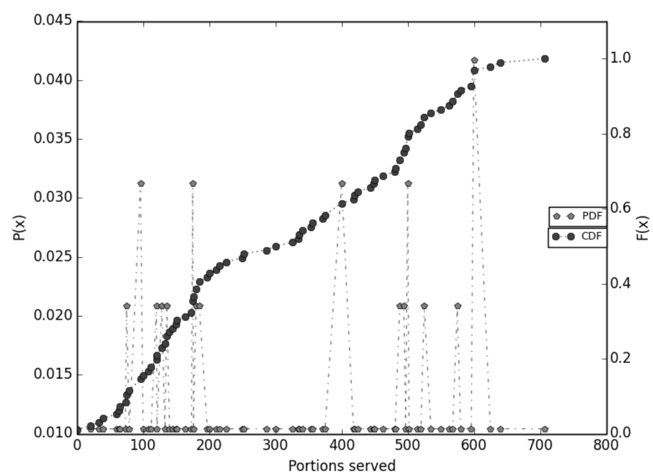


Figure 3.6: PDF and CDF of demand for beef ravioli at one dining facility

The same way, from CBORD we obtain procurement cost $c = \$0.50$ and the weight of a portion beef ravioli 90.72g, and we compute a disposal cost of $h = \$0.007746$ per portion. Figure 3.7 presents the total expected cost for a range of production levels under each of the low- and high-estimates of shortfall cost. The production levels corresponding to CDF values 0.4 and 0.6 are 200 and 400, respectively, generating implied shortfall cost estimates ranging between $p = \$0.8784$ and $p = \$1.3094$ per portion. Observe that since disposal costs are based on item weight, all three menu items have comparable disposal costs (ranging between $0.006075 and $0.00823), since their per-portion weights are similar (ranging between 71.2 and 96.4 g).

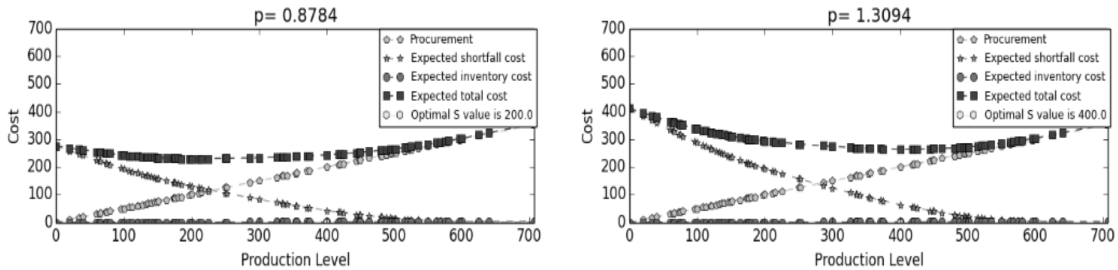


Figure 3.7: Total expected costs as a function of production level for beef ravioli, for lowest and high-estimate of shortfall costs

Similar to the values observed for french fries, the shortfall cost estimates for both the chicken sandwich and beef ravioli menu items are between 1.5 and 3 times larger than the procurement cost. However, while shortfall costs for chicken sandwich and beef ravioli are more than 100 times larger than these items' disposal costs, for french fries shortfall costs are relatively smaller (between 30 and 50 times larger than disposal costs), although still much larger than disposal costs. These cost comparisons are again consistent with the stated preference of CDS management to avoidance of shortfalls.

3.2.2 Determining impact of including environmental costs on optimal production levels

For french fries, recall that the holding cost was $h = \$0.006075$ per item when only disposal costs are considered, and that the environmental costs were estimated to range between $0.000645 and $0.02389 per overproduced item. Thus, over the range of environmental costs estimated in Table 3.1, we estimate that the disposal cost per overproduced item would range between $0.00672 and $0.029965, were the social costs of life cycle embodied CO2 added to the disposal cost. Figure 3.8 shows how the optimal production level varies across this range, for both the low- and high-estimate of per-item shortfall cost p.

At the low estimate of shortfall cost, the optimal production level decreases from 127 (without environmental cost) to 114 portions (at upper estimate of environmental costs), a 10.2 percent reduction. At the high estimate of shortfall cost, the optimal production level decreases from 167 (without environmental cost) to 149 portions (at upper estimate of environmental costs), a 10.8 percent reduction; the related probability that overproduction occurs has reduced from 61.3 percent to 56.7 percent.

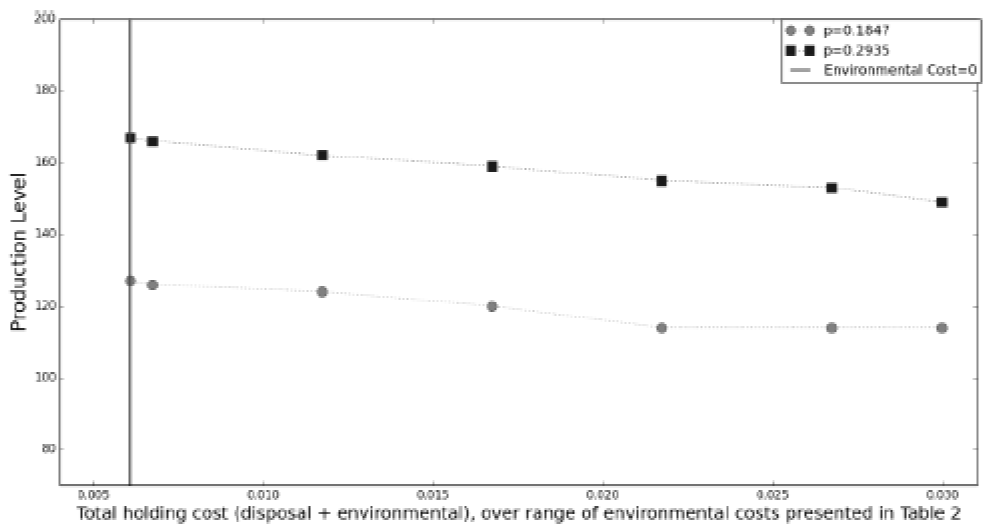


Figure 3.8: Impact of environmental cost on optimal production level for french fries

If we modify the assumption regarding the interval in which the optimal production level lies, to CDF values of 0.2 and 0.8 (as in Figure3.3), at the low estimate of shortfall cost, the optimal production level for french fries decreases from 102 (without environmental cost) to 92 portions (at upper estimate of environmental costs), a 9.8 percent reduction. At the high estimate of shortfall cost, the optimal production level decreases from 203 (without environmental cost) to 189 portions (at upper estimate of environmental costs), a 6.9 percent reduction. These results, presented in Figure 3.9 below, are fairly consistent with the extent of the reduced production levels presented in Figure 3.8, and suggest that the impacts of including environmental considerations on the optimal production level of this menu item are consistent across a range of plausible shortfall values.

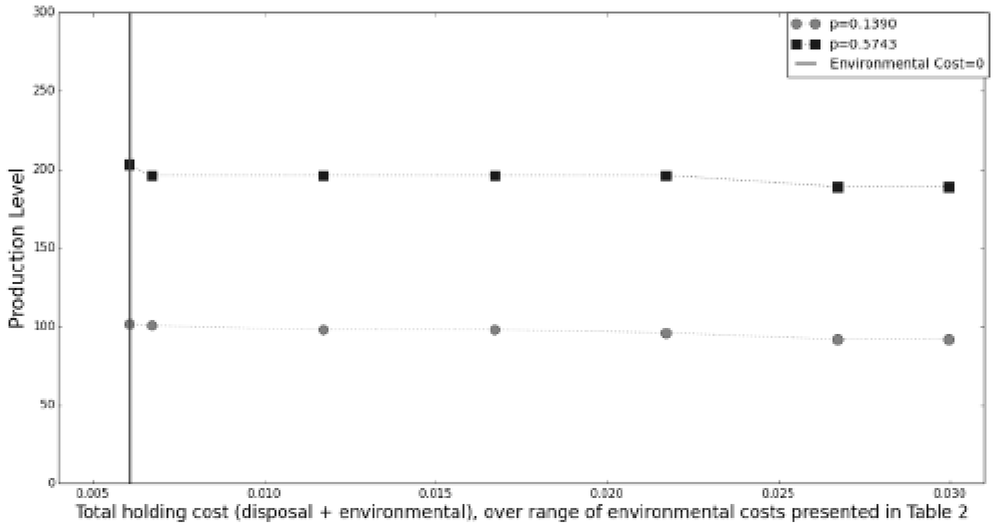


Figure 3.9: Impact of environmental cost on optimal production level for french fries

Figures 3.10 and 3.11 present a similar analysis for chicken sandwich and beef ravioli, respectively. For the chicken sandwich menu item, at the low estimate of shortfall cost, the optimal production level decreases from 364 (without environmental cost) to 360 portions (at upper estimate of environmental costs), a 1.1 percent reduction. At the high estimate of shortfall cost, the optimal production level decreases from 463 (without environmental cost) to 448 portions (at upper estimate of environmental costs), a 3.2 percent reduction; the related probability that overproduction occurs has reduced from 58.6 percent to 56.6 percent.

For the beef ravioli menu item, at the low estimate of shortfall cost, the optimal production level decreases from 200 (without environmental cost) to 163 portions (at upper estimate of environmental costs), an 18.5 percent reduction. At the high estimate of shortfall cost, the optimal production level decreases from 400 (without environmental cost) to 300 portions (at upper estimate of environmental costs), a 25 percent reduction; the related probability that overproduction occurs has reduced from 61.5 percent to 49.9 percent.

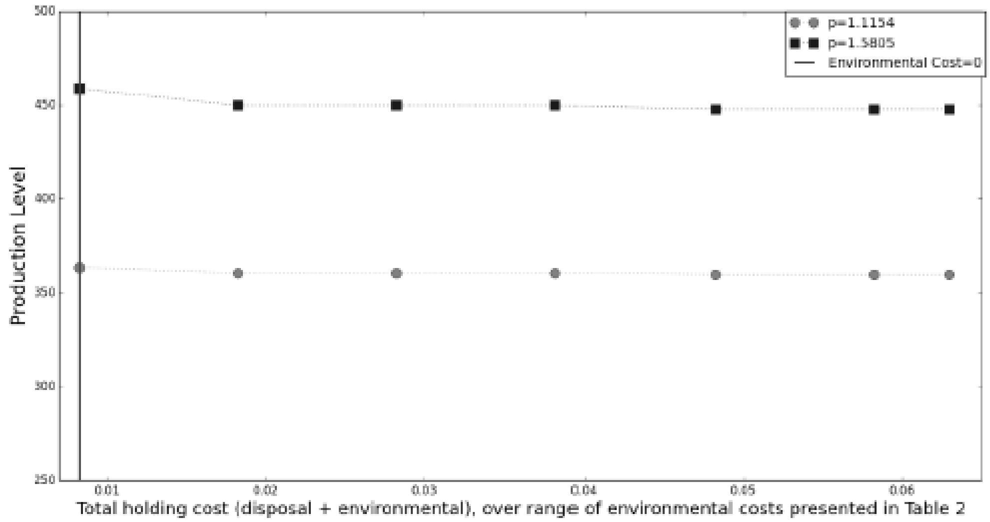


Figure 3.10: Impact of environmental cost on optimal production level for chicken sandwich

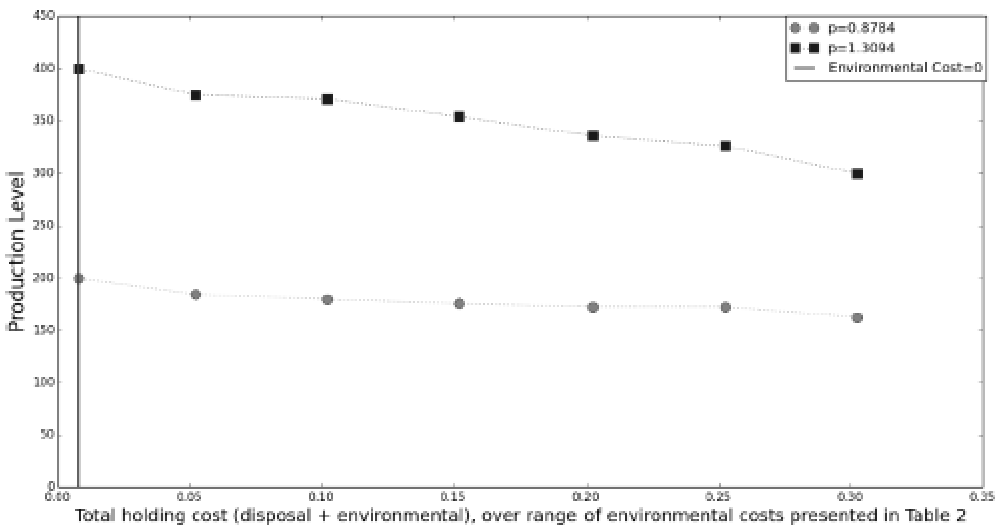


Figure 3.11: Impact of environmental cost on optimal production level for beef ravioli

The larger reduction in optimal production levels for beef ravioli when environmental costs for overproduction are included is most readily explained by comparing the relative magnitude of its environmental cost to its procurement cost; its upper estimate of environmental cost is equal to 60.7 percent of its procurement cost. This percentage is much lower for the other two food items, equal to 21.7 percent and 8.4 percent for french fries and chicken sandwich, respectively. Thus, the impact of including the environmental costs associated with waste overproduction have a greater impact on the newsvendor calculation for beef ravioli than on the other two menu items considered.

We further observe that the percent reduction in optimal production levels for chicken sandwich when environmental costs for overproduction are included is considerably less than the percent reduction for french fries, even though chicken sandwich has a much larger environmental cost than french fries (more than 20 times larger at the lower estimate of environmental costs, more than twice as large at the higher estimate). This can again be explained by the relative size of these environmental costs to procurement costs for these two food items.

3.3 Conclusion

Institutional food service providers face the common production planning problem in the presence of uncertain demand. AYCTE facilities present a challenge to the use of standard inventory optimization models (such as the newsvendor formulation), since there is no immediate lost sales revenue associated with underproduction of any individual item to serve as a shortfall cost. Given the absence of existing literature detailing how one might compute shortfall costs in such an environment, we developed an approach to infer the value that current management places on shortfalls. Assuming that the University of Missouri's CDS is currently making near-optimal production decisions, given their current set of incentives, we used a newsvendor formulation to identify the shortfall cost implied by their historical production levels. For the three food items considered (*french fries*, *chicken sandwich*, *beef ravioli*), we observed that these implied per-portion shortfall costs were considerably (between 1.5 and 3 times) larger than the per-portion procurement costs, consistent with statements made by CDS management during interviews regarding their aversion to shortfalls.

For single period menu items (such as the three menu items considered in this analysis), for which all overproduction above demand must be discarded at the end of a meal, the current lack of consideration of environmental costs leaves disposal costs as the only element of a holding cost. For CDS, the relatively small per-portion disposal costs (ranging between 1/18 and 1/67 of the per-item procurement costs, for the menu items considered) do not provide a strong incentive to avoid overproduction, beyond the incentive generated by the procurement cost of overproduced food.

However, there is growing awareness that, beyond just the landfill costs associated with disposal of overproduced food, there are also environmental costs associated with food waste. Utilizing data from life cycle analyses of the CO2 embodied in three different food types (fried potatoes, chicken, and beef), along with estimates of the social cost of carbon, we estimated a range of environmental costs associated with the life cycle CO2 emissions for the three menu items considered. Upper estimates of the environmental cost per portion were much larger than the disposal costs, ranging between four times the disposal cost (for french fries) and 39 times the disposal cost (for beef ravioli), consistent with the generally-accepted finding that meat products, and beef in particular, have much higher life cycle CO2 emissions on a per-gram basis than do plant products.

When we add these estimates of the environmental cost to the disposal cost (to generate a holding cost for the model), keeping the shortfall costs and procurement costs constant, we see the optimal production levels decrease, by a relatively small amount for some items (less than 4 percent reduction for chicken sandwich), but by a much larger amount for items containing beef (between 18 and 25 percent for beef ravioli). Somewhat surprisingly, we observed that the percent reduction in optimal production levels for chicken sandwich when environmental costs for overproduction are included is considerably less than the percent reduction for french fries, even though chicken sandwich has a much larger environmental cost than french fries. This suggests that the inclusion of environmental costs in the disposal cost of an item does not influence optimal production levels across different menu items in a manner proportional to the items' per-portion environmental costs, and instead requires analysis through an inventory optimization approach.

Were CDS to maintain their current implied shortfall cost, the inclusion of environmental costs would modify their incentives such that they would be much more willing to incur shortfalls for certain items, particularly, items containing beef. Based on the very different levels of embodied CO2 in different food items (as presented in Table 1), this finding would be expected to apply more-generally to food service providers who are interested in reducing the environmental impacts associated with their food waste.

However, CDS management makes production decisions for multiple menu items for each meal. This research suggests that, were environmental costs added to CDS management's purview, the aversion to underproduction would weaken more for items whose environmental cost is high relative to procurement cost (such as beef). Given demand uncertainties, and the likely fungibility of demand at AYCTE facilities across menu items, one could expect management to select production levels with a higher probability of overproduction for relative low- environmental-cost items, and a related reduction in the production level (and attendant increase in the probability of shortfalls) for relative high-environmental-cost items.

The early version of this research is presented to CDS leadership, who subsequently shared it with their entire management team. CDS has now developed a Sustainability committee, and are working to establish targeted goals related to sustainability issues, including a reduction in food waste.

Chapter 4

Optimal Production Planning in an Environment Utilizing Leftovers

4.1 Unconstrained Nonlinear Programming and Hooke Jeeves:

The food service provider is faced with two initial decisions regarding food items: the amount of each *ingredient* to order from the supplier, and the amount of each *menu item* to produce; note that each of these decisions needs to be made on a recurring basis. Each day, the food service provider makes these decisions based on the amount of inventory available, differentiating between inventory of ingredients (referred to as *pre-production* inventory), and inventory of prepared menu items (referred to as *post-production* inventory, commonly called "leftovers"). Ingredients have a limited storage life, and can potentially be wasted prior to their use in production due to spoilage or expiration. Similarly, due to food safety concerns, leftovers have a limited storage life, requiring that leftover inventories also be tracked by age (number of days since menu item production). This inventory of leftovers gives rise to a third decision facing the food service provider: the amount of leftovers to serve each day. we denote each of these decisions and inventory types as follows:

I_{mt}: pre-production inventory of ingredient *m* at the end of day *t*

J_{kt}: post-production inventory (leftovers) of age *k* days at the end of day *t*

R_{mt}: ordering decision (amount ordered from supplier) for ingredient *m* at the end of day *t*

P_{nt}: production decision (amount to be produced) for menu item *n* at the beginning of day *t*; $\sum_n A_{nm}P_{nt} \leq I_{m,(t-1)}\ \forall m,t$, where A_{nm} is a data parameter defining the amount of ingredient *m* required to produce one portion of menu item *n*

Y_{nkt}: leftover substitution decision (amount to be served) for leftovers of age *k* days substituted for menu item *n* at the beginning of day *t*; $\sum_n Y_{nkt} \leq J_{(k-1),(t-1)}\ \forall k,t$

Assume that the food service provider has access to a forecast of demand for each menu item on each day. After the food service provider makes the day's production and leftover service decisions, the actual demand for each menu item is then observed. Should the total items served exceed the total demand, excess items enter post-production inventory, otherwise a shortfall occurs. we denote the forecast, demand and shortfall as follows:

F_{nt}: forecast demand for menu item *n* on day *t*

D_{nt}: actual demand for menu item *n* on day *t*

S_{nt}: shortfall for menu item *n* on day *t*; $S_{nt} = max\{D_{nt} - P_{nt} - \sum_k Y_{nkt}\,, 0\}$

In the event that either pre- or post-production inventory items exceed their maximum-allowed storage life occur in this system, these items are wasted, denoted as below:

V_{mt}: wasted pre-production inventory of ingredient *m* at the end of day *t*

W_{nkt}: wasted post-production inventory (leftovers) of menu item *n* of age *k* days at the end of day *t*

Note that this model considers only pre-consumer food waste; post-consumer food waste (e.g., plate waste) is not addressed in this analysis. Figure 4.1 presents a graphical representation of the flow of ingredients and menu items through this production and inventory system

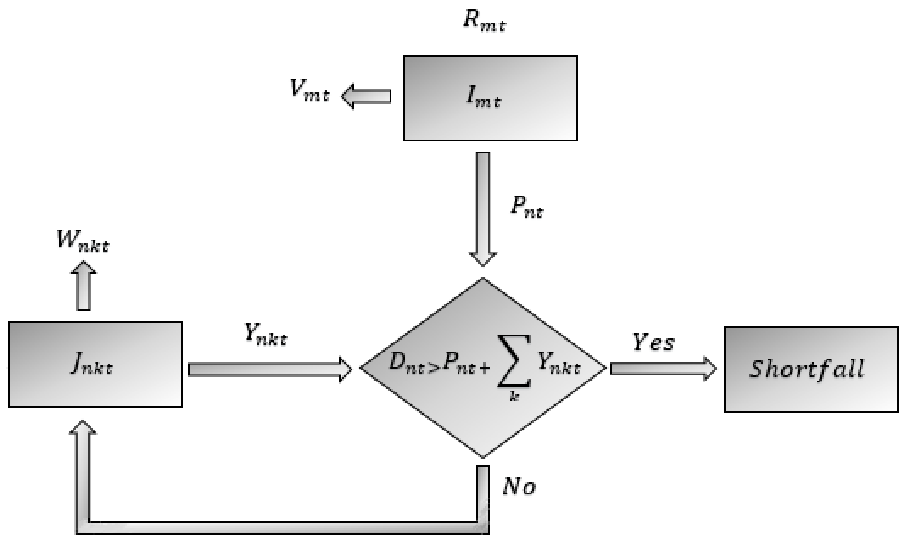


Figure 4.1: Flow of items through production and inventory system

The optimization model will operate on three variables for each menu item and each day under consideration. The first decision variable relates to the production decision P_{nt}: variable X_{nt}, referred to as variance, specifies the adjustment to the forecast production level. When $X_{nt} > 0$, production will exceed the forecasted demand, when $X_{nt} < 0$, production will be less than the forecasted demand.

$$P_{nt} = F_{nt} + X_{nt} - \sum_k Y_{nkt}\,;\; P_{nt} \leq \left\lfloor \frac{I_{mt}}{A_{mn}} \right\rfloor \tag{1}$$

The second and third decision variables relate to the leftover service decision Y_{nkt}. Our second decision variable is the *threshold*, denoted H_n, where H_n is a non-negative integer, which is the minimum forecast level for which an item can potentially allow for substitution by leftovers. This variable controls the extent to which items with a small forecast level are actually produced. The final decision variable in this model is denoted *percent*, denoted Q_n, where $0 \leq Q_n \leq 1$, detailing the percentage of forecast demand for menu item *n* for which leftovers will be substituted, should sufficient leftovers exist in the inventory (assuming that the threshold value has been satisfied).

$$\sum_k Y_{nkt} \leq F_{nt} * \min\{\max\{F_{nt} - H_n + 1,0\}, Q_n\} \quad (2)$$

Institutional food service providers face a fundamental tradeoff between a desire to minimize waste (generally, associated with overproduction) and a desire to avoid shortfalls below demand (associated with underproduction). In AYCTE operations, there is no lost marginal revenue associated with lost sales that can be used to measure the shortfall cost, complicating any attempt to determine a minimum-cost solution. Instead, we will utilize a multi-criteria optimization approach to identify the efficient frontier of points lying between the minimum-waste and minimum-shortfall solutions. This is accomplished through use of a penalty function approach that allows for solutions to be identified using unconstrained nonlinear programming. Define the following optimization model parameters:

α: targeted maximum waste level

μ: scalar penalty parameter

Our objective function is then defined as follows:

$$\min\left\{\sum_{n,t} S_{nt} + \mu * \max\left\{\sum_{n,k,t} W_{nkt} + \sum_{m,t} V_{mt} - \alpha, 0\right\}\right\} \tag{3}$$

By solving this optimization over the range of all possible values for α, across a range of values for μ, the efficient frontier can be identified, showing the minimum amount of shortfall necessary to achieve any desired level of waste. Because it is not possible to specify the derivatives of this function, other than through use of numerical methods, a derivative-free pattern search algorithm was employed applying the Hooke-Jeeves search algorithm (Hooke and Jeeves, 1961). In the literature, there are many pattern search approaches such that Nelder-Mead methods, generalized pattern search, or generating set search. One of the best-known pattern search methods is Hooke-Jeeves. The main idea in the Hooke-Jeeves algorithm is to find an improving directions, not necessarily the direction of steepest descent. This is done by changing the current point by small amounts in each variable direction and checking whether objective function value improves or get worse (Chinneck, 2004).

The Hooke-Jeeves algorithm performs two types of search: exploratory search and pattern search (Bazaraa *et al.*, 2006). In exploratory search, a cyclic coordinate search is performed, with a sequential univariate line search optimization performed along each variable (Hooke and Jeeves, 1961). Figure 4.2 shows process of this cyclic coordinate search.

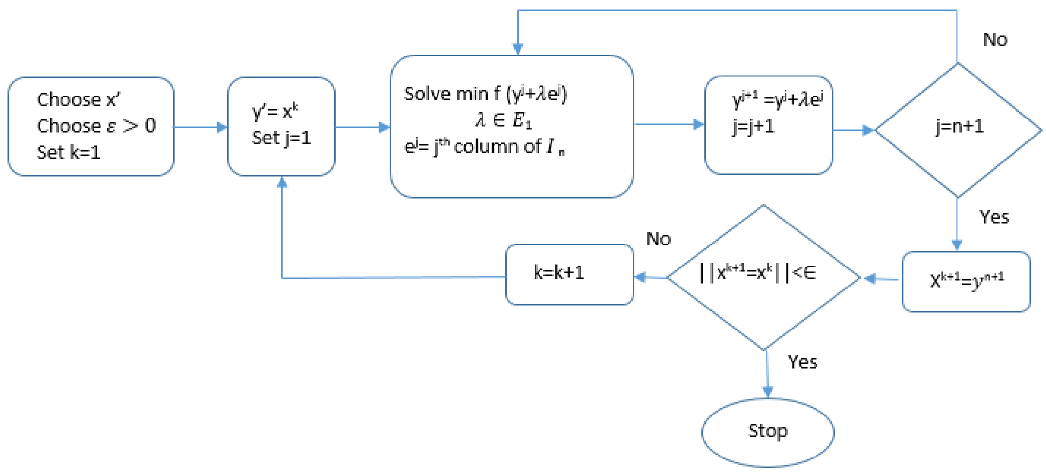


Figure 4.2: Cyclic Coordinate Search. Graph from Dr. McGarvey IMSE 8220 Class notes

When one iteration of the cyclic coordinate search is completed, and a line search performed for each variable, the exploratory search is completed. The pattern search consists of a single step, in which a univariate line search is performed along the direction defined by the difference of the current solution (at the end of the exploratory search) and the solution at the initiation of the exploratory search. A new exploratory search is then performed, and the process repeats until converging to a solution. Figure 4.3 shows the process of Hooke Jeeves with cyclic coordinate search.

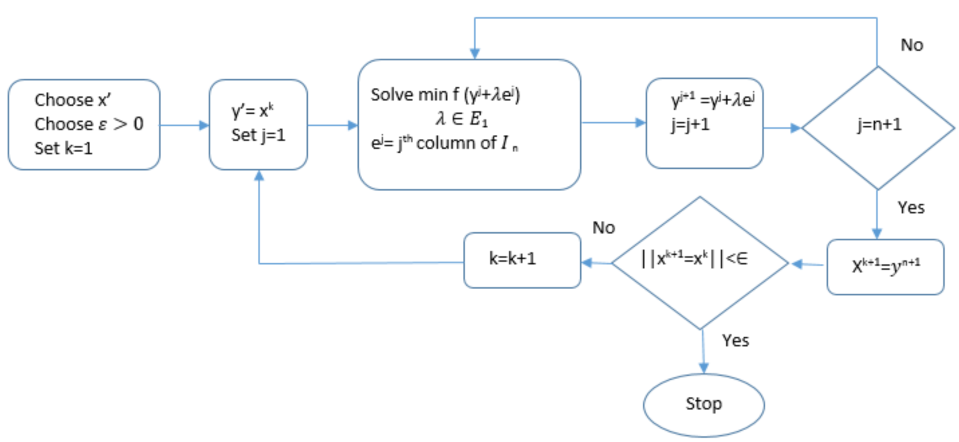


Figure 4.3: Hooke-Jeeves with Line Search. Graph from Dr. McGarvey IMSE8220 Class notes

4.1.1 Alternative Metric for waste

Measuring shortfall with respect to portions demanded (but not served) is a reasonable assumption, since this measure provides an impression of the number of times a customer demand was not satisfied. However, measuring waste with respect to portions may be less justifiable. To the extent that the food service operator is concerned with the waste management impact of wasted food, the weight of wasted food is a potentially more useful metric, since solid waste management tipping fees are typically based on the total waste disposed. The weight of wasted food can be incorporated into objective function (3) by multiplying W_{nkt} by the per-portion weight of menu item *n* and multiplying V_{mt} by the per-portion weight of ingredient m. Note that in this case, parameter α would be defined as the targeted maximum weight of food waste.

However, as discussed in the previous section, there are environmental costs associated with food waste that extend beyond waste management considerations. Within this analysis, we will consider the lifecycle CO2 emissions embodied in wasted food as our metric of environmental impacts. Thus, in a similar fashion, we will incorporate the environmental impact of wasted food into objective function (3) by multiplying W_{nkt} by the per-portion CO2-eq of menu item *n* and multiplying V_{mt} by the per-portion CO2-eq of ingredient m. Note that in this case, parameter α would be defined as the targeted maximum pounds of embodied CO2-eq in wasted food.

In this study, we consider a set of approximately 100 different menu items. To determine environmental effect associated with each wasted food item, it is necessary to identify the ingredients for each menu item. The ingredients associated with each menu item are contained in CBORD, along with the weight of each ingredient, allowing the weight of each menu item to be computed. We derived the CO_2-eq per kg of food values in most instances from(González *et al.*, 2011); the full set of CO_2-eq assumed values, along with references in table 4.1.

Ingredients	Reference	CO2-eq
kg beef	Gonzalez et al (2011)	29
kg cheese	Gonzalez et al (2011)	8.8
kg pork	Gonzalez et al (2011)	8.2
kg chicken	Gonzalez et al (2011)	4.7
kg turkey	http://www.greeneatz.com/foods-carbon-footprint.html	10.9
kg fish	Gonzalez et al (2011)	3.1
kg imitated crab	Pollock: Consumption of pollock has continued, as it is the "secret ingredient" in breaded fish sticks, food service fish fillets and imitation crab. Because of that I assume fish CO2 amount. http://www.seafoodwatch.org/-/m/c4de19eac4f24657a23f12e17b392b2c.pdf	3.1
kg egg	Gonzalez et al (2011)	3
kg brown rice	Gonzalez et al (2011)	1.2
kg white rice	Gonzalez et al (2011)	1.2
kg whole milk	Gonzalez et al (2011)	1
kg bean (avg)	Gonzalez et al (2011)	0.86
kg soybean	Gonzalez et al (2011)	0.72
kg maize	Gonzalez et al (2011)	0.67
kg wheat	Gonzalez et al (2011)	0.58
Cocunut milk	http://sodeliciousdairyfree.com/environmental-footprint	0.1
kg vegetable (avg)	Gonzalez et al (2011) took average of vegetable	0.18
kg broccoli	Gonzalez et al (2011)	0.37
kg pea	Gonzalez et al (2011)	0.49
kg field tomatoes	Gonzalez et al (2011)	0.3
kg potato	Gonzalez et al (2011)	0.19
kg carrots	Gonzalez et al (2011)	0.12
kg onions	Gonzalez et al (2011)	0.1
kg winter squash	Gonzalez et al (2011)	0.09
kg fruit (avg)	Gonzalez et al (2011) took average of fruit	0.34

kg orange	Gonzalez et al (2011)	0.3
kg apple	Gonzalez et al (2011)	0.3
kg nuts	http://www.greeneatz.com/foods-carbon-footprint.html	2.3
kg yogurt	http://pure.au.dk/portal/files/45485022/anna_20flusj_.pdf	1.23
kg margarine	Katarina Nisselon et all 2010, http://link.springer.com/article/10.1007/s11367-010-0220-3	0.67
kg mushrooms	http://www.ijesd.org/papers/412-L00034.pdf	1.9
kg sour cream	http://pure.au.dk/portal/files/45485022/anna_20flusj_.pdf	2.7
kg peanut butter	for peanut butter estimates, a sum of Farm+Buying point + Sheller +Blancher +Roaster (retail, use and disposal left out due to gonzalez boundary inconsistencies) McCarty Breandan	1.255
kg sugar	Gonzalez et al (2011)	0.233
kg olive oil	http://www.oliveoilsource.com/page/useful-number-conversions, Avraamides, 2008	4.28
kg tortilla	http://www.tasteofhome.com/recipes/homemade-tortillas	2.11
kg bread	took assumption from Meisterling, 0.67 kg whole wheat in 1 kg bread. multiplied by the CO2e estimate for wheat.	0.39
kg pasta	http://nationalfestivalofbreads.com/nutrition-education/wheat-facts	0.65
kg mix cake	http://shrinkthatfootprint.com/food-carbon-footprint-diet	0.6

Table 4.1:CO2 -eq of ingredients

4.1.2 Application

As an application demonstrating our optimization procedure for food service production, consider the AYCTE operations performed by Campus Dining Services (CDS) at the University of Missouri (MU). CDS provided access to their installation of the CBORD software system (www.cbord.com), which CDS uses to track production, sales and inventory management data.

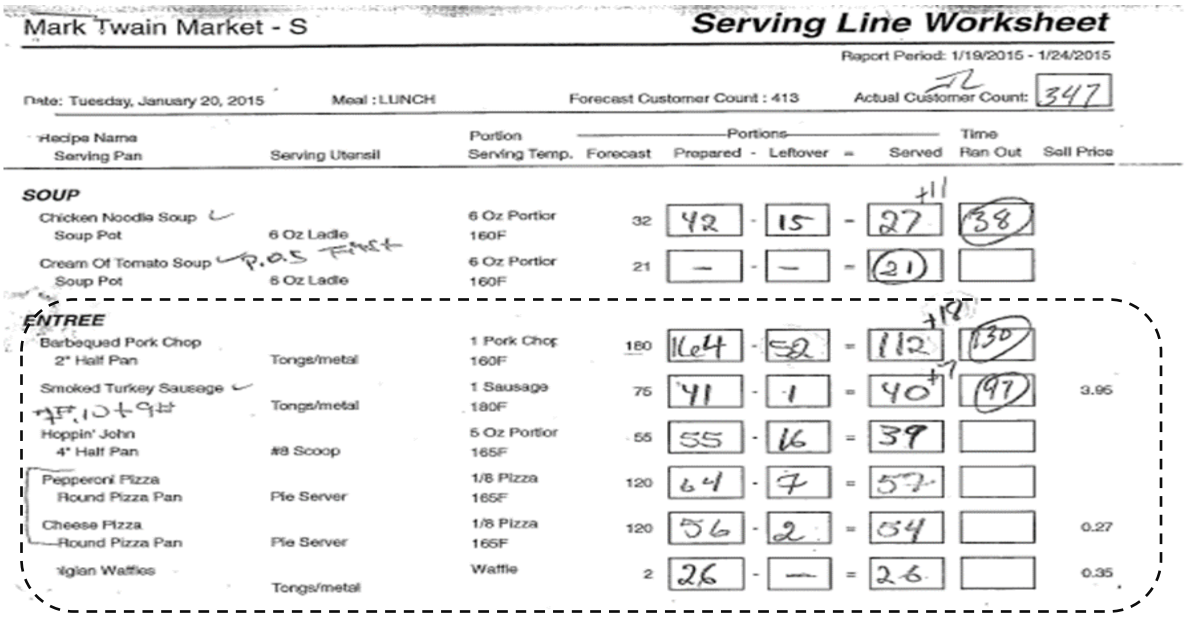
The CBORD system provides a forecast demand level three weeks in advance of the production date to inform planning activities. In general, CDS AYCTE operations perform menu planning three weeks in advance of production day. Purchasing is made only on Mondays, Wednesdays and Thursdays, and ordered items are received two business days after an order is placed. These ingredients are then stored until production day, when any necessary preparation activities occur (e.g., thawing frozen items). Cooking operations occur on production day; menu items are then served to customers, with leftovers (where allowed, given food safety and quality considerations) entering the post-production inventory. Leftovers can be stored for a maximum of three days, after which any remaining leftovers must be discarded.

For this application, we will assume that all ordering decisions are based on the demand forecasts provided by CBORD, given the order frequencies and lead times discussed in the previous paragraph. Each Monday, orders will be placed to support the forecast demand for the following Thursday and Friday. Each Wednesday, orders will be placed to support the forecast demands for the following Saturday, Sunday and Monday. Each Thursday, orders will be placed to support the forecast demands for the following Tuesday and Wednesday.

In this analysis, we will focus on the pre-production inventory associated with a single item (frozen five pound bags of beef). Because this is a frozen ingredient item, its storage life is sufficiently long such that expiration is not a significant concern. Three days in advance of production of a menu item requiring beef, pre-production inventory is removed from the freezer and placed at room temperature to thaw until production day. Each thawed bag is cooked in its entirety, and the cooked beef is then ready to be incorporated into a menu item (e.g., beef Stroganoff).

On production day, the production level for any given menu item could vary from the forecast, due to production adjustments (denoted X_{nt} in the previous section), and/or substitution with leftovers (controlled by the H_n and Q_n variables discussed in the previous section). CBORD then tracks the demand (sales) information, at the menu item level.

Using the CBORD system, the number of portions produced for each menu item for each meal were extracted over the first five weeks period of the Spring 2015 semester for a single AYCTE CDS facility, Mark Twain Market. Over this time interval, a total of 20,360 customers were served a total of 28,690 entrée items. During serving operations, CDS staff monitor the number of portions served for each menu item using a serving line worksheet. An example sheet is presented in Figure 4.4, showing an extract for a single meal served at Mark Twain Market, an AYCTE facility operated by CDS. Substitution by leftovers is tracked on these sheets: observe the "+18" appearing in the "Portions_Served" column for menu item "Barbequed Pork Chop"; this indicates that 18 portions of leftovers were served from this station, in addition to 112 servings of the menu item (unfortunately, the specific leftover item(s) that were served here are not specified). We obtained the serving line worksheets for every meal over this five-week period from the Mark Twain Market facility, and used this data to augment the CBORD data and obtain a complete picture of demand, production, and leftover utilization at this facility.



Mark Twain Market - S

Serving Line Worksheet

Report Period: 1/19/2015 - 1/24/2015

Date: Tuesday, January 20, 2015 Meal : LUNCH Forecast Customer Count : 413 Actual Customer Count: 347

Recipe Name / Serving Pan	Serving Utensil	Portion / Serving Temp.	Forecast	Prepared	Leftover	Served	Time Ran Out	Sell Price
SOUP								
Chicken Noodle Soup / Soup Pot	6 Oz Ladle	6 Oz Portion / 160F	32	42	15	27 (+11)	38	
Cream Of Tomato Soup / Soup Pot	6 Oz Ladle	6 Oz Portion / 160F	21	—	—	21		
ENTREE								
Barbequed Pork Chop / 2" Half Pan	Tongs/metal	1 Pork Chop / 160F	180	164	52	112 (+18)	130	
Smoked Turkey Sausage	Tongs/metal	1 Sausage / 180F	75	41	1	40 (+7)	47	3.95
Hoppin' John / 4" Half Pan	#8 Scoop	5 Oz Portion / 165F	55	55	16	39		
Pepperoni Pizza / Round Pizza Pan	Pie Server	1/8 Pizza / 165F	120	64	7	57		
Cheese Pizza / Round Pizza Pan	Pie Server	1/8 Pizza / 165F	120	56	2	54		0.27
Belgian Waffles	Tongs/metal	Waffle	2	26	—	26		0.35

Figure 4.4: Serving Line Worksheet

Rather than modeling each individual menu item, we grouped all menu items into one of four different food types, based on the primary ingredient in the menu item: “Beef”, “Pork&Poultry&Fish”, “Vegetable” and “Other”. The “Other” group consists mostly of grain-based items such as “Belgian Waffles”, “Pancakes”, etc.

Having obtained a weight and CO2-eq value for each menu item, we then computed an average per-portion weight and an average per-portion CO-eq for each of the four food types. Table 1 presents these average per-portion values for each food type included in our analysis.

Type of Food	Average Portion g	Average CO2 emission
Beef	110.5	1545.7g
Pork&Poultry&Fish	116.5	414.61g
Vegetable	115.35	221.24g
Other	194.7	54.97g

Table 4.2: Average weight and CO2-eq per portion

Recall that the optimization model presented in section 3 contains three types of decision variables: production variance X_nt , leftover utilization threshold H_n and leftover utilization percent, denoted Q_n. For each of these variables, there is an instance created for each combination of (a) day of the week [Monday through Sunday], (b) meal [lunch and dinner], (c) food type [Beef, Pork&Poultry&Fish, Vegetable, Other], and (d) preparation type [fried or not fried]. We differentiate between these two preparation types because fried food cannot be retained as leftovers for use in a future meal, requiring that all overproduction of fried items must be discarded. There are 66 instances of each of the three variable types, because not all combinations existed in the data (e.g., there were no Sunday-lunch-Other-Fried items). In total, our model has 198 decision variables.

Each variable was assumed to have an allowable upper bound and lower bound within the optimization. All *percent* variables were assumed to have a lower bound of 1 percent and an upper bound of 10 percent, to prevent excessive substitution by leftovers for any menu item. All *threshold* variables were assumed to have a lower bound of 10 portions and an upper bound of 80 portions, to prevent substitution for items with a low production level (such items might be special production for customers with dietary restrictions). All *variance* variables were assumed to have a lower bound of -50 percent and an upper bound of 50 percent.

These variable bounds are enforced in our optimization through use of a barrier function. Let *a* and *b* denote the lower and upper bounds, respectively, for some variable *z*. Provided that the initial value for each variable lies within its allowable bounds, a barrier function of the following form provides an effective means for ensuring that the optimization search avoids solutions violating these bound constraints, β here is a scalar penalty parameter:

$$\beta * \left[\left(\max\left\{\frac{a-x}{b-a}, 0\right\}\right)^2 + \left(\max\left\{\frac{x-b}{b-a}, 0\right\}\right)^2\right] \tag{4}$$

We add a version of barrier function (4) for each of the 198 decision variables to objective function (3) to generate the function that will be minimized using our Hooke-Jeeves search algorithm.

As discussed in previous section, we implement a multi-criteria optimization approach to identify the efficient frontier of points lying between the minimum-waste and minimum-shortfall solutions. Thus, the shortfall target parameter α is varied across an interval, starting from a minimum value of 0, in which case the target is for zero waste. Once this model is solved, the α value is increased, relaxing the waste constraint, and the model is solved again, generating a new solution with increased total waste and decreased total shortfall. The process is then repeated, increasing the value of α until a solution is obtained with total shortfall equals zero.

For this computational testing, we set the penalty parameters $\mu = 1$ and $\mu = 10$, and $\beta = 1{,}000$, placing an extremely high penalty on the barrier function, to ensure that our variables stayed within the desired upper and lower bounds.

4.1.3 Leftovers Usage Policy

We consider two alternative policies governing the usage of leftovers. Recall that there is no restriction governing the similarity of food types when substituting a menu item with leftovers, a menu item of type Vegetable could potentially be substituted with leftovers of type Beef. Because all leftovers can be retained in post-production inventory for a maximum of three days, leftovers of age k=3 days will be used first, when those are exhausted leftovers of age k=2 days will be used next, and when those are exhausted leftovers of age k=1 day will be used.

The first leftover policy will attempt to minimize the weight of leftovers by utilizing leftover in decreasing order of portion weight, within each leftover age grouping. Thus, the heaviest leftovers, on a per-portion basis, from age k=3 days will be used first, followed by the next-heaviest leftovers from age k=3 days, continuing until all leftovers from age k=3 days have been utilized. At that point, the heaviest leftovers from age k=2 days will be used, etc. We denote this policy as *Heavy policy*.

The alternative leftover policy will attempt to minimize the GHG emissions associated with wasted food by utilizing leftovers in decreasing order of CO2-eq emissions, within each leftover age grouping. Thus, the leftovers with the greatest CO2-eq emissions, on a per-portion basis, from age k=3 days will be used first, followed by the leftovers with the second largest CO2-eq emissions from age k=3 days, continuing until all leftovers from age k=3 days have been utilized. Based on the values appearing in Table 1, this policy will utilize Beef items first, then Pork&Poultry&Fish items next, then Vegetable items, and finally Other items. At that point, Beef leftovers from age k=2 days will be used, etc. Denote this policy as *meat policy*.

4.2 Results

4.2.1 Drawing inferences from the optimization model result for weight of waste

Figure 4.5 below presents the efficient frontier identified by our optimization procedure when the waste target is defined in terms of the weight of wasted food, under the Heavy policy. This graph demonstrates the tradeoff between shortfall portions and grams of food waste, ranging from a minimum-waste, maximum-shortfall endpoint to a maximum-waste, minimum-shortfall endpoint. Because the total demand was for 28,178 portions across this data set, the maximum shortfall solution corresponds to a situation in which 4.36% of demand (in aggregate) encountered shortfalls.

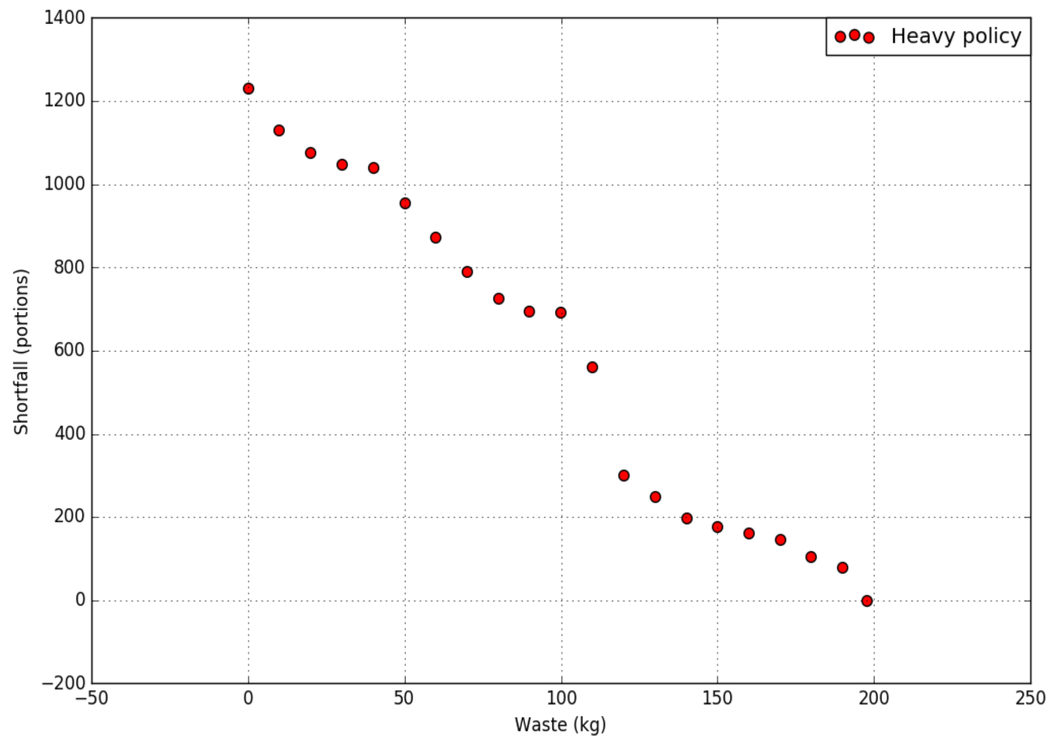


Figure 4.5: Efficient frontier, optimizing tradeoff between shortfall and mass of waste

While the optimization model allows for the identification of efficient frontiers, an additional set of analyses are necessary to examine the corresponding model solutions and identify the relationships between decisions (i.e, our 198 decision variables) that allow for waste to be reduced at the minimum-achievable increase in shortfalls. This was accomplished through a regression analysis relating the model's 198 decision (independent) variables to the total weight of waste (dependent) variable, across all points in the efficient frontier of Figure 4.5. This statistical analysis is complicated because the upper and lower bound limitations assumed for variables induces multicollinearity in our model, since some variables might always lie at a bound value across all solutions on the efficient frontier. Multicollinearity poses a problem to regression analysis because it makes it difficult to assess the relative importance of each independent variable in the model (Wang, 1996). Several approaches have been developed in the literature to address multicollinearity, the most common being: (a) principal component analysis (PCA) (Liu R X *et al.* (2003); (b) partial least square (PLS) analysis (Merz and Pazzani, 1999); and (c) ridge regression (Wang, 1996).

In this study, we elected to perform a principal component regression analysis, using SPSS 17. This analysis was accomplished via the following steps, based on Liu R X *et al.* (2003):

1. First, perform a stepwise regression analysis with all independent variables, as in (Thompson, 1995); (Zuorro *et al.*, 2016), to identify the p independent variables at a 0.05 significance level; this model was found to provide an extremely good fit, with adjusted R-square value of 0.999. Then test for existence of multicollinearity by examining the variation inflation factor (VIF) values. These results appear in Table 2.

Coefficient	*Value*	*t stat*	*p*	*Collinearity Statistics*	
				Tolerance	*VIF*
β_0	647.955	5.249	0.000		
β_{51}	-106.769	-7.012	0.000	0.710	1.409
β_{69}	-599.200	-2.222	0.041	0.232	4.312
β_{140}	2.050	3.645	0.002	0.393	2.544

β_{150}	-1180.103	-7.674	0.000	0.156	6.401

Table 4.3: Stepwise regression coefficient and collinearity statistics of the regression for mass metric

After eliminating non-significant predictors, the following reduced model is obtained.

$$y = \beta_0 + \beta_{51}X_{51} + \beta_{69}X_{69} + \beta_{140}X_{140} + \beta_{150}X_{150} \tag{5}$$

The independent variables identified as significant are:

X_{51}: Variance_Wednesday_Lunch_Beef

X_{69}: Variance_Wednesday_Dinner_Vegetable

X_{140}: Threshold_Sunday_Dinner_Vegetable

X_{150}: Variance_Monday_Lunch_ Pork&Poultry&Fish -Fried

Observe that none of the *percent* variables were identified as significant. Examination of the multicollinearity test in table 5 shows that there are significant predictor variables with VIF value greater than 1, suggesting that there is moderate correlation between those variables. A principal component analysis can next be conducted to address this multicollinearity problem.

2. Proceed with a PCA having (in our case) $p = 4$ independent variables. This analysis transforms a set of correlated variables to set of uncorrelated principal components.

We first need to check the sampling adequacy, to ensure that we have a sufficiently large sample size for PCA to produce a reliable result. Here four variables are used to implement principal component analysis. The results of a Kaiser-Meyer-Olkin test for sampling adequacy, and Bartlett's test, are significant (p<0.001), indicating that the sample is large enough to perform a PCA analysis.

Table 3 presents the results of the PCA, with Eigenvalues appearing in column "Total". (Kaiser, 1960) proposed the K1 method, in which factors that have eigenvalues greater than one are retained for interpretation. Based on this approach, components 1 and 2 are retained for further analysis. The cumulative variance proportion of the first principal component (C_1) is 56.514%, while that of the first two principal components (C_1 and C_2) is 82.298%; suggesting that the first two principal component explain 82.298 % of the overall variability.

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	2.261	56.514	56.514
2	1.031	25.783	82.298
3	.622	15.556	97.853
4	.086	2.147	100.000

Table 4.4: The eigenvalues, % of variance and coefficient for each principal component for mass metric

3. Compute the standardized independent variables and the values of the k principal components, according to the following formulae. Table 4 presents the value of a_{ij}, the coefficients of the principal component matrix:

$$Y' = (Y - \bar{Y})/S_Y \tag{6}$$

$$X_i' = (X_i - \bar{X})/S_X \; (i = 1, .. p) \tag{7}$$

$$C_i = a_{i1}X_1' + a_{i2}X_2' + \cdots + a_{ip}X_p' \quad i = 1, \dots, p \tag{8}$$

Component	Component Matrix Standardized independent variable			
	X_{51}'	X_{69}'	X_{140}'	X_{150}'

1	0.718	0.795	-0.457	0.951
2	0.150	0.475	0.881	-0.087

Table 4.5: Principal component matrix coefficients for mass metric

The following instances of equation (8) demonstrate the relationship between the four standardized independent variables and the two principal components:

$$C_1 = 0.718X'_{51} + 0.795X'_{69} - 0.457X'_{140} + 0.951X'_{150} \tag{9}$$

$$C_2 = 0.150X'_{51} + 0.475X'_{69} + 0.881X'_{140} - 0.087X'_{150} \tag{10}$$

4. Build the standardized principal component regression equation with the first principal component, then build the standardized principal component regression with both the first and second principal components, these results appear in Table 5. Select the better of the two regression equations on the basis of the larger adjusted R^2 value and the smaller standard error of estimate, these values appear in Table 6.

Model	B'_i	t	P	Collinearity Statistics	
				Tolerance	VIF
1 C_1	-0.435	-23.161	0.000	1.000	1.000
2 C_1	-0.435	-27.716	0.000	1.000	1.000
C_2	0.104	3.035	0.007	1.000	1.000
$R_{C1, C2}$= 0.000.					

Table 4.6: Standardized principal component regression coefficients and collinearity statistics for mass metric

Standardized principal component regression equation	Adjusted R^2	Std. Error of the Estimate	F	P

$\hat{y}_1' = -0.435C_1$	0.964	0.1897	536.442	0.000
$\boldsymbol{\hat{y}_2' = -0.435C_1 + 0.104C_2}$	**0.975**	0.1586	388.726	0.000

Table 4.7: Goodness of fit statistics for standardized principal component regression equations for mass metric

Regression $\hat{y}_2' = -0.435C_1 + 0.104C_2$ is selected as the better equation, since its adjusted R^2 (0.975) is slightly larger and its standard error of estimate (0.1586) is slightly smaller. Moreover, this equation's *F* value of 388.726 is highly significant (*P*<0.001).

5. Restate the principle component regression equation in terms of the standardized independent variables.

$$
\begin{aligned}
\hat{y}_1' &= -0.435C_1 + 0.104C_2 \\
&= -0.435 * (0.718X_{51}' + 0.795X_{69}' - 0.457X_{140}' + 0.951X_{150}') \\
&\qquad +0.104 * (0.150X_{51}' + 0.475X_{69}' + 0.881X_{140}' - 0.087X_{150}') \\
&= -0.297X_{51}' - 0.296X_{69}' + 0.290X_{140}' - 0.423X_{150}'
\end{aligned}
\tag{11}
$$

6. Compute parameters L_y, the sum of squares of dependent variable Y, and L_{x_i}, the sum of squares of independent variable X_i, then use these parameters to transform the standardized linear regression equation into a general linear regression equation, in terms of the original variables, as follows:.

$$b_i = b_i'(L_y/L_{x\_i})^{1/2} \quad (i = 1, \ldots K \le p) \tag{12}$$

$$b_0 = \bar{Y} - \sum b_i \bar{X}_i \, (i = 1, \ldots K \le p) \tag{13}$$

$$\hat{y} = b_0 + \sum b_i X_i \, (i = 1, \ldots K \le p) \tag{14}$$

The general linear regression equation is obtained as:

$$\hat{y} = 357.113 - 120.306\, X_{51} - 1266.38\, X_{69} + 3.207\, X_{140} - 829.482\, X_{150} \tag{15}$$

Because our focus is not on predicting the amount of food waste generated per week, we will not focus our interpretation on the magnitude of the regression coefficients. Rather, we wish to know which variables have a significant positive impact on the weight of food waste generation, and which have a significant negative impact; thus, we focus on the sign of each coefficient.

Recall how the *variance* decision variable X is defined: When $X > 0$, production will be less than the forecasted demand, when $X < 0$, production will exceed the forecasted demand. Observe that all three of the significant *variance* variables (Variance_Wednesday_Lunch_Beef, Variance_Wednesday_Dinner_Vegetable, Variance_Monday_Lunch_ Pork&Poultry&Fish -Fried) each have a negative regression coefficient, implying that production in excess of the forecasted demand is associated with increased waste and reduced shortfalls. This result is consistent with our expectations, and suggests that reduced production on Wednesdays is desirable for items that could potentially be utilized as leftovers (recall that overproduction of fried items, as with variable X_{150}, cannot be stored in post-production inventory and utilized as leftovers).

Conversely, the significant *threshold* variable (Threshold_Sunday_Dinner_ Vegetable) has a positive regression coefficient. Recall how the *threshold* decision H_n is defined: when H_n increases, the minimum forecast level for which an item can potentially allow for substitution by leftovers is increased, and thus these item's total substitution with leftovers is reduced. Again, the result is consistent with our expectations, and suggests that increasing the substitution with leftovers is desirable for Sunday dinner production.

4.2.2 Drawing inferences from the optimization model results for environmental impact of waste

Figure 4.6 below represents the efficient frontier identified by our optimization procedure when the waste target is defined in terms of the CO2-eq of wasted food, under the Meat policy.

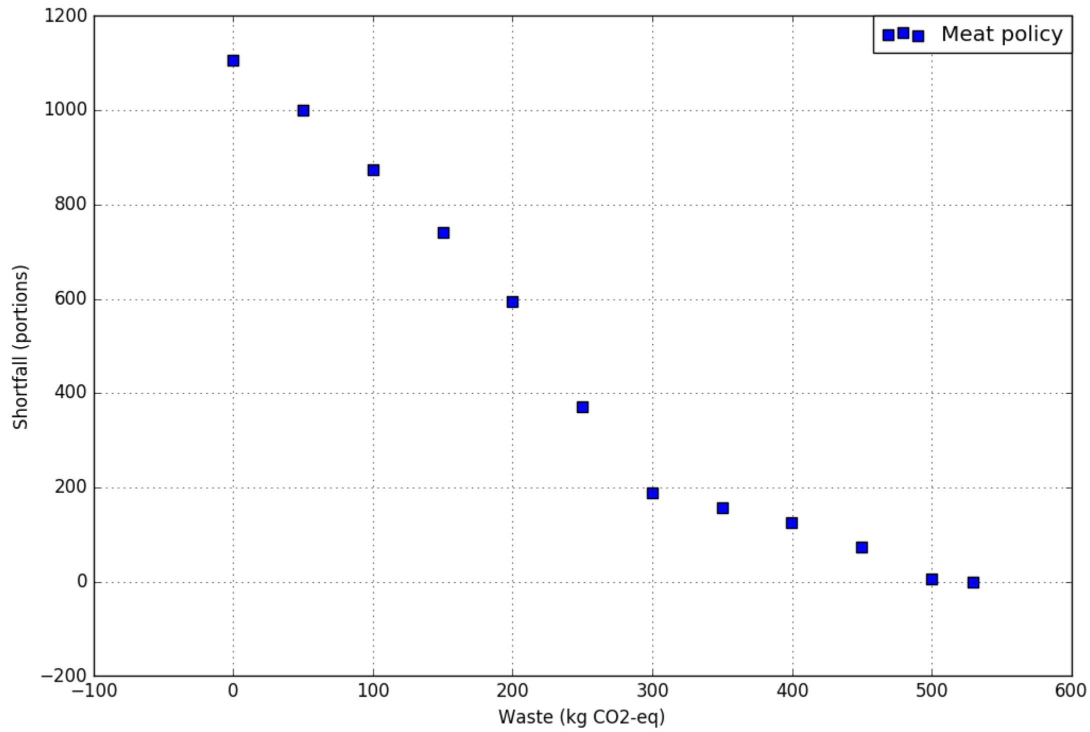


Figure 4.6: Efficient frontier, optimizing tradeoff between shortfall and CO2-eq of waste

The process described in Section 4.2.1 was applied to the model's 198 decision (independent) variables impact on the total kg CO2-eq of wasted food (dependent) variable, across all points in the efficient frontier of Figure 4.6. This process identified the following regression equation:

1. First, perform a stepwise regression analysis with all independent variables, as in (Thompson, 1995); (Zuorro *et al.*, 2016), to identify the *p* independent variables at a 0.05 significance level; this model was found to provide an extremely good fit, with adjusted R-square value of 0.999. Then test for existence of multicollinearity by examining the variation inflation factor (VIF) values. These results appear in Table 2.

Coefficient	*Value*	*t stat*	*p*	*Collinearity Statistics*	
				Tolerance	*VIF*

β_0	323.121	3.044	0.016		
β_{51}	-560.192	-3.759	0.006	0.651	1.535
β_{105}	-443.117	-3.501	0.008	0.263	3.807
β_{134}	3.297	3.019	0.017	0.243	4.117

Table 4.8: Stepwise regression coefficient and collinearity statistics of the regression for GHG metric

After eliminating non-significant predictors, the following reduced model is obtained.

$$y = \beta_0 + \beta_{51}X_{51} + \beta_{105}X_{105} + \beta_{134}X_{134} \tag{16}$$

The independent variables identified as significant are:

X_{51}: Variance_Wednesday_Lunch_Beef

X_{105}: Variance_Friday_Lunch_Vegetable

X_{134}: Threshold_Sunday_Dinner_Beef

Observe that *percent* variables were not identified as significant. However, examination of the multicollinearity test in table 2 shows that there are significant predictor variables with VIF value greater than 1, suggesting that there is moderate correlation between those variables. A principal component analysis can next be conducted to address this multicollinearity problem.

2. Proceed with a PCA having (in our case) $p = 3$ independent variables. This analysis transforms a set of correlated variables to set of uncorrelated principal components.

We first need to check the sampling adequacy, to ensure that we have a sufficiently large sample size for PCA to produce a reliable result. Here four variables are used to implement principal component analysis. The results of a Kaiser-Meyer-Olkin test for sampling adequacy, and Bartlett’s test, are significant (p<0.001), indicating that the sample is large enough to perform a PCA analysis.

Table xxx presents the results of the PCA, with Eigenvalues appearing in column "Total". Kaiser (1960) proposed the K1 method, in which factors that have eigenvalues greater than one are retained for interpretation. Based on this approach, components 1 is retained for further analysis. The cumulative variance proportion of the first principal component (C_1) is 77.751%; suggesting that the first principal component explain 77.751 % of the overall variability.

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	2.333	77.751	77.751
2	.527	17.576	95.327
3	.140	4.673	100.000

Table 4.9: The eigenvalues, % of variance and coefficient for each principal component for GHG metric

3. Compute the standardized independent variables and the values of the k principal components, according to the following formulae. Table xxx presents the value of a_{ij}, the coefficients of the principal component matrix:

$$Y' = (Y - \bar{Y})/S_Y \tag{17}$$

$$X' = (X - \bar{X})/S_X \ (i = 1, .. p) \tag{18}$$

$$C_i = a_{i1}X_1' + a_{i2}X_2' + \cdots + a_{ip}X_p' \quad i = 1, \dots, p \tag{19}$$

	Component Matrix		
	Standardized independent variable		
Component	$VAR51'$	$VAR105'$	$VAR134'$

1	0.783	0.919	-0.936

Table 4.10: Principal component matrix coefficients for GHG metric

The following instances of equation (8) demonstrate the relationship between the seven standardized independent variables and the two principal components:

$$C_1 = .783VAR51' + .919VAR105' - .936VAR134' \tag{20}$$

4. Build the standardized principal component regression equation with the first principal component, then build the standardized principal component regression with both the first and second principal components, these results appear in Table 5. Select the better of the two regression equations on the basis of the larger adjusted R^2 value and the smaller standard error of estimate, these values appear in Table 6.

Model	B_i'	t	P	Collinearity Statistics	
				Tolerance	VIF
1 C_1	-0.422	-17.156	0.000	1.000	1.000

Table 4.11: Standardized principal component regression coefficients and collinearity statistics for GHG metric

Standardized principal component regression equation	Adjusted R^2	Std. Error of the Estimate	F	P
$\hat{y}_1' =$**-0.422***C_1	**0.964**	0.1901	294.337	0.000

Table 4.12: Goodness of fit statistics for standardized principal component regression equations for GHG metric

Observe that we have only one coefficient C_1 in the first regression model has a p-value of 0.000 is significant at the 0.05 level. Regression $\hat{y}_1' = -0.422 * C_1$ is selected as the best equation, since its adjusted R^2 (0.975) is larger enough. Moreover, this equation's F value of 294.337 is highly significant (P<0.001).

5. Restate the principle component regression equation in terms of the standardized independent variables.

$$\hat{y}_1' = -0.422 * C_1$$
$$= -0.422 * (.783VAR51' + .919VAR105' - .936VAR134') \quad (21)$$
$$= -0.330VAR51' - 0.388VAR105' + 0.395VAR134'$$

6. Compute parameters L_y, the sum of squares of dependent variable Y, and L_{x_i}, the sum of squares of independent variable X_i, then use these parameters to transform the standardized linear regression equation into a general linear regression equation, in terms of the original variables, as follows:

$$b_i = b_i'(L_y/L_{x\_i})^{1/2} \quad (i = 1, \dots K \leq p) \quad (22)$$

$$b_0 = \bar{Y} - \sum b_i \bar{X}_i \, (i = 1, \dots K \leq p) \quad (23)$$

$$\hat{y} = b_0 + \sum b_i X_i \, (i = 1, \dots K \leq p) \quad (24)$$

The general linear regression equation is obtained as:

$$\hat{y} = 368.225 - 632.645\, X_{51} - 400.291\, X_{105} + 3.382\, X_{134} \quad (25)$$

Recall how the variance decision variable X is defined: When $X > 0$, production will be less than the forecasted demand, when $X < 0$, production will exceed the forecasted demand. Because our focus is not on predicting the amount of food waste generated per week, we will not focus our interpretation on the magnitude of the regression coefficients. Rather, we wish to know which variables have a significant positive impact on the weight of food waste generation, and which have a significant negative impact; thus we focus on the sign of each coefficient. Observe that for the three variables having a negative regression coefficient (Variance_Wednesday_Lunch_Beef, Variance_Friday_Lunch_ Vegetable), production in excess of the forecasted demand is associated with increased waste and reduced shortfalls.

Conversely, for the one variable with a positive regression coefficient (Threshold_Sunday_Dinner_Beef), production in excess of the forecasted demand is associated with decreased waste and increased shortfalls.

4.3 Discussion and Conclusion

Food service operations in an AYCTE environment need to consider two conflicting objectives: a desire to reduce overproduction food waste (and its corresponding environmental impacts), and an aversion to shortfalls (in which some customer demands go unsatisfied). A particular challenge in AYCTE operations is the absence of any lost marginal revenue associated with lost sales that can be used to measure the shortfall cost, complicating any attempt to determine a minimum-cost solution. This research presented a multi-criteria optimization approach to identify the efficient frontier of points lying between the minimum-waste and minimum-shortfall solutions. In particular, we identify optimal production adjustments relative to demand forecasts, demand thresholds for utilization of leftovers, and percentages of demand to be satisfied by leftovers, considering two alternative metrics for overproduction waste: mass (in kg); and GHG emissions (in kg CO2-eq), to account for the embodied chemical usage during farming, transportation, and landfill decomposing of overproduced food waste.

We illustrate our approach with an application to empirical data from food service operations over a five-week period at the University of Missouri CDS. When food waste is measured using a weight of wasted food metric, our approach identifies an efficient frontier ranging from a solution with approximately 1,200 portion shortfalls (4.2% of the total demand, in portions) and zero waste, to a solution with zero shortfalls and approximately 200 kg of overproduction food waste. When food waste is measured using a CO2-eq of wasted food metric, our approach identifies an efficient frontier ranging from a solution with approximately 1,100 portion shortfalls (3.8% of the total demand, in portions) and zero waste, to a solution with zero shortfalls and approximately 530 kg of CO2-eq associated with overproduction food waste. These results can be contrasted with our estimates of the actual CDS overproduction waste over this time period, which were 98 kg of overproduction food waste, accounting for 547 kg of CO2-eq.

A statistical analysis of the changes in decision variable values across each of the efficient frontiers identified the key variables that could be modified to reduce the amount of wasted food at minimal increase in shortfalls (or, alternatively, to reduce the amount of shortfalls at minimal increase in waste). When food waste is measured using a weight of wasted food metric, it would be preferable to reduce wasted food by decreasing the demand target for two meal-food type parings on Wednesdays (Lunch_Beef and Dinner_Vegetable), decreasing the demand target for Lunch_ Pork&Poultry&Fish -Fried on Mondays (recall that overproduction of fried items cannot be stored in post-production inventory and utilized as leftovers), and decreasing the minimum forecast level for which a Sunday_Dinner_Vegetable item can potentially allow for substitution by leftovers. When food waste is measured using the CO2-eq of wasted food metric, it would be preferable to reduce wasted food by decreasing the demand target for Lunch_Beef on Wednesdays, decreasing the demand target for Lunch_Vegetables on Fridays, and decreasing the minimum forecast level for which a Sunday_Dinner_Beef item can potentially allow for substitution by leftovers. We observe a consistent preference across both waste metrics to reduce the demand target below the forecast level on Wednesday lunches, and a desire to increase the potential substitution by leftovers for Sunday dinners.

There are several potential avenues for expanding the research presented in this paper. This research did not consider the set of ordering decisions necessary to maintain a pre-production inventory of ingredients necessary to allow for production of menu items. Further research could integrate these decisions, potentially trading off the cost of maintaining pre-production and post-production inventories. Moreover, within this research, our model was able to identify the optimal production decisions considering a known set of demands across a finite time horizon, allowing for identification of which decisions, for which day-meal-food item combinations, would allow for food waste to be reduced at minimal increase in shortfalls. Additional research is necessary to translate these concepts to environments with unknown, stochastic demands, to allow for integration of these models into decision support systems for food service providers.

Chapter 5

Optimal Production Planning in an Environment Utilizing Leftovers with uncertain and correlated demand

5.1 Unconstrained Nonlinear Programing-Hooke Jeeves and Kernel Density Estimation:

A major assumption in the work presented in Chapter 4 is that the optimization model was allowed to search over a set of known demands. However, production planning in an AYCTE environment is subject to uncertain demands. Consider the example shown in Table 5.1, containing MU CDS data from Spring Semester 2015: here the first five weeks' cycle starts January19 and ends February 22, the second five-week cycle starts February 23 and ends March 29, and the third-week cycle begins March 30 and ends May 3. Lastly, there is forth-week cycle, but this cycle covers only two weeks which begins May 4 and ends May 15. Feb 13 is the Friday in the fourth week of the first cycle, March 20 occupies the same position in the second cycle, April 24 the same position in the third cycle. Recall our discussion of cycle menus in Chapter 2. Observe that each of these days has the same menu items for lunch. In those days, they are producing breaded cat fish, Cajun pork loin, vegetable creole, sausage pizza, cheese pizza, and Belgian waffle as entrées. However, while the same items were produced on each day, demands for those items were different on each day. However, CDS anticipated these variations, to some extent, as the forecast amounts also vary across each cycle.

Menu Item	Feb 13			March 20			April 24		
	Demand	Forecast	Error	Demand	Forecast	Error	Demand	Forecast	Error
Breaded Cat fish	251	130	121	147	233	-86	121	241	-120
Cajun Pork Lion	129	100	29	154	120	34	92	124	-32
Vegetable Creole	19	20	-1	24	18	6	23	19	4
Sausage Pizza	96	88	8	40	89	-49	70	92	-22
Cheese Pizza	94	96	-2	48	87	-39	42	90	-48
Belgian Waffles	8	7	1	4	7	-3	4	7	-3

Table 5.1: 4th week Friday lunch demand, forecast and forecast error

CDS uses forecasting to project the demand for future meals. Forecasting is a key aspect of production and provides the baseline for decision making and planning (Spears and Gregorie, 2006). Although CDS uses CBORD which has statistical technique to forecast number of production, eventually adjusted that forecast based on the expert judgement, because of special considerations such as game day or weather conditions.

We know that demand forecasting accuracy is important to inventory control (Buffa and Miller, 1979; Silver *et al.*, 1998) . However, determining better forecasting methods is not a focus of this dissertation. The primary consideration of this chapter is to define optimal production adjustments, given a set of demand forecast, in order to minimize waste (and its corresponding environmental impacts), and shortfall (in which some customer demands go unsatisfied), when demand is uncertain and correlated.

In the literature, there are different approaches to solving such the demand uncertainty problems.

Most of the studies assume that demand is uncertain but that its distribution is known, often following common distributions such as the Normal, gamma, or Poisson. Given set of empirical data, in order to define distribution of data, some fitting method, such as Maximum Likelihood Estimator or Bayesian Estimator is needed. In this case some assumption such as normality or consistency needs to be satisfied. It is difficult to satisfy such an assumption when the data set is small.

To overcome problems with small data set, some distribution-free approaches have been studied. A distribution-free approach aims to estimate the density function directly from data without assuming a particular form from any distribution. The simplest form of non-parametric density estimation is the histogram (Chandrasekaran, 2007; Jafarizadeh *et al.*, 2013). However, using a histogram has several disadvantages, namely that the density estimation depends on the starting position of the bins, and problems with dimensionality, since the number of bins grows exponentially with the number of dimensions (Li and Adelson, 2008) . Kernel density estimation is a technique that makes improvements over the histogram approach.

The basics of kernel density estimation formulation are based on Sheather (2004). Let $X_1, X_2, \ldots X_n$ denote a sample of size n from a random variable with density f. The kernel density estimate of f at the point x is given by

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{26}$$

where the kernel K satisfy $\int K(x)dx = 1$ and the smoothing parameter h is known as the bandwith.

In this dissertation, a basic kernel density estimator is used by scipy.stats.kde module python coding.

The CDS chef attempts to produce a diverse and flexible array of food items. When each five-week cycle menu is prepared, the items offered at each meal are selected to provide for daily human nutritional requirements. In addition, the plan needs to accommodate differences in consumer preferences, since some CDS customers are vegan while others don't like vegetables. As a result of this diversity, different menu options need to be served. This diversity is beneficial for consumers but it complicates production for both the producer and their suppliers (Fisher *et al.*, 1994).

One problem associated with forecasting demands in such a multi-product system is correlation. Net inventories of items are correlated because of correlation of across demand items (Song, 1998). In a food production environment, the demands of two products might be correlated because of customer eating behavior. Since demand decision are correlated (e.g. french fries served with hamburgers), their production decisions need to account for this correlation. Figure 5.1 shows the demand correlation between french fries and hamburgers for CDS data covering the period January 19 to February 22. Observe that when demands for one item are high, demands for the other item are also generally high. Similarly, low demands for one item generally coincide with low demands for the other item. The correlation coefficient for these data is 0.773, suggesting relatively strong linear relationship. It seems reasonable to assume that this correlation should impact demand forecasts.

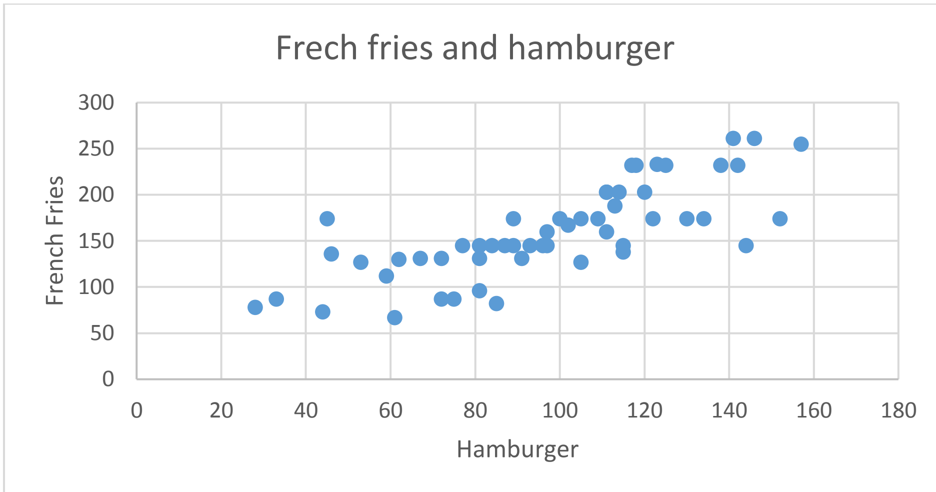


Figure 5.1:Correlation: French fries and hamburger

Before applying the kernel density estimation to demands, the correlation between the items needs to be identified. Rather than identifying correlation between individual menu items (such as french fries and hamburgers), we identified correlations between the food types examined in Chapter 4, for each day of the week. For example, we wanted to identify if correlations exist between the demands on Monday for beef types items and vegetable type items.

We identify correlation based on the metric *percent error of demand*, computed as the subtraction of forecast from demand number, with this difference then divided by the forecast. We used this approach rather than basing it on the error value because the magnitudes of forecasts can vary greatly across different items, suggesting that a relative metric such as percent error would provide for a better impression of forecast accuracy. We determined correlation between the food groups on specific days using data from the first five-week cycle of spring semester 2015. The percent error of demand was computed for each individual menu item on each day, and then a correlation test was performed across the subset of all data points belonging to each food type group to identify the existence of correlation. The results of this analysis are as follows:

- There is no correlation between food groups on Monday.
- On Tuesday, “Pork&Poultry&Fish” has negative correlation with “Other” item group, Pearson value= –0.672, p-value=0.033.
- On Wednesday “Pork&Poultry&Fish” has strong positive correlation with “Vegetable” item group, Pearson value=0.901, p-value=0.000.
- There is no correlation between food groups on Thursday.
- On Friday, “Pork&Poultry&Fish” has strong positive correlation with “Vegetable” item group, Pearson value=0.972 p-value=0.006.
- On Saturday, “Pork&Poultry&Fish” has positive correlation with “Other” item group, Pearson value=0.879, p-value-0.05.
- On Sunday, there is strong positive correlation between “Beef” and “Pork&Poultry&Fish” item groups, and also between “Beef” and “Vegetable” item groups, Pearson values=0.696 and 0.833 and p-values=0.025 and 0.003, respectively.

As mentioned earlier, CDS uses cycle menu system, in each five-week cycle they are producing same menu items at each meal. In order to model unknown, stochastic for demands, we will utilize the first five weeks’ cycle as my training data, then we will utilize the probability distributions and correlations based on the first cycle to optimize production on the unknown demands for remaining cycles.

Another issue related to multi-product service is substitutability. If the desired item is not available, a customer can elect to receive the second-most preferable item. Ganesh *et al.* (2014) analyzed the impact of substitution in a multi-level supply chain. They found that ignoring product substitution can cause a significant overestimation of the value of information sharing. Another kind of substitution in a multi-product environment is customers changing their mind when they are trying to buy a product by using a risk pooling effect. Eynan and Fouque (2003) come up with a new approach called "demand reshape" to improve company profit by encouraging its customers to buy another item instead of what they intend to purchase by taking advantage of the risk pooling effect.

In the CDS example, we assume that such substitution can occur and does not require substitution by the same type of food. For example, if demand exceeds supply for a vegetable type food such as cheese pizza, we allow that demand to potentially be satisfied by any available item, for example, beef ravioli. In our study, we allow full substitutability to occur within a single meal. If there is not enough of any particular item to meet customer demand, substitutability is applied and excess portions of any other item served at that meal can be used to meet unsatisfied demands. Consider the implications of demand correlation on production in such an environment: when demands are negatively correlated, if production levels for both items are similar, overproduction of one item during a meal can potentially be used to satisfy the shortfalls below demand for the negatively correlated item. However, when demands are positively correlated, if production levels for both items are similar, shortfalls below demand could occur for both correlated items with no potential for substitution to meet demands, whereas overproduction for both correlated items might also occur, in which case there is no opportunity for this overproduction to be used as substitution for either item and both overproductions must be entered into the leftovers inventory.

5.1.1 Application

This new model formulation, which includes demand uncertainty, becomes even more complex than the previous chapter's study, which was already difficult due to nonlinearities. Rather than developing a simulation based approach for solving this nonlinear stochastic optimization problem, we extended the optimization technique utilized in chapter 4 (Hooke-Jeeves search) to include kernel density estimation. We will utilize the same metrics in this study as those examined in chapter 4, namely, shortfall portions, mass of wasted food, and CO2-eq of wasted food.

In this new model, the *threshold* and *percent* variables are defined identically as before. However, we now replace the production *variance* variable X_n with a variable corresponding to the *shortfall probability* of production at a given level, we denote this new variable SP_n . Given the distribution of error percentages for each item in the training data (first five weeks of demands), we utilize kernel density estimation to define a probability of shortfall for each production level, relative to the forecast demand.

The optimization model thus has three types of decision variables: Shortfall probability, SP_n, leftover utilization threshold H_n and leftover utilization percent, denoted Q_n. For the threshold and percent variables, there is an instance created for each combination of (a) day of the week [Monday through Sunday], (b) meal [lunch and dinner], (c) food type [Beef, Pork&Poultry&Fish, Veggie, Other], and (d) preparation type [fried or not fried]. We differentiate between these two preparation types because fried food cannot be retained as leftovers for use in a future meal, requiring that all overproduction of fried items must be discarded. The shortfall probability variable is created for each combination of day of week and food type.

Having used the first five weeks of the Spring 2015 semester as our training data, we will utilize data from the remainder of this semester to test our model. During this period, there are two breaks during which CDS is not operating, Spring and Easter break. Because of having a break of two or more days, the last Friday before Spring break, and the last Friday before Easter break correspond to particularly important decisions, because any overproduction on those dates cannot be used as leftovers. Because of this, we define new variables to cover this situation, differentiating those dates from other Fridays. In total, our model contains 184 decision variables.

5.1.2 Leftovers Usage Policy

Recall the two leftovers usage policies, *Meat* and *Heavy* that were discussed in Chapter 4. We considered a third leftovers usage policy here, *Beef*, that would utilize all beef items first, before using any other leftovers, in an attempt to control for GHG effects, since beef items are known to have much greater CO2-eq per kg than other food items. In this new policy, first all Beef types leftovers of maximum allowable age are utilized, then all Beef type leftovers of the second greatest age are utilized, etc. After all beef items are utilized, we repeat this process using the oldest Pork&Poultry&Fish items first, then the second-oldest Pork&Poultry&Fish items, etc. When we compare the waste and shortfall generated by this policy to the performance of the previous two policies, we find that Beef policy is a dominated strategy. That is, the Meat and Heavy policies generate less waste at any shortfall level. Accordingly, for the remainder of this chapter we will examine the performance of our stochastic optimization model with respect to only the Meat and Heavy policies

5.2 Results

5.2.1 Drawing interferences from optimization model results for weight of waste metric

Figure 5.2 below presents the range of waste, using the weight of waste metric, that can be achieved under each leftovers usage policy, assuming different values for the penalty term μ. This graph demonstrates the tradeoff between shortfall portions and grams of food waste, ranging from a minimum-waste, maximum-shortfall endpoint to a maximum-waste, minimum-shortfall endpoint for each μ value. Observe that, for each different value of μ that is considered, there is a gap between the Meat and Heavy policy, with the Meat policy never outperforming the Heavy policy. This supports the hypothesis that using the Heavy policy should give better results than Meat policy, when the objectives involves minimizing the mass of waste under correlated and uncertain demand.

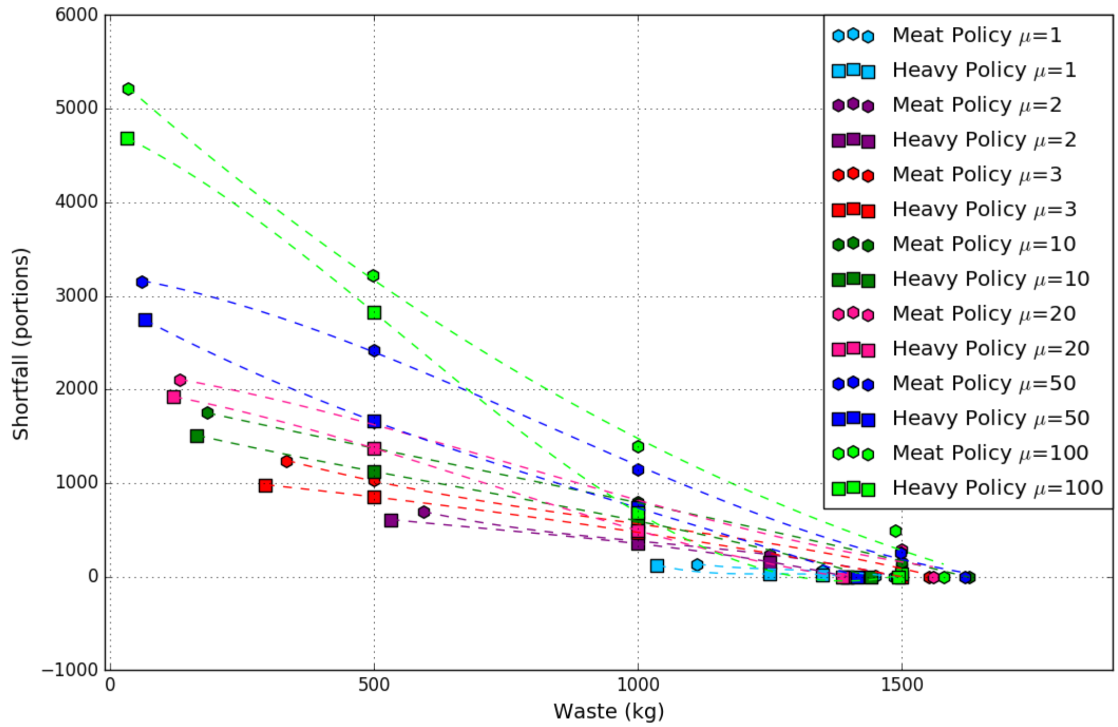


Figure 5.2: Shortfall versus Waste (kg), all potential μ values

Figure 5.3 below presents the efficient frontier identified by our optimization procedure across all examined μ values when the waste target is defined in terms of the weight of wasted food, under Heavy policy. Because the total demand was for 56,219 portions across this data set, the maximum shortfall solution corresponds to a situation in which 7.91% of demands (in aggregate) encountered shortfalls.

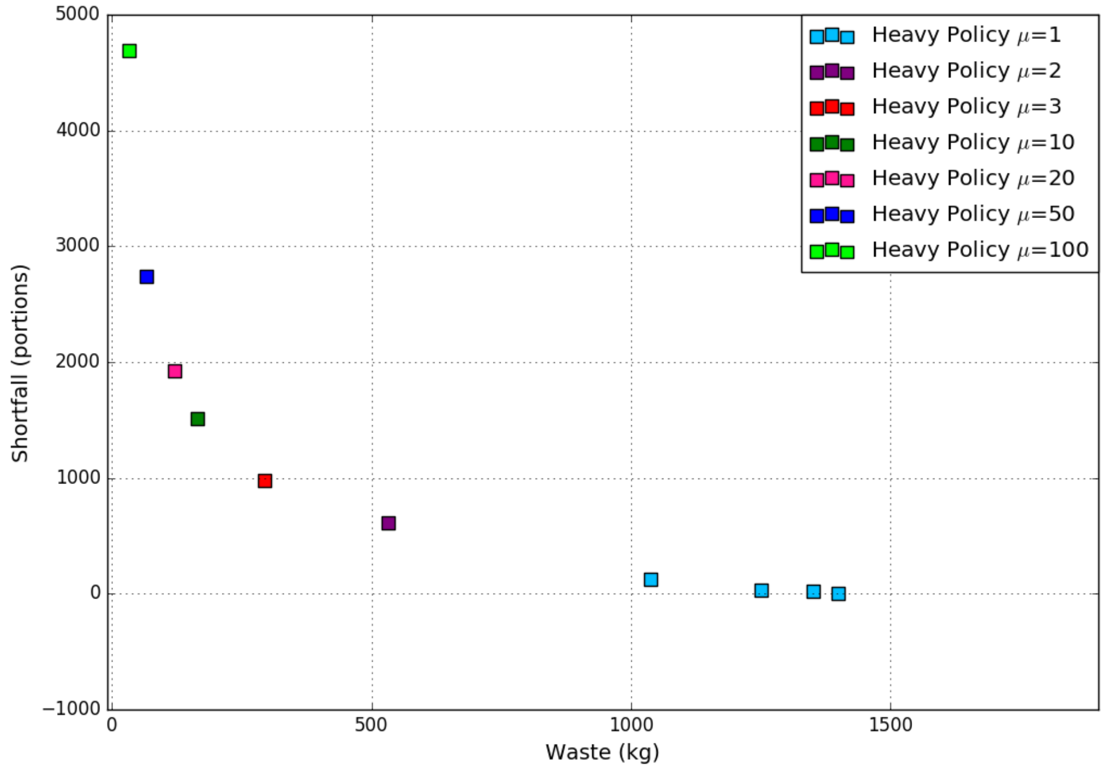


Figure 5.3: Efficient frontier, optimizing tradeoff between shortfall and mass of waste for Heavy Policy

The process described in Chapter 4 was applied to the model's 184 decision (independent) variables, identify their impact on the total mass of wasted food (dependent) variable, across all points in the efficient frontier of Figure 5.3. This process identified the following regression equation:

$$\hat{y} = -640.119 + 7.691\, X_{12} + 8.883\, X_{58} + 5.545\, X_{84} + 656.98\, X_{172} \qquad (27)$$

with the following set of significant independent variables

X_{12}: Threshold_Monday_Dinner_Pork&Poultry&Fish

X_{58}: Threshold_Thursday_Dinner_Beef

X_{84}: Threshold_Sunday_Lunch_Pork&Poultry&Fish

X_{172}: Shortfall_probability_Saturday_Other

We observe that the three significant *threshold* variables each have a positive regression coefficient, suggesting that increasing the substitution with leftovers reduces waste at minimal increase in shortfall and is desirable for Monday and Thursday dinner, and Sunday Lunch production, which is consistent with our expectations.

However, there is one significant variable *shortfall probability*, and this variables has a positive coefficient, implying that an increase in shortfall probability (which is accomplished by a decrease in the production level) is associated with an increase in the mass of wasted food, which is not consistent with our expectations.

Figure 5.4 below presents the efficient frontier identified by our optimization procedure across all examined μ values when the waste target is defined in terms of the weight of wasted food, under the Meat policy.

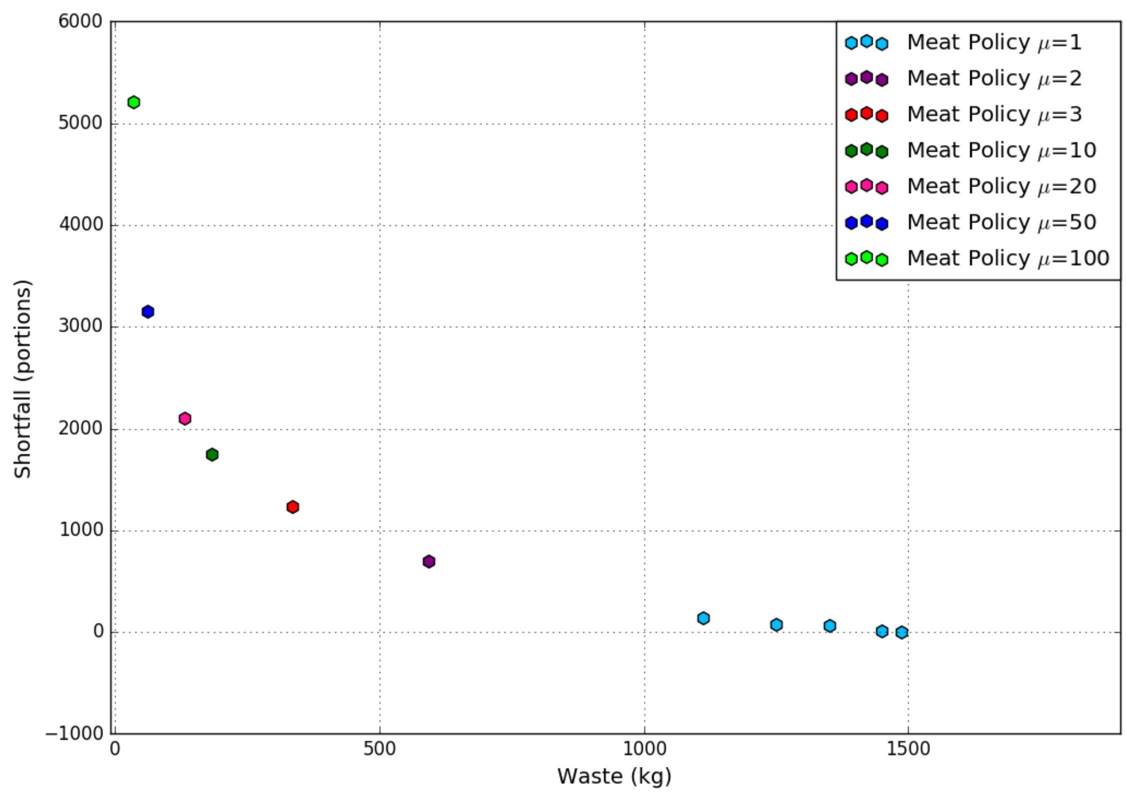


Figure 5.4:Efficient frontier, optimizing tradeoff between shortfall and mass of waste for Meat Policy

The same regression process was applied again across all points in the efficient frontier of Figure 5.4. This process identified the following regression equation:

$$\hat{y} = 36663.85 + 6.56\, X_{94} - 4264.25\, X_{154} - 1729.17 X_{173} \tag{28}$$

with the following set of significant independent variables

X_{94}: Threshold_Sunday_Dinner_Vegetable

X_{154}: Shortfall_probability_Tuesday_Pork&Poultry&Fish

X_{173}: Shortfall_probability_Sunday_ Beef

Observe that the two significant *shortfall probability* variables each have a negative regression coefficient, implying that an increase in shortfall probability is associated with a decrease in the mass of wasted food, which is consistent with our expectation.

Similarly, the significant *threshold* variable (Threshold_Sunday_Dinner_ Vegetable) has a positive regression coefficient. Recall how the *threshold* decision H_n is defined: when H_n increases, the minimum forecast level for which an item can potentially allow for substitution by leftovers is increased, and thus these item's total substitution with leftovers is reduced. Again, the result is consistent with our expectations, and suggests that increasing the substitution with leftovers is desirable for Sunday dinner production, generating waste reductions at minimal increase in shortfall.

5.2.2 Drawing optimization model result for environmental impact of waste for both policies with different μ values

Figure 5.5 below presents the range of total kg CO2-eq of wasted food that can be achieved under each leftovers usage policy, assuming different values for the penalty term μ. This graph demonstrates the tradeoff between shortfall portions and total kg CO2-eq of wasted food, ranging from a minimum-waste, maximum-shortfall endpoint to a maximum-waste, minimum-shortfall endpoint for each μ values. Observed that, for each different value of μ that is considered, there is a gap between the Meat and Heavy policy, with the Heavy policy never outperforming the Meat policy. This supports the hypothesis that using the meat policy should give better results than the heavy policy, when the objective involves minimizing the Co2-eq of wasted food under correlated and uncertain demand.

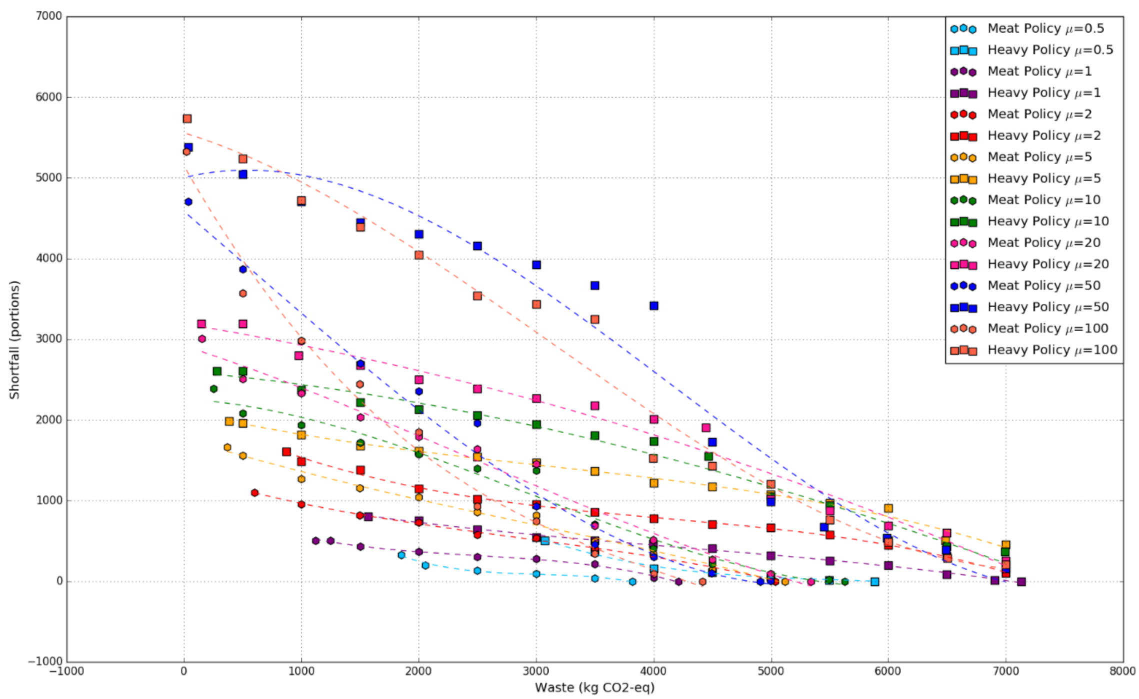


Figure 5.5: Shortfall versus Waste (kg CO2-eq), all potential μ values

Figure 5.6 below presents the efficient frontiers identified by our optimization procedure across all examined μ values when the waste target is defined in terms of total kg CO2-eq of wasted food, under the Meat policy.

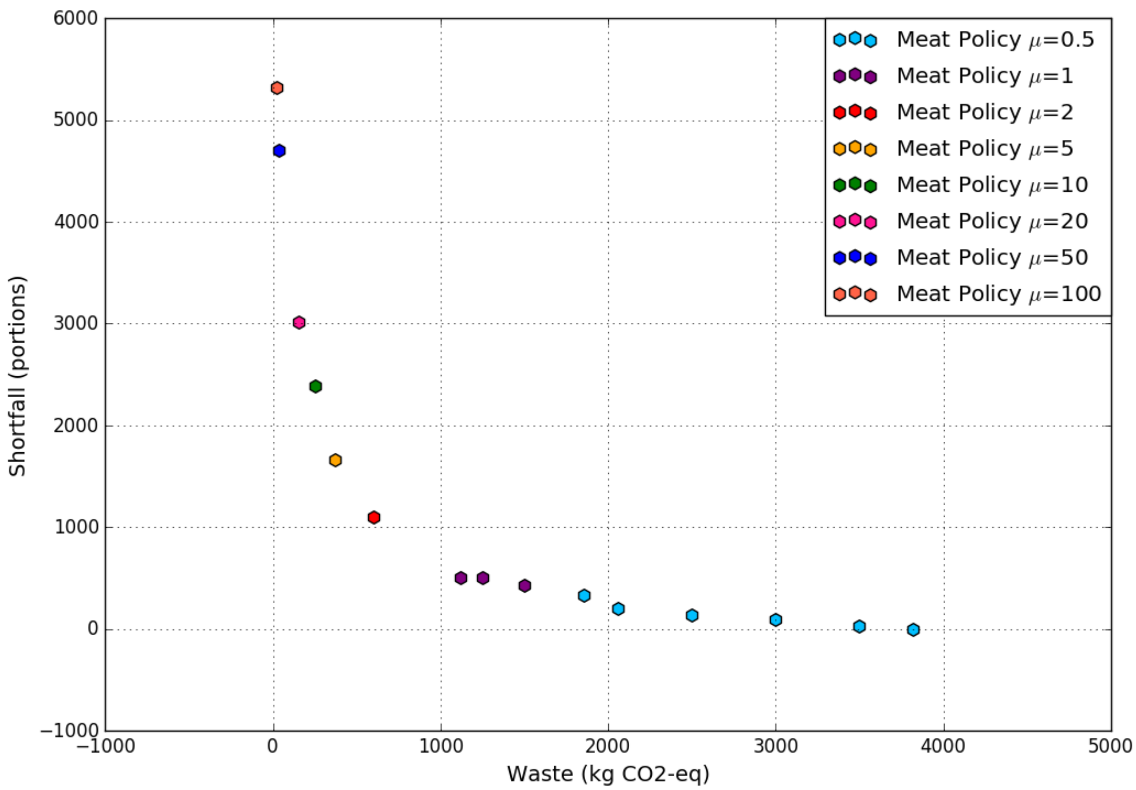


Figure 5.6:Efficient frontier, optimizing tradeoff between shortfall and of total kg CO2-eq wasted food for Meat Policy

The process described in Chapter 4 was again applied to the model's 184 decision (independent) variables, now identifying their impact on the kg CO2-eq of wasted food (dependent) variable, across all points in the efficient frontier of Figure 5.6. This process identified the following regression equation:

$$\hat{y} = 22806.87 - 1140.92\, X_{27} - 560.87\, X_{29} + 2.42\, X_{30} + 6.79\, X_{36} - 1476.35 X_{149} + 1937.27\, X_{156} - 7700.49\, X_{157} - 2138.63 X_{161} + 1484.07\, X_{172} \tag{29}$$

with the following set of significant independent variables

X_{27}: Percent_Tuesday_Dinner_Pork&Poultry&Fish

X_{29}: Percent_Tuesday_Dinner_Vegetable

X_{30}: Threshold_Tuesday_Dinner_Vegetable

X_{36}: Threshold_Wednesday_Lunch_ Pork&Poultry&Fish

X_{149}: Shortfall_probability_Monday_ Beef

X_{156}: Shortfall_probability_Tuesday_ Other

X_{157}: Shortfall_probability_Wednesday_ Beef

X_{161}: Shortfall_probability_Thursday_ Beef

X_{172}: Shortfall_probability_Saturday_ Other

The two significant *percent* variables (Percent_Tuesday_Dinner_Pork& Poultry&Fish, Percent_Tuesday_Dinner_Vegetable) each have a negative coefficient, implying that increased substitution by leftovers is associated with reduced waste, as expected. Additionally, the two significant *threshold* variables each have a positive regression coefficient, suggesting that reducing substitution with leftovers would increase the GHG waste amount, as expected, at minimal increase in shortfalls, and is desirable for Tuesday Dinner and Wednesday Lunch production.

However, the *shortfall probability* variables have positive and negative regression coefficients. The three beef items with significant *shortfall probability* variables each have negative regression coefficient, implying that an increase in shortfall probability is associated with a decrease in the mass of wasted food, which is consistent with our expectation. Conversely, the two other items' *shortfall probability* variables each have a positive coefficient, implying that an increase in shortfall probability (which is accomplished by a decrease in the production level) is associated with an increase in the mass of wasted food, which is not consistent with our expectations.

Figure 5.7 below presents the efficient frontier identified by our optimization procedure across all examined μ values when the waste target is defined in terms of total kg CO2-eq of wasted food, under Heavy policy.

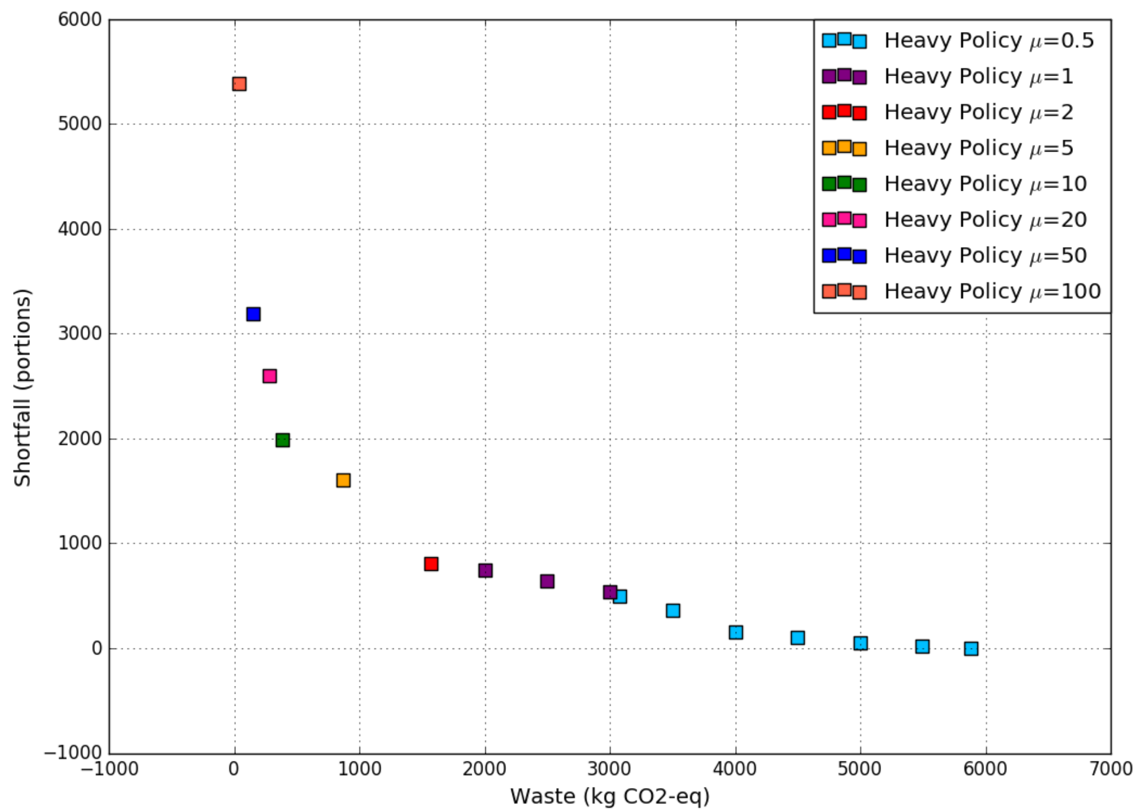


Figure 5.7: Efficient frontier, optimizing tradeoff between shortfall and of total kg CO2-eq wasted food for Heavy Policy

The same regression process was applied again across all points in the efficient frontier of Figure 5.7. This process identified the following regression equation:

$$\hat{y} = 23666.39 + 25.12X_6 + 3.50X_{76} - 961.60X_{91} - 863.08X_{109} - 2616.15X_{158} - 2932.58X_{175} - 6097.94X_{183} \quad (30)$$

with the following set of significant independent variables

X_6: Threshold_Monday_Lunch_Vegetable

X_{76}: Threshold_Saturday_Lunch_Pork&Poultry&Fish

X_{91}: Percent_Sunday_Dinner_Pork&Poultry&Fish

X_{109}: Percent_Wednesday_Lunch_Beef_Fried

X_{158}: Shortfall_probability_Wednesday_Pork&Poultry&Fish

X_{175}: Shortfall_probability_Sunday_Vegetable

X_{183}: Shortfall_probability_Easter_Friday_Other

Again, we observe that the two significant *threshold* variables each have a positive regression coefficient, suggesting that increasing the substitution with leftovers is desirable for and Monday Lunch, and Saturday Lunch production. Also, we observe that two *percent* variables each have negative coefficient, implying that increased substitution by leftovers is associated with reduced waste at minimal increase in shortfall. These sigs of each of these coefficients are all consistent with our expectations.

The *shortfall probability* variables each have negative regression coefficients, as expected. Vegetable, Pork&Poultry&Fish and Easter Friday other item's *shortfall probability* variables have negative regression coefficients, implying that increasing these values can reduce the CO2-eq of wasted food at minimal increase in shortfall.

5.3 Discussion and Conclusion

One problem that the food service industry shares in common with almost any production planning environment is demand uncertainty. When demand correlation is joined to this uncertainty, the problem becomes even more complex. This research examines this real-life situation, applying a multi-criteria optimization approach to identify efficient frontier for points lying between the minimum-waste and minimum-shortfall solutions within an AYCTE environment having uncertain and correlated demand. Such food service operations need to consider two conflicting objectives: a desire to reduce overproduction food waste (and its corresponding environmental impacts), and an aversion to shortfalls (in which some customer demand go unsatisfied). We identify optimal production adjustments relative to demand forecasts, demand thresholds for utilization of leftovers, and percentages of demand to be satisfied by leftovers, considering two alternative metrics for overproduction waste: mass (in kg); and GHG emissions (in kg CO2-eq), to account for the embodied chemical usage during farming, transportation, and landfill decomposing of overproduced food waste.

We illustrate our approach with an application to empirical data from food service operations over the Spring 2015 semester at the University of Missouri CDS. When food waste is measured using a weight of wasted food metric, our approach identifies an efficient frontier, using a heaviest-items first leftovers usage policy, that ranges from a solution of with approximately 5,000 portion shortfalls (correspond to 7.91% of the total demand, in portions) and zero waste, to a solution with zero shortfalls and approximately 1,400 kg of overproduction food waste.

When food waste is measured using a CO2-eq of wasted food metric, our approach identifies an efficient frontier, using a greatest-CO2-eq first leftover policy, that ranges from a solution with approximately 5,300 portion shortfalls (corresponds to 9.43% of the total demand, in portion) and zero waste, to a solution with zero shortfalls and approximately 3,700 kg of CO_2-eq associated with overproduction food waste.

A statistical analysis of the changes in decision variable values across each of the efficient frontiers identified the key variables that could be modified to reduce the amount of wasted food at minimal increase in shortfalls (or, alternatively, to reduce the amount of shortfalls at minimal increase in waste). When food waste is measured using a weight of wasted food metric, it would be preferable to reduce wasted food by using the Heavy policy. Under either the Heavy or Meat policy, increasing the substitution of leftovers by reducing the threshold can potentially decrease the mass of waste amount. In particular, reducing the threshold variable to allow for increased use of leftovers would be desirable for Monday_Dinner_Pork&Poultry&Fish, Tuesday_Dinner_Beef, and Sunday_Lunch_Pork&Poultry_Fish (under the Heavy policy); reducing the threshold variable to allow for increased use of leftovers would be desirable for Sunday_Dinner_Vegetable (under Meat policy).

Under the Meat policy, increasing the shortfall probability for Tuesday_ Pork&Poultry&Fish and for Sunday_Beef items would be desirable for reducing the mass of waste at minimal increase in shortfalls. However, under the Heavy policy, decreasing the shortfall probability for Saturday_Other items would be desirable. This is a counterintuitive result, since decreasing the shortfall probability corresponds to increasing the production level for these items. However, additional examination of this variable shows that it has significant correlation with other variables. We observed other, non-statistically significant correlations (coefficient of -0.835with p-value equal to 0.003) with Beef items on this day. These correlations help to explain this unexpected result. An examination of stepwise regression suggests that the Saturday_other variable is capturing some of the effect of other variables (in particular, Beef and Pork&Poultry&Fish items) that the regression analysis did not deem significant and which were dropped from the regression.

When food waste is measured using the CO2-eq of wasted food metric, it would be preferable to reduce total CO2 emission by using the Meat policy. Under either the Heavy or Meat policy, increasing the substitution of leftovers by reducing the threshold and increase the percent variables can potentially decrease the total CO2-eq of wasted food which is consistent with our expectations. In particular, reducing the threshold variable to allow for increased use of leftovers would be desirable for Tuesday_Dinner_Vegetable and Wednesday_Lucnh_Pork&Poultry&Fish (under the Meat policy); reducing the threshold variable to allow for increased use of leftovers would be desirable for Monday_Lunch_Vegectale and Sturday_Lunch_Pork&Poultry&Fish (under the Heavy policy). Increaseing the percent variable to allow for increased use of leftovers would be desirable for Tuesday_Dinner_Pork_Poultry&Fish and Tuesday_dinner_Vegetebale (under the Meat policy); increasing the percent variable to allow for increased use of leftovers would be desirable for Sunday_Dinner_Pork&Poultry&Fish and Wednesday_Lunch_Beef_Fried (under the Heavy policy).

Our research also found some of the shortfall probability variables to be significant for CO2-eq of wasted food metric, suggesting that modifying these values would be desirable for reducing the mass of waste at minimal increase in shortfalls. Under the Heavy policy, we find that increasing the probability of shortfall would potentially decrease the total CO2-eq of wasted food, which is consistent with our expectations; uch a strategy is desirable for Wednesday_Pork&poultry&Fish and Sunday_Vegetable and Easter_Friday_Other. Under the Meat polic, we find similar result, with increasing the shortfall probability desirable for Monday Beef, Wednesday Beef, and Thursday Beef. However, there is again some difficulty in interpreting two other significant variables, this time under the Meat policy. For Tuesday_other and Saturday_Other, the regression coeeficnet is positive, suggesting that decreasing the probability of shortfall would decrase the total CO2-eq of wasted food, which is not consistent with our expectations. Here again, additional examination of these variables shows them to have significant correlation with other variables, in particular a negative correlation with meat (Beef and Pork&Poultry&Fish) items from Monday through Sunday. We observed other, non-statistically significant correlations as coefficient of -0.648 with p-value equal to 0.017 on Monday Beef, coefficient of -0.831 with p-value equal to 0.000 on Monday Pork&Poultry&Fish, coefficient of -0.885 with p-value equal to 0.000 on Tuesday Pork&Poultry&Fish, coefficient of -0.811 with p-value equal to 0.001 on Wednesday Beef, coefficient of -0.857 with p-value equal to 0.000 on Wednesday Pork&Poultry&Fish, coefficient of -0.775 with p-value equal to 0.002 on Thursday Beef, coefficient of -0.766 with p-value equal to 0.002 on Thursday Pork&Poultry&Fish, coefficient of -0.602 with p-value equal to 0.030 on Friday Pork&Poultry&Fish, coefficient of -0.727 with p-value equal to 0.005 on Sunday Beef. These correlations help to explain this unexpected result. The negative correlations suggest that overproduction of Other type items, which have a per-portion CO2-eq that is approximately 8 times less than that per Pork&Poultry&Fish portion and approximately 30 times less than that per Beef portion, could be desirable: in the event that Other demands are lower than expected, their excess portions could be used to satisfy the higher than expected demands (due to negative correlation) for Beef and Pork&Poultry&Fish items. As discussed above for the analysis under the total weight of food waste matric, an examination of the stepwise regression suggests that the Satuday_Other variable is capturing some of the effect of other variables (in particular, Beef items) that the regression analysis did not deem significant and which were dropped from the regression.

This research did not consider the set of ordering decisions necessary to maintain a pre-production inventory of ingredients necessary to allow for production of menu items. Further research could integrate these decisions, potentially trading off the cost of maintaining pre-production and post-production inventories.

Chapter 6

Conclusions

6.1 Summary

This chapter concludes this thesis by summarizing the major findings that emerged from the activities performed in addressing the research questions. The contribution of these thesis outcomes discussed, particularly for academia, industry and decision makers. The first study examines how optimal food production policies at an AYCTE facility would change were life cycle cost estimates of embodied CO_2 included in the disposal costs associated with overproduction, in an aim to study production planning possibilities in a situation that places increased emphasis is on the environmental impacts of overproduction. The academic contribution of this research is a new approach for computing shortfall costs in an environment that has no immediate lost sales revenue associated with underproduction of any individual item to serve as a shortfall cost. We developed an approach to infer the value that current management places on shortfalls based on historical management decision.

However, beyond just the landfill costs associated with disposal of overproduced food, there are also environmental costs associated with food waste. Utilizing data from life cycle analyses of the CO_2 embodied in three different food types (fried potatoes, chicken, and beef), along with estimates of the social cost of carbon, we estimated a range of environmental costs associated with the life cycle CO_2 emissions for the three menu items considered. We presented an early version of this research to CDS leadership, who subsequently shared it with their entire management team. CDS has now developed a Sustainability committee, and are working to establish targeted goals related to sustainability issues, including a reduction in food waste.

The second study presented a multi-criteria optimization approach to identify the efficient frontier of points lying between the minimum-waste and minimum-shortfall solutions when leftovers can be served up to three days after initial production. In particular, we identify optimal production adjustments relative to demand forecasts, demand thresholds for utilization of leftovers, and percentages of demand to be satisfied by leftovers, considering two alternative metrics for overproduction waste: mass (in kg); and GHG emissions (in kg CO2-eq), to account for the embodied chemical usage during farming, transportation, and landfill decomposing of overproduced food waste. A statistical analysis of the changes in decision variable values across each of the efficient frontiers is then performed to identify the key variables that could be modified to reduce the amount of wasted food at minimal increase in shortfalls. The academic contribution of this research is performing a technical method to minimize overproduction food waste when leftovers is served in the future.

The final study is an adaptation of the second study to a more realistic application, in which demands are correlated and uncertain. We again utilized an optimization model to reduce the amount of wasted food at minimal increase in shortfalls when both new production and leftovers can be served. Demand uncertainty and demand correlations are addressed using a kernel density estimation approach. The same metrics (mass of waste, and CO2 equivalent of wasted food) are used to identify optimal production adjustments relative to the demand forecast, demand threshold, and percentage. The implications of this study for food service operators are in hospital, collage/university or military service. The academic contribution of this research is performing a technical method to minimize overproduction food waste by using leftovers in the future when demand is uncertain and correlated.

6.2 Study Limitations

Any academic industrial engineering study faces challenges identifying a sufficient real-world data set. Because MU CDS granted us access to their CBORD system, we were able to overcome this problem in this dissertation. CDS uses CBORD to store ordering, production and inventory data. However, variances in daily production are tracked as worksheet line data in hard copy and are not saved online. Even though this data is hard copy, we were able to access the 2014 and 2015 data because of the CDS data storage policy.

One challenge, due to our interest to measure the environmental implications of food waste, was the identification of each menu item's GHG-eq. Since estimates of the CO_2-eq for each ingredient varies across different studies (and some ingredients appear to be unstudied in the CO_2-eq literature), identification of CO_2-eq for each menu item was challenging.

Given the difficulties in manually examining and interpreting the worksheet line data, along with estimating the CO_2-eq of menu items, applying this research to an entirely different set of menu items would require significant pre-processing to apply this research to a different application setting. However, as environmental considerations such as CO_2-eq become more common, should this metric become standard reporting on menu items (much as calories, or grams of fat are today), implementation of this research in a different setting would be greatly facilitated. Regardless, our ability to make general inferences about production adjustments at the food type level is somewhat limited due to our restricted data set, covering one semester at MU.

A final limitation is computational complexity. In the problems studied in chapters 4 and 5, we used a Hooke-Jeeves iterative algorithm to solve the optimization problems. Each iteration continues until a termination criteria, defined in terms of epsilon value, is met. Given the numbers of variables considered (198 and 184, respectively) and the large number of optimization runs necessary to generate the entire efficient frontier, the fact that some optimization runs require up to 8 hours to solve presents a challenge for implementation in a decision support tool. That said, a less strict termination criteria could obtain reasonably good solutions in a short amount of time, if necessary.

6.3 Future Research

There are time, scope and availability restrictions associated with PhD research

that can be improved upon in future works, suggesting several potential avenues for expanding this research. The most-significant future research would aim to develop software tools applying these models to aid AYCTE food service providers with their production and inventory ordering decisions, building on this analysis to both illuminate the valuation of shortages implied by current actions, and to suggest how the unavoidable conflict between shortfalls and overproduction might be traded off across different menu items in order to minimize environmental costs.

A second future research topic would be to add pre-production inventory decisions to this optimization model. In chapters 4 and 5, we did not consider the set of ordering decisions necessary to maintain a pre-production inventory of ingredients necessary to allow for production of menu items. Further research could integrate these decisions, potentially trading off the cost of maintaining pre-production and post-production inventories. Pre-production inventory control involves ordering planning. However, expanding the scope of the research to include pre-production inventory will cause the model of the system to become considerably more complicated. Because some ingredients (pre-production inventories) can potentially be used in multiple menu items (post-production items), such as ground beef that can be used in both "Sloppy Joe" as well as "homemade meatloaf", and more-complicated inventory model would be required.

A final avenue for future research would be to examine the integration of alternative forecasting methods into the optimization. The primary interest here would not be solely on the accuracy of different forecasting methods, but rather on identifying the impact of forecasting improvements on the production model. Taken together, such an approach could potentially shift the entire efficient frontiers "down and to the left", allowing for reductions in both shortfalls and waste.

APPENDIX

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