Modeling the Tradeoff between Inventory and Capacity to Optimize Return on Assets in Production Scheduling

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Abstract

In the agrochemical industry, companies are challenged with an extreme seasonality in demand driven by the crops' growing cycles. Therefore, balancing supply with such fluctuating demand has been a struggle for most companies due to their capacity constraints. One way to accommodate the demand is to stock enough inventory ahead of the peak seasons, while the other is to increase the production capacity so that the companies can react to the changing demand more quickly. However, either alternative comes at a significant cost.

This paper examines the optimal mix of production capacity and inventory for a company to meet customers' demand at the highest net present value (NPV) of operating assets value add (OAVA). We use a multi-period, multi-stage, multi-product mixed integer linear optimization model to determine the best combination of resources. Viable resource options include stocking inventory ahead of the peak seasons, enhancing output through overtime, outsourcing production activities to a third party, and acquiring new assets for a particular production stage. The results show that the optimal OAVA comes from a combination of all these viable resources.

Additionally, the master production schedule, the resulting inventory levels, and the recommended timings for external resources and asset acquisition are important takeaways from our model. They serve not only as the guidance of the company's day-to-day operations, but also as the quantitative analysis necessary to communicate with stakeholders across different functional teams with potentially conflicting interests.

Thesis Supervisor: Dr. Bruce Arntzen
Title: Executive Director, Supply Chain Masters Program

"I have friends in overalls whose friendship
I would not swap for the favor of kings."
Thomas Alva Edison

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In the middle of difficulty lies opportunity."
Albert Einstein

1. Introduction

1.1 Motivation

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In the fall of 2012, Alan A[1], the Global Supply Chain manager of a division in a large agrochemical company, was assessing how his division could increase output after receiving a financial report by the company's management review committee. The report indicated significant lost sales during the past two quarters, damaging the company's profitability, and Alan's group was directly responsible for them.

Alan had seen this coming six months earlier. The moment when the production manager reported that production couldn't catch up to demand due to a recent upside, the sales team could not stop yelling: "No farmer will wait on us before starting their growing season! They love our products but are now buying from others. That's easy money going into competitors' pockets. Easy money!"

Unfortunately, in-house capacity had already reached near-full utilization, and the request for extra capacity would take 2~3 years for the long-winded process of evaluation, approval paperwork and final follow-through. Outsourced resources were 40% more expensive than in-house resources but were already engaged given such an extenuating situation. Despite this, there was still a long way to go before being able to fulfill the upsized demand. Pre-built inventory wasn't available, as the factory had purposely kept it low to minimize inventory holding costs, even though they did not have upside manufacturing capacity.

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[1] The names and characters in the story of this section are fictitious.

As Alan was pondering actions that would have prevented the losses, his desk phone rang. "The sales forecast for next year is looking at a potential 20% increase, with another 20% for the year after. Whatever went wrong this year, FIX IT, before it gets bigger!" the sales manager thundered.

Alan looked at the clock. It was about time to talk with the MIT research team about how to address the challenge, one that had significant financial impact, but involved stakeholders from cross-functional areas with conflicting interests. He wondered how these young professionals from MIT would approach such a headache and help turn the situation around.

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In a large but almost empty study room on the MIT campus, Cindy Wu was shutting down her computer, ready to rest her dry and tired eyes after staring at the screen all night. She looked up at the clock and found the arms already pointing to 2am. Jose Duhart, raising his head from stacks of papers after scrutinizing them for hours, stretched his neck and made a final comment, "Tomorrow is going to be our big day. We'll be solving a puzzle that's worth millions of dollars." "Agreed. And I feel rich already," joked Cindy as usual.

Cindy Wu and Jose Duhart were the two MIT SCM students who signed up for this project due to the challenging business nature of the agrochemical industry, where the demand pattern was highly seasonal and thus more difficult to plan and fulfill. Their advisor, Dr. Bruce Arntzen, had cautioned them about the complexity of this project as it required heavy quantitative and analytical skills, as well as software modeling and debugging techniques.

"Even better," both students commented excitedly. Indeed, nothing motivated them more than intense intellectual exercises. Most importantly, knowing that the insights they would acquire through this research could be applied to industries and businesses with similar challenges empowered them to work even harder.

After an entire night's hard work, the whiteboard captured the priorities for the next steps.

1. Define the problem and challenges faced by managers.
2. Define the key questions that our project strives to answer.
3. Review relevant literature to understand the tradeoff between capacity and inventory; find out potential research methodologies and performance indicators.
4. Understand the production process and the theory of constraints, and set up a linear programming model.
5. Validate the linear programming model and analyze the output.
6. Provide recommendations to assist with managerial decision making.

As they walked back to their dorms, conversations were still on-going.

"Pre-building inventory eliminates the need for capacity investment, and vice versa. Between the two extremes, there must be a middle ground that presents the best tradeoff." "..., which is one of the key objectives of this project. And the real challenge would be finding consensus between managers with conflicting goals." "True. It's gonna be a solution that requires joint improvement effort across all functional teams." "... also a guideline for all of these teams to know which product to produce, for how much volume and at what time."

From this point forward, the youthful duo ventured on an intellectual challenge that would test their skills as analysts, modelers, problem solvers and effective communicators.

1.2 Problem Statement

Our sponsoring company is an agrochemical company offering herbicides, pesticides and seed technologies that minimize the level of undesirable weeds, insects and diseases. Due to the seasonal fluctuation of demand in the agricultural industry, fulfilling customers' demand is a challenge that, if not handled well, might lead to significant loss of sales. In fact, the company has suffered from revenue losses for this reason in the past years. As the agrochemical market keeps growing, allocating resources to fulfill customers' demand is one of the company's top priorities.

One way to accommodate the fluctuating demand is to stock enough inventory ahead of the peak seasons. The other extreme is to increase the production capacity so that the company can react to the changing market demand more quickly. Traditional management practice prescribed that businesses should maximize asset utilization in order to reduce costs. Therefore, many plant managers would starve the plant of new equipment and rely on pre-building inventory to meet seasonal demand. This approach yielded excellent equipment utilization at the expense of overall financial performance. Literature shows that relying solely on pre-built inventory to meet variable demand is not optimal. Hence, the question that this project seeks to answer is: What is the optimal mix of production capacity and inventory for the company to meet customers' demand at the highest net present value (NPV) operating assets value add (OAVA) over the planning horizon?

The project, given the limited time frame, will focus on a single weed killer product, codename Mustang, because its current production capacity cannot fulfill its total demand for the peak months. This project will use a multi-period mixed linear programming model to find an optimal solution for the company's production planning. The solution will include the inventory level per period, the utilization rate for each of the resources involved in the manufacturing of Mustang, the total costs of implementing this solution, and the NPV for OAVA. To this end, we will explore the information available on several aspects of the current production processes, including the current capacities of each line producing Mustang, the demand of Mustang in the past, and the manufacturing cost per unit.

This project aims to improve the company's financial performance and customer service level by both fulfilling demands in peak seasons while achieving the highest level of return on operating assets in the form of OAVA. The research results, including the optimization model, research methodologies and implications, can be leveraged by different product lines within the same industry or even different industries with similar problems.

"If I've seen further than others, it is by standing on shoulders of giants."
Isaac Newton

2. Literature Review

This literature review is presented in four sections. We start by discussing the tradeoff between capacity and inventory management, as well as the devious concept of achieving higher financial return with a lower capacity utilization rate. In the second section we cover the research methodologies available to optimize the mix between capacity and inventory across different industries, product characteristics and business needs. Subsequently, we present the performance indicators that determine the effectiveness of applying certain tradeoff scenarios according to different business strategies. In the final section, we summarize the methodologies and performance indicators that we adopt in this research based on our sponsor company's business needs and challenges.

2.1 The Tradeoff between Capacity and Inventory

Common management practice suggests that businesses should maximize asset utilization to reduce costs. As Hayes and Wheelwright (1984) commented, "Unused capacity generally is expensive." As a result, managers normally favor excess inventory over excess capacity in response to seasonality and fluctuation in demand.

However, Krajewski et al. (1987) and Monden (1981) found that under a Just-In-Time strategy, production lines need to keep extra capacity by 10% to 18% to buffer the need for extra inventory and maintain the equipment lifetime. Goldratt and Cox (1992) further challenged the assumption that capacity utilization is directly correlated with the net benefit to a manufacturing company. They stated that capacity utilization in non-restriction assets is irrelevant, while at bottlenecks it should be as high as possible.

Colgan (1995) took an extra step by studying the capacity utilization and inventory policies in a personal computer production line, building optimization models to simulate alternative scenarios, and comparing the financial results from these scenarios. He concluded that maximized utilization rates do not necessarily drive the best financial results.

Bradley and Glynn (2002) derived the same conclusion with a different approach. They developed a mathematical expression to assist in deciding the joint optimization of inventory and capacity based on "minimum cost operation" and found that high capacity utilization might not always suit the cost-down purpose as capacity may not always be expensive. Their numerical model further showed that the total cost could increase significantly if the capacity level was overly restricted.

Based on these research findings, we understand that both capacity and inventory are indispensable factors that need to be balanced and jointly considered in seeking an optimized financial benefit for an organization. As Goldratt and Cox (1992) explained, keeping extra inventory or extra capacity beyond a certain limit should be deemed unproductive and, therefore, eliminated because it is an effort that either leaves the net profit unaffected or decreases it. Consequently, finding the right mix between these two factors is one of the key objectives of this research project.

2.2 Previous Research Methodologies to Build Upon

Goldratt and Cox (1992) developed the theory of constraints in a manufacturing process and introduced the concept of finding next constraints continuously after the existing one is resolved. The measures in controlling the flow of production process are the metrics in identifying constraints. We will use Goldratt and Cox's approach for this project; by reviewing the production process on an ongoing basis and incrementing capacity at the constraints, we will be able to increase capacity as a whole and identify new constraints in the system.

Building on the theory of constraints, Colgan (1995) identified several tradeoff scenarios, called "line configurations" in his research, by finding constraints one after another on a personal computer production line. He further built a multi-period and multi-station mathematical model for a single product line. The model simulated the financial performance of these scenarios based on the optimized return on operating assets (ROOA), a strategy that we will elaborate upon in the next section. Colgan's work serves our research as a baseline from which we can leverage the mathematical construction of the model. Our scope will expand on Colgan's formulation because it involves more than one product line, thus adding a multi-product complexity.

Bradley and Glynn (2002) took a different approach towards finding a joint optimization of capacity and inventory. They derived a mathematical expression based on the minimum cost operation for a single-product, single-station, make-to-stock manufacturing process. As with Colgan's, Bradley and Glynn's work serves as a baseline in understanding the mathematical modeling. Building on their work, this research will go beyond a single product, station and time period.

Jammernegg and Reiner (2007) studied the change of business processes from make-to-order to assemble-to-order in the telecommunication and automotive industries, and simulated the optimal solutions of different tradeoff scenarios based on both costs and service level objectives. As with Colgan's and Bradley & Glynn's, this optimization model is limited to a single period and single product.

Mincsovics et al. (2009) introduced in their model the concept of contingent capacity, which refers to the additional capacity that can be acquired with a given lead time and can be disposed of after it is no longer required. Additionally, they dealt with a product which can be backlogged and associated a cost for backorders, aiming to determine the optimal permanent capacity of a system and acquire contingent capacity accordingly. They stated that the relative value of contingent capacity is inversely proportional to the lead time it takes to be available. At the same time, contingent capacity's value is directly proportional to the cost of backordering. In the production process that we studied during the development of this thesis project, adding capacity requires a significant dollar investment and cannot be disposed of. Hence, once we add extra capacity it is permanent. We can leverage from Mincsovics's work by assuming an infinite time to dispose of installed equipment.

2.3 Operating Assets Value Add (OAVA) as the Key Performance Indicator (KPI)

Goldratt and Cox (1992) introduced relevant key performance indicators (KPI), such as throughput, inventory, and operational expense, as well as a way to measure and manage these indicators. These authors provide a baseline approach to find a constraint in a production process, increment its capacity, which then increases the net throughput of the system, and loop back to finding new constraints in the system. These steps are part of the methodology this thesis project relies on. In the mathematical expression developed by Bradley and Glynn (2002), the minimum average operating cost was the main metric in the objective function that drives the optimal capacity and inventory policies. Jammernegg and Reiner (2007) included β-service level (fill rate), delivery performance and work-in-process pallets as performance improvement measures.

The concept of return on assets (ROA) has been used across several industries by decision makers (Anthony and Dearden 1980, Kaplan and Atkinson 1989), despite its weaknesses such as its short-term representation of the company's financial performance instead of an overall evaluation throughout the lifetime of the equipment. The ROA serves as an introduction to one of the main metrics that we will be using in this thesis project, which is the Return on Operating Assets (ROOA).

Colgan (1995) and Bradley and Arntzen (1999) adopted the derivative form of ROA and termed it the Return on Operating Assets, which bypassed some corporate level financial details irrelevant to the research scope and focused on the company's financial gain resulted directly from the invested assets. 3M's ROOA Capacity Planning Project Team (1994) introduced a modified linearized ROOA metric, termed operating assets value add (OAVA), to reflect the financial gain. OAVA is a linear expression and can thus be optimized using mixed-integer linear programming, as opposed to ROOA, which is a ratio and thus non-linear. These metrics will serve as a basis to decide the best line configuration and at the same time the best asset utilization for the entire production process.

2.4 Summary

From the literature review above, we understand that to help the company fulfill its highly seasonal and fluctuating demand, a joint optimization strategy of both capacity and inventory policies is essential. Furthermore, a multi-product, multi-station and multi-period model is necessary to capture the complexity and challenges of the company's business practices. Finally, we will adopt a modified ROOA metric, the OAVA, to directly reflect the financial gain introduced by a particular capacity investment.

"We shape our buildings;
thereafter, our buildings shape us."
Winston Churchill

3. Methodology

Our methodology is comprised of three sections. We start by introducing the company's existing production process to understand its business need and potential areas for optimization. Subsequently, we build a linear programming optimization model that supports multi-period, multi-product and multi-station characteristics. Following the theory of constraints, the model will identify limitations in the company's production process and the optimal line configuration as a potential solution to address these constraints. The output of the simulation will include the master production plan and the combination of all viable resource options.

Since it takes 2 to 3 years to implement a decision to add line capacity, we are modeling for a 10-year horizon. While the demand each year displays a similar pattern of seasonality with the peak in Sept., Oct. and Nov., the overall demand profile moves higher each year as sales increase. The model is looking out 10 years in advance trying to determine the optimal operating strategy in each month of this horizon and when to add capacity.

3.1 Understanding the Production Process

The company's production process consists of four main stages: pre-mix, formulation, storage and packaging, as illustrated in Figure 3-1. In the pre-mix stage, active ingredients are added into a heated tank for preliminary mix before flowing into the formulation stage, where more ingredients are added and mixed for a longer period of time. After formulation, the chemical product is stored in the tanks in the storage stage and will be packaged into different sizes of containers according to the demand in the packaging stage.

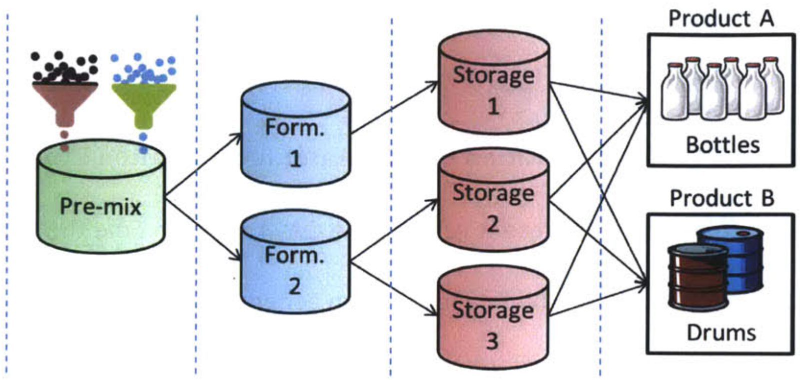

Figure 3-1. Conceptual Model of the Production Process

3.2 Understanding the Theory of Constraints

From the four stages in the production process, also called "stations" in our research and software model, our model will find out where the first constraint bottleneck is by calculating the capacity in all stations. In our research, a constraint is defined as the station in the production process where the capacity is lowest among all stations and, upon capacity expansion, could increase the output in both the station and the whole process. Out of the four stations in the production process, we are considering capacity expansion at three stations: pre-mix & formulation, storage and packaging.

After identifying the first constraint and increasing the station's capacity to fix the first constraint, the bottleneck will no longer be found in the same station. Our model repeats the process to find the second constraint, the third, etc., as needed by the research. Figure 3-2 shows the conceptual constraint identification process.

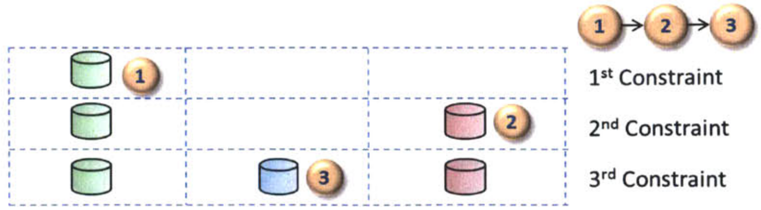

Figure 3-2. The Illustration of Constraint Identification Process

The model will calculate the net present value of the OAVA for each time the constraint's capacity is increased, to evaluate the financial return generated by the operating assets. Starting from the baseline where no additional capacity is invested, the OAVA might go either up or down after a capacity investment decision is made. As more capacity is added, the OAVA values corresponding to each capacity alternative are captured and compared.

Additionally, other factors that can change the OAVA are working overtime, outsourcing and pre-building inventory (either intermediate or finished goods). By working overtime we can slightly expand the capacity of each stage incurring in the additional cost of the extra time for labor and utilities. Outsourcing to a third-party manufacturer can offset or delay the system's need to increase its capacity in one or multiple stages, but at the cost of paying a high markup for the labor and utilities components. Finally, pre-building inventory can avoid the need for investing in a capacity expansion, but instead will come at the cost of holding such inventory for the total time it was held.

The model will evaluate OAVA using different combinations of acquiring extra capacity, working overtime, outsourcing, and pre-building inventory. Each new combination will yield a different OAVA. Every time the new value for OAVA is higher than the previous one, the model will keep that line configuration. At some point, the value of OAVA will reach its peak, and future investment, whether it is on capacity, overtime, inventory, or outsourcing, will no longer push OAVA higher and might even cause it to decrease. That peak value is where the model finds the optimal solution.

3.3 Setting up a Linear Programming Model

Now that we have understood the production process and the potential bottlenecks, we will further develop a mathematical representation of the system that a computer can understand and optimize. The software tool we will be using for this optimization is LINDO Systems Inc.'s *What'sBest!,* a powerful add-in tool to Microsoft Excel's Solver. *What'sBest!* has the advantage of dealing with multiple times the decision variables and constraints that Excel Solver can handle.

3.3.1 Objective Function

We start by defining the objective function Z as the NPV of the OAVA at the annual discount rate r over the planning horizon and aim to maximize it.

$$MAX\!: Z = NPV(r, OAVA)$$

$$Z = \sum_{t=0}^{T}\left(\frac{(Revenue_t - Cost_t) \times (1 - Tax) - Cost\ of\ Capital \times Asset\ Value_t}{(1+r)^t}\right)$$

Where:

T = number of time periods in the planning horizon; for our research 120 periods

r = Annual holding cost expressed as a percentage, for our research 12%

Breaking down each component of the objective function we obtain the following:

- **Revenue**

Revenue is estimated by first calculating the total cost of goods produced and then marking that up by a factor.

$$Revenue_t = \sum_{\forall i}\left(D_{i,t} \times \sum_{\forall M}(R_{M,i} + L_{M,i} + U_{M,i})\right) \times F_{rev}$$

Where:

$D_{i,t}$ = Demand of product i at time t

$R_{M,i}$ = Cost of raw materials in machine M per unit of product i

$L_{M,i}$ = Cost of labor in machine M per unit of product i

$U_{M,i}$ = Cost of utilities in machine M per unit of product i

F_{rev} = Factor for revenue markup

Since demand caps the amount of product that can be sold, revenue comes from the demand multiplied by the associated manufacturing costs times a coefficient, defined by the company, which in our research was set to 135%.

- **Cost**

$$Cost = Holding\ Cost + Production\ Cost + Depreciation$$

The cost function has 3 main components that can be broken down to the following:

  - **Holding Cost**

$$Holding\ Cost_t = \sum_{\forall M,i}\left(\frac{Inv_{M,i,t} + Inv_{M,i,t-1}}{2} \times \sum_{m=1}^{M}(R_{m,i} + L_{m,i} + U_{m,i})\right) \times r$$

Where:

$Inv_{M,i,t}$ = Inventory in machine M of product i at time t

As Silver et al. (1998) put it, holding cost includes the cost of opportunity of the investment, the expenses of managing warehouses, handling and counting, special storage necessities, deterioration, damage, shrinkage, and obsolescence among others. In this research, we first average the ending inventory of two subsequent time periods, and then multiply it by the cumulative manufacturing cost up to the current stage in the productive process as the inventory value. Finally, we multiply the inventory value by the annual holding cost. Thus, the cost of holding finished goods is always higher than holding work-in-process inventory. For our research, we used an annual holding cost of 12%.

- **Production Cost**

$$Production\ Cost = Manufacturing + Outsourcing + Overtime$$

There are different ways in which the company can get the necessary products to satisfy demand: either by manufacturing the products in-house or outsource to a third party at a premium cost. In addition, the manufacturing process can be done in either the regular time or the more expensive overtime option if required.

- **Manufacturing Cost**

$$Manufacturing_t = \sum_{\forall M,i} \left(P_{M,i,t} \times \left(R_{M,i} + L_{M,i} + U_{M,i}\right)\right)$$

Where:

$P_{M,i,t}$ = Produced units at machine M of product i at time t

Each stage in the production process has the need for raw materials, labor and utilities input, all of which come with an associated cost. The manufacturing cost is calculated as the product of the number of produced units multiplied by the sum of all cost components.

- **Outsourcing Cost**

$$Outsourcing_t = \sum_{\forall i} \left(Out_{i,t} \times \sum_{\forall M} \left(R_{M,i} + \left(L_{M,i} + U_{M,i}\right) \times F_{out}\right)\right)$$

Where:

$Out_{i,t}$ = Outsourced units of product i at time t

F_{Out} = Factor for outsourced products

A third party supplier of finished goods can manufacture the product at a higher price than producing it in-house. However, the cost for the raw materials remains exactly the same, given that the company provides the external contractor all the required raw materials. The labor and utilities costs increase by a markup of F_{Out} which the company established at 40%. Similar to the manufacturing cost, we multiply the number of outsourced products by the associated costs to calculate the outsourcing cost.

- **Overtime (OT) Cost**

$$Overtime_t = \sum_{\forall M,i} \left(Over_{M,i,t} \times \left(R_{M,i} + \left(L_{M,i} + U_{M,i} \right) \times F_{over} \right) \right)$$

Where:

$Over_{M,i,t}$ = Produced units during OT at machine M of product i at time t

F_{over} = Factor for production under overtime

As in the outsourcing cost, the cost for raw materials remains unchanged. Similarly, the costs for labor and utilities are increased by a markup of F_{over} which is set to 25%. Similar to the manufacturing cost, we multiply the number of products manufactured during overtime by the associated costs to calculate the overtime cost.

- **Depreciation**

$$Depreciation_t = \sum_{\forall M,k} \left(B_{M,t,k} \times \frac{V_{M,k}}{L_M} \right)$$

Where:

$V_{M,k}$ = Value of a brand new machine M with capacity alternative k

$B_{M,t,k}$ = 0 if we choose not to invest for machine M at time t in alternative k
1 if we choose to invest for machine M at time t in alternative k

L_M = Useful lifespan of machine M expressed in number of time periods

In our research, we use a straight-line depreciation approach to account for the cost of machines. Once a new machine is added, the model adds a fixed amount depreciation payment for all future periods. We multiply the binary variable times the fraction of the cost for the corresponding machine. The company considers L_M to be 10 years, which is equal to 120 time periods.

- **Cost of Capital**

$Cost\ of\ Capital$ = is a constant value that the company determines at which it considers the minimum annual return on capital investment should be. For our research, we were provided a Cost of Capital of 12% but can be adjusted in the model to test different scenarios and perform sensibility analysis.

- **Average Asset Value**

$$Average\ Asset\ Value = Proxy\ Capacity\ Value + Inventory\ Value$$

The operating assets that the company employs in the production process consist of two main points; namely, capacity and inventory. On one hand, capacity encompasses everything related to machinery and physical equipment such as containers, tank, packing lines, etc. On the other hand, inventory refers to either work in progress (WIP) flowing through the system or finished goods (FG).

- **Proxy Capacity Value**

$$Proxy\ Capacity\ Value = \frac{1}{n} \times \sum_{t=1}^{n} \sum_{\forall M,k} \left(B_{M,t,k} \times \frac{V_{M,k}}{2} \right)$$

We decided to use an approximation for the capacity value since it significantly trims complexity on calculations while illustrating the point of having to make an additional investment at the same time. The proxy contrasts with the instantaneous value in that it considers the average value of the asset, since this will be replaced after the end of its useful life. Figure 3-3 depicts the conceptual pattern that the asset value will follow, given that no capacity increase will be pursued over time.

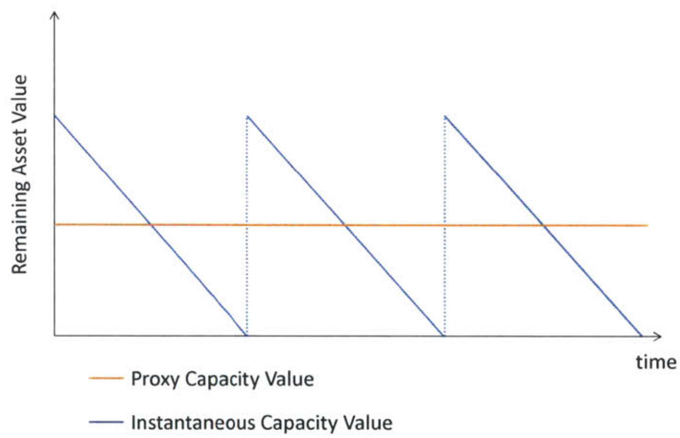

Figure 3-3. Proxy Value given no capacity increases

Similarly, the asset value increases when it undergoes an expansion in capacity. Figure 3-4 shows the conceptual behavior of the proxy value when capacity changes.

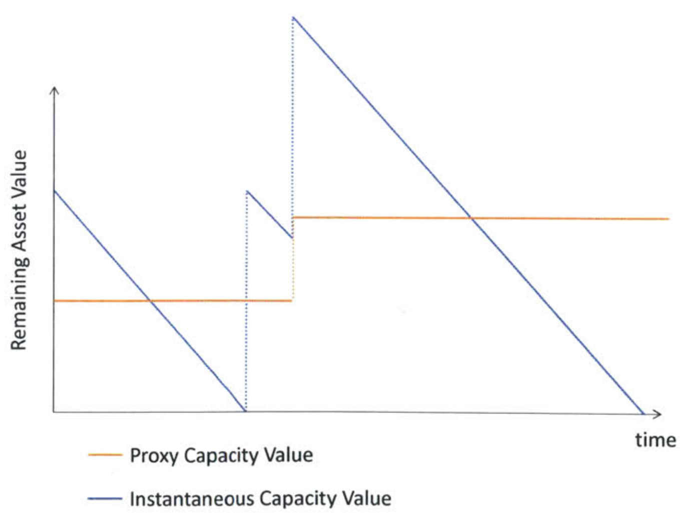

Figure 3-4. Proxy Value when there is a capacity increase

The model first captures half of the value of the equipment at each time period. Then it multiplies the half value by the binary variable as the proxy value. Finally, it takes the average of these proxy values over the whole planning horizon.

- **Inventory Value**

$$Inventory\ Value = \frac{1}{n}\left(\sum_{\forall M,i,t}\left[\frac{Inv_{M,i,t} + Inv_{M,i,t-1}}{2} \times \sum_{m=1}^{M}\left(R_{m,i} + L_{m,i} + U_{m,i}\right)\right]\right)$$

The other part of the assets corresponds to the inventory. The model captures the value of all work in progress and finished goods in the production process and takes the average over the planning horizon.

3.2.2 Constraints of the Model

The model will be subject to the following bounds:

- **Meet Demand**

For each product, a demand pattern broken down in each time period must be met.

$$Inv_{N,i,t-1} + P_{N,i,t} + Out_{i,t} + Over_{N,i,t} - Inv_{N,i,t} \geq D_{i,t} \qquad \forall i,t$$

Where:

N = Number of machines in the production process

Since machine N is the last stage in the production chain, it turns WIP into FG. Thus, demand will be satisfied with the summation of last period's FG ending inventory and this period's FG production, plus outsourced items and FG produced during overtime minus the FG inventory left behind at the end of the period.

- **Stage Dependence**

Production in a given stage cannot exceed the production of the previous stage plus the inter-stage inventory.

$$Inv_{M-1,i,t-1} + P_{M-1,i,t} - Inv_{M-1,i,t} \geq P_{M,i,t} \qquad \forall M, i, t$$

- **Capacity Limit**

The machines cannot produce more than a certain limit, defined by the available work hours and the time it takes to produce each product.

$$\sum_{\forall i} \left(P_{M,i,t} \times T_{M,i}\right) \leq K_{M,t} \qquad \forall M, i, t$$

Where:

$T_{M,i}$ = Time it takes for machine M to produce a unit of product i

$K_{M,t}$ = Capacity available in time units for machine M at time period t

For a multi-product model, production capacity cannot simply be defined in terms of volume produced, since the consumption of resources for each product could be significantly different. Instead, we define time available at each machine as capacity. The number of units produced of each product times the amount of time required to produce each must be less than or equal to the available capacity for that machine.

- **Capacity Expansion**

Alternatives for choosing extra capacity in each machine are mutually exclusive.

$$\sum_{\forall k} B_{M,t,k} = 1 \qquad \forall M, t$$

Furthermore, any capacity installed in the past must be present in the current time period. In other words, the present capacity of any piece of equipment must be at least, as much as the capacity in the previous period.

$$B_{M,t-1,k} \leq B_{M,t,k} \qquad \forall M, t, k$$

- **Outsourcing**

The third party vendor will only accept contracts that exceed certain amount of product. At the same time, the external manufacturer is constrained by a fixed value.

$$\sum_{\forall i} Out_{t,i} \geq \beta_t \cdot X_t \qquad \forall t$$

$$\sum_{\forall i} Out_{t,i} \leq \beta_t \cdot Y_t \qquad \forall t$$

Where:

β_t = Binary variable to decide whether to pursue outsourcing at time period t

X_t = External manufacturer's minimum acceptable contract at time period t

Y_t = External manufacturer's capacity limit at time period t

- **Non-Negativity**

Values for inventory, units produced and finished goods must be greater than or equal to zero.

$$Inv_{M,i,t} \geq 0$$

$$P_{M,i,t} \geq 0$$

- **Integer numbers**

This constraint is optional. We can force the model to use only integer numbers for the decision variables, in case it is not possible to produce fractions of units at a given stage or for a particular product. In this research, we don't use this constraint so that the model could be kept linear and the computing complexity is kept low.

$$P_{M,i,t} \in \mathbb{Z}$$

Additionally, to see the expected value for any particular variable at any period of time t of the model, we will have different state variables and decision variables:

- **Number of production units in each stage**

These will be the decision variables of the model. These numbers represent the quantity of each product that each machine will produce at each time period.

- **Amount of inventory at each stage**

This results when the sum of the current production and the inventory from the previous period exceeds the demand for the current time period and is recorded for each product at each time period.

- **Amount of consumed capacity for each machine at each time period**

With the constraint and logic among all variables properly set up, our linear programming model's algorithm will determine the production schedule and the capacity alternatives that maximize our objective function, as well as display the costs and other state variables that give us insight into a more cost-effective manufacturing process.

"All models are wrong, but some are useful."
George E.P. Box

4. Data Analysis

In this section, we will introduce the linear programming model constructed to find out the mix of capacity and inventory that generates the most operating assets value add (OAVA). Detailed instructions of how to use the model are also covered. The planning time horizon within the scope of this research is 10 years with each month as an individual period.

4.1 Input Data of the Linear Programming Model

4.1.1 Cost Components and Takt Time

Figure 4-1 below summarizes the cost components that comprise the production costs and inventory holding costs. For brevity, "Product" is shortened as "Prod", "Raw Material" as "Raw", "Pre-Mix & Formulation" as "PM&G", "Packaging" as "PCK", "hour" as "hr", and "kiloliter" as "kL". The production cost of each product consists of raw material, labor and utility, with the units defined as dollar per kiloliter, whereas the inventory holding cost is a function of both the production cost and the monthly holding cost coefficient. The "Takt time" is defined as the time it takes (measured by hour) to produce one kiloliter of a product and is used to calculate the consumed capacity in a certain stage.

The cells in yellow provide cost components and takt time for the stage "PM&F", while the cells in green are for "PCK."

Cost/Prod	Prod 1	Prod 2	Unit
Monthly Holding	1.25%		%
Raw (PM&F)	2,670	1,660	$/kL
Raw (PCK)	360	360	$/kL
Labor (PM&F)	620	600	$/kL
Labor (PCK)	460	450	$/kL
Utilities (PM&F)	80	60	$/kL
Utilities (PCK)	40	30	$/kL
Takt time (PM&F)	0.40	0.40	hr/kL
Takt time (PCK)	0.32	0.32	hr/kL

Figure 4-1. Cost Components and Takt time of both products

Such cost components, as well as other important cost information, including annual cost of capital, overtime markup, outsourcing markup, tax and use of depreciation, can be filled in by the user through the "Inputs" tab.

4.1.2 Demand Forecast

The demand forecast could be filled in by the user for each product through the "Forecast" tab. The data will then be populated into the model in the same format as shown in Figure 4-2 below as another set of input needed to set up constraints.

	Y1_Jan	Y1_Feb	Y1_Mar	Y1_Apr	Y1_May	Y1_Jun	Y1_Jul	Y1_Aug	Y1_Sep	Y1_Oct	Y1_Nov	Y1_Dec	Y2_Jan
Prod 1	145	303	432	276	160	403	239	339	952	801	1,142	743	305
Prod 2	307	644	918	586	340	857	508	720	2,023	1,703	2,427	1,578	648

Figure 4-2. Excerpted Table for the 10-year Demand Forecast

4.1.3 Capacity Increase Options

As applicable to our sponsor company's operations, there are three options to increase capacity: acquiring new assets, outsourcing and overtime.

- **Acquiring New Assets**

Pre-Mix & Formulation (PM&F), Storage, and Packaging (PCK) are the three stations that can acquire assets and upgrade capacity limits. Figure 4-3 shows the different capacity levels and their corresponding value in the three upgradable stations. For brevity and better clarity, "Capacity" was renamed as "Kap".

Capacity Option		Kap Limit (hr)	Value ($)
1	PM&F'	850	$ 3,000,009
2	PM&F"	1,000	$ 7,000,009
3	PM&F"'	1,200	$ 11,000,009
1	PCK'	1,000	$ 2,000,009
2	PCK"	1,100	$ 3,000,009
3	PCK"'	1,200	$ 4,000,009
Capacity Option		**Kap Limit (kL)**	**Value ($)**
1	Storage'	250	$ 400,009
2	Storage"	500	$ 800,009
3	Storage"'	750	$ 1,200,009

Figure 4-3. Assets Value and Capacity Limits for Acquired Assets

For the denotation, PM&F' refers to the baseline capacity option for the station PM&F; PM&F'' refers to the 2nd option other than the baseline; PM&F''' refers to the 3rd option other than the previous two. The same rule follows for Storage and PCK.

- **Outsourcing**

The outsourcing expense is accounted for as a 40% markup. There's a minimum volume requirement but no upper limit for outsourcing production activities.

- **Overtime**

Similar to Outsourcing, a 25% markup is added to the production costs. Capacity increase through Overtime has upper limits as shown in Figure 4-4. For brevity, "Overtime" is shortened as "OT".

Overtime Option		Kap Limit (hr)
1	PM&F OT	200
2	PCK OT	170

Figure 4-4. Capacity Limits for Overtime

4.2 Output Data of the Linear Programming Model

As a general guideline, all the decision variables generated by the model are stored in yellow cells of the spreadsheet.

4.2.1 Master Production Schedule (MPS) and Inventory

One of the most important outputs of our model is the master production schedule that plans production into a 10-year time frame and decides the inventory level for each period. Figure 4-5 shows the excerpted table of the MPS. For brevity, "Year1" was shortened as "Y1", "Inventory" as "Inv", "Finished Goods" as "FG", and "intermediate" as "int". Numbers 1 and 2 refer to product 1 and 2 respectively. The yellow cells are the decision variables generated directly by *What'sBest!*, while inventory levels are calculated by the model simultaneously.

	Y1_Jan	Y1_Feb	Y1_Mar	Y1_Apr	Y1_May	Y1_Jun	Y1_Jul	Y1_Aug	Y1_Sep	Y1_Oct
	145	303	432	276	160	403	239	339	952	801
	307	644	918	586	340	857	508	720	2,023	1,703
Production										
Stage (PCK) prod (1) (kL)	145	303	432	276	160	403	239	339	952	801
Inv (FG) (1) (kL)	-	-	-	-	-	-	-	-	-	-
Stage (PCK) prod (2) (kL)	307	644	918	586	340	857	508	1,643	1,673	1,824
Inv (FG) (2) (kL)	-	-	-	-	-	-	-	924	574	695
Stage (PM&F) prod (1) (kL)	145	303	432	276	160	403	239	339	952	801
Inv (int) (1) (kL)	-	-	-	-	-	-	-	-	-	-
Stage (PM&F) prod (2) (kL)	307	644	918	586	340	857	615	1,786	1,173	1,324
Inv (int) (2) (kL)	-	-	-	-	-	-	107	250	250	250

Figure 4-5. Excerpted Table for MPS and Inventory

4.2.2 Capacity Management

As mentioned earlier, PM&F, Storage and PCK are the three stations that can acquire assets to upgrade capacity limits and each has three capacity levels. Our model uses binary valuables to enable the functionality to suggest the timing of upgrading the capacity to a certain level for the best OAVA result. As shown in Figure 4-6, three rows of binary variables, highlighted in yellow as the decision variables, are laid out to match with the three different capacity levels. For each period, the binary variable "1" indicate the capacity level that generates the best OAVA.

Pre-Mix & Formulation	Y1_Jan	Y1_Feb	Y1_Mar	Y1_Apr	Y1_May	Y1_Jun	Y1_Jul	Y1_Aug	Y1_Sep	Y1_Oct
Binary (PM&F')	1	1	1	1	1	1	1	1	1	1
Binary (PM&F'')	0	0	0	0	0	0	0	0	0	0
Binary (PM&F''')	0	0	0	0	0	0	0	0	0	0

Figure 4-6. Excerpted Table for Acquiring New Assets

The same rule follows for Storage, PCK, Outsourcing and Overtime.

4.3 Analysis of MPS and Inventory

To analyze the behaviors of our optimization model, we use Excel macros to generate graphical representations of the demand patterns and the corresponding MPS and inventory levels for multiple capacity increase scenarios. These graphical representations are an intuitive way to analyze our formulation and facilitate our verification of the model's functionalities. Figure 4-7 shows the production process, which include the two production stages, PM&F and PCK, and two inventory categories, Intermediate and Finished Good (FG). Numbers 1 and 2 distinguish the two different product lines.

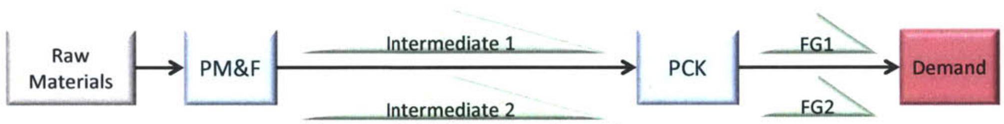

Figure 4-7. Production Process

The following subsections cover the verification process, in which four scenarios were laid out to observe the production plan and inventory level changes associated with different capacity limits. The baseline is observed in the first scenario, and the data in the following scenarios are compared with those in either the baseline or the previous scenario so that one variable was changed while others remain the same.

4.3.1 Baseline MPS and Inventory Levels

Without investment in extra capacity in this scenario, we intend to observe the baseline production plan and inventory levels of the two products with different values and demand patterns. We tested our model with some dummy numbers that are designed to validate the model's behaviors: The costs for product 1 were set higher than product 2 while other variables remain the same. The results are presented in Figure 4-8, where the demands of the two products are represented by the line patterns, and production units and pre-built inventory units by the columns in different charts. The columns in darker blue and green represent product 1, while lighter colors represent product 2.

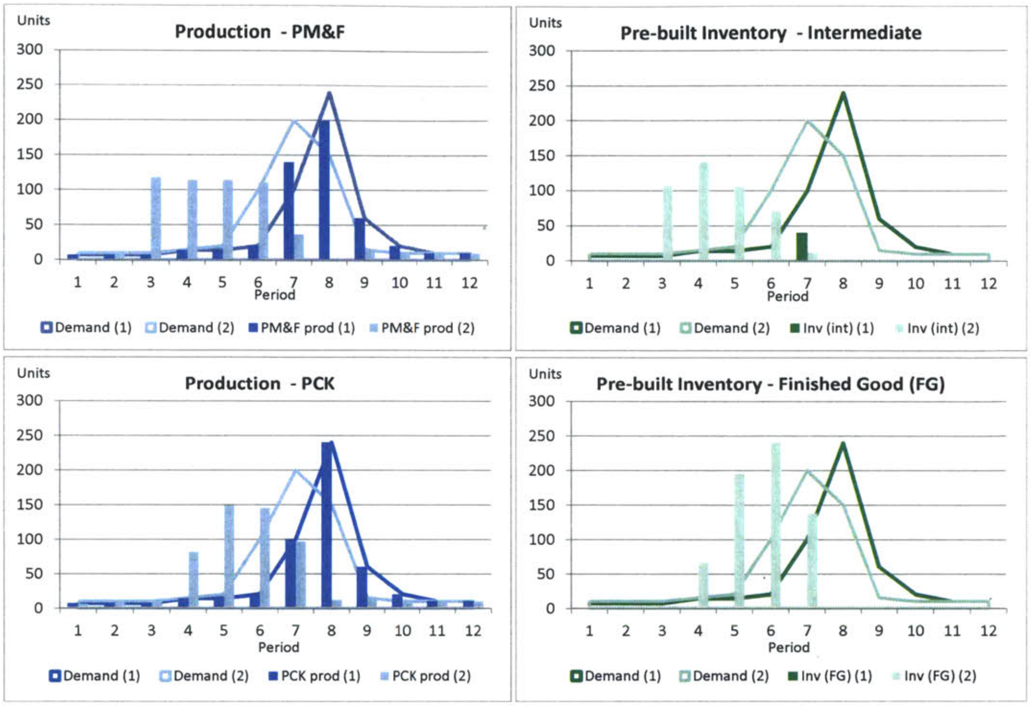

Figure 4-8. Production and Inventory Levels for Baseline Capacity

Figure 4-8 shows that our model has made the more expensive product, Product 1, be built closer to its demanded date and prebuild the cheaper product, Product 2, instead. This is as we had expected, since the inventory holding cost is a function of the product's value, and keeping the more expensive product's inventory low allows the model to retain lower costs and hence higher OAVA.

However, one thing to take notes here is as Bradley and Arntzen (1999) pointed out in their research finding, "instead of always prebuilding the least expensive products into inventory, a plant should prebuild the products that have the lowest ratio of value to processing time." That is, if there are other variables different for the two products, such as the production time it takes to build the products, these other factors need to be taken into account in the comparison as well.

4.3.2 Baseline vs. Upgraded PM&F

When PM&F is upgraded and all other factors remain the same, we expect that intermediate inventory levels go down and that the PM&F production plans follow the demand patterns more closely while the finished good inventory and PCK production plans remain the same. Figure 4-9 below backs up this inference.

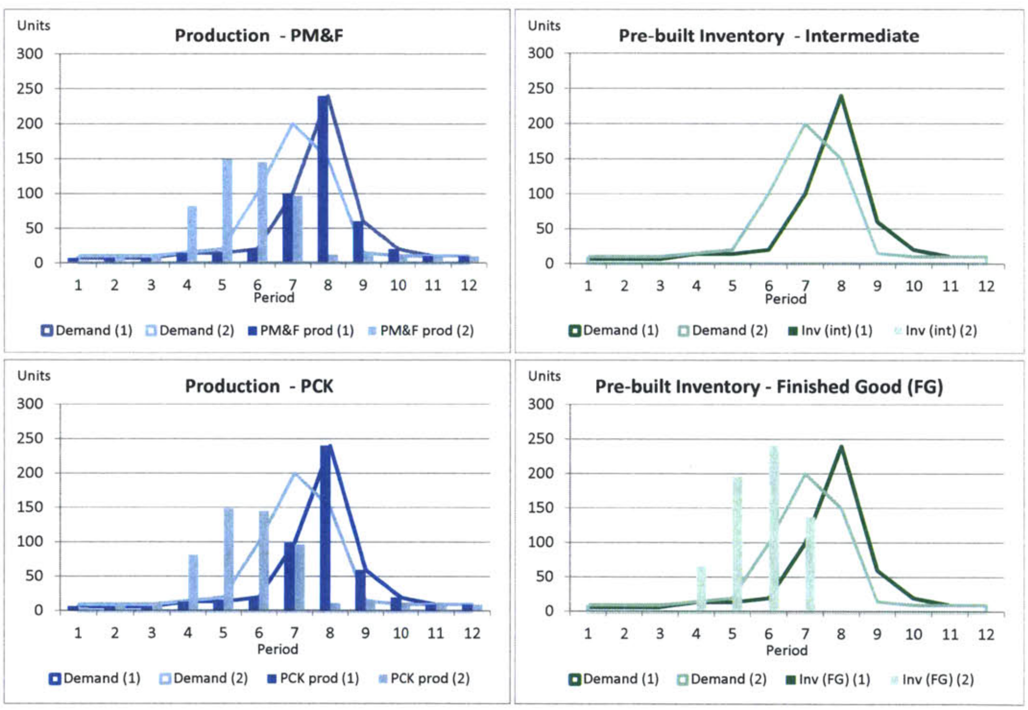

Figure 4-9. Production and Inventory Levels with Upgraded PM&F Capacity

4.3.3 Baseline vs. Upgraded PCK

Similar to the previous scenario, when PCK is upgraded and all other factors remain the same, we expect that finished good inventory levels go down and that the PCK production plans follow the demand patterns more closely, as shown in Figure 4-10.

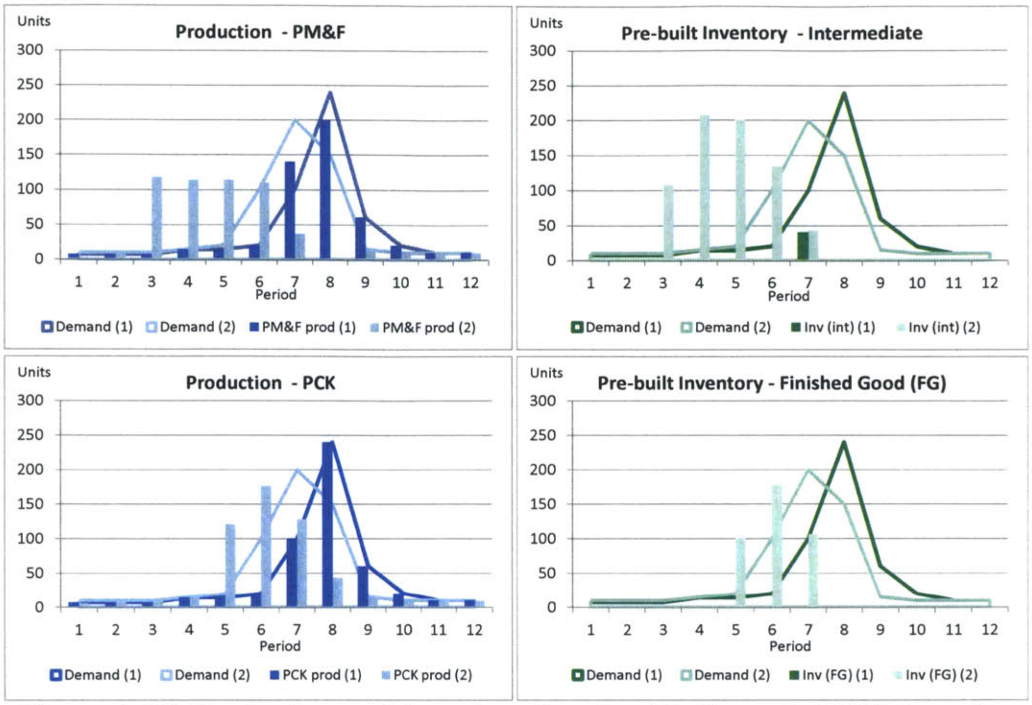

Figure 4-10. Production and Inventory Levels with Upgraded PCK Capacity

Additionally, intermediate inventory has to go higher so as to feed the PCK's upgraded facility that has higher productivity now. This is the "waterbed" effect of inventory: when the demand remains the same, the inventory can be moved to upstream stations to reduce the cost incurred at the finished good stage but the total inventory volume (in units, not dollars) will remain the same.

4.3.4 Baseline vs. Upgraded PM&F and PCK

When both PM&F and PCK are upgraded, we expect to see the combined effect of the previous two scenarios. That is, both intermediate and finished good inventory levels go down, and both PM&F and PCK production plans follow the demand patterns more closely. Figure 4-11 below backs up this inference.

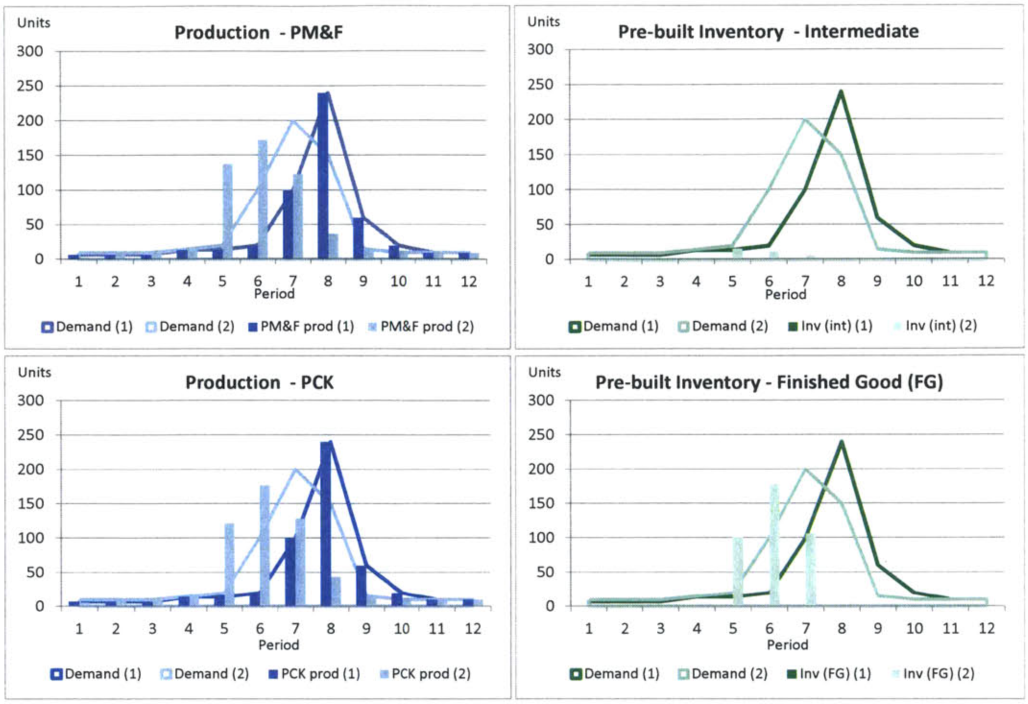

Figure 4-11. Production and Inventory Levels with Upgraded PM&F and PCK Capacity

The waterbed effect mentioned in the previous scenario is not observed here because the inventory is now pushed further upstream to the raw material stage, which is out of our observation scope.

These four scenarios in the verification results demonstrate that the model functions as it was designed.

4.4 Analysis of Capacity Management

The outputs of our model show some interesting results for capacity management considerations and will be elaborated below.

4.4.1 Acquiring New Assets

Since the investment in acquiring new assets increases the value of operating assets significantly, and the straight-line depreciation as an operational cost recurring from the first period of the asset acquisition further burdens the operating assets value add (OAVA), our model suggests to acquire new assets for all three expandable stations only after exhausting other capacity increase options such as outsourcing and overtime resources.

The yellow shaded areas in Figure 4-12 and 4-13 below illustrate the capacity increase timings for PM&F in Year 5 and Year 8 respectively. The 1st and 2nd capacity upgrades for PM&F don't take place until the August of the 5th and the 8th year.

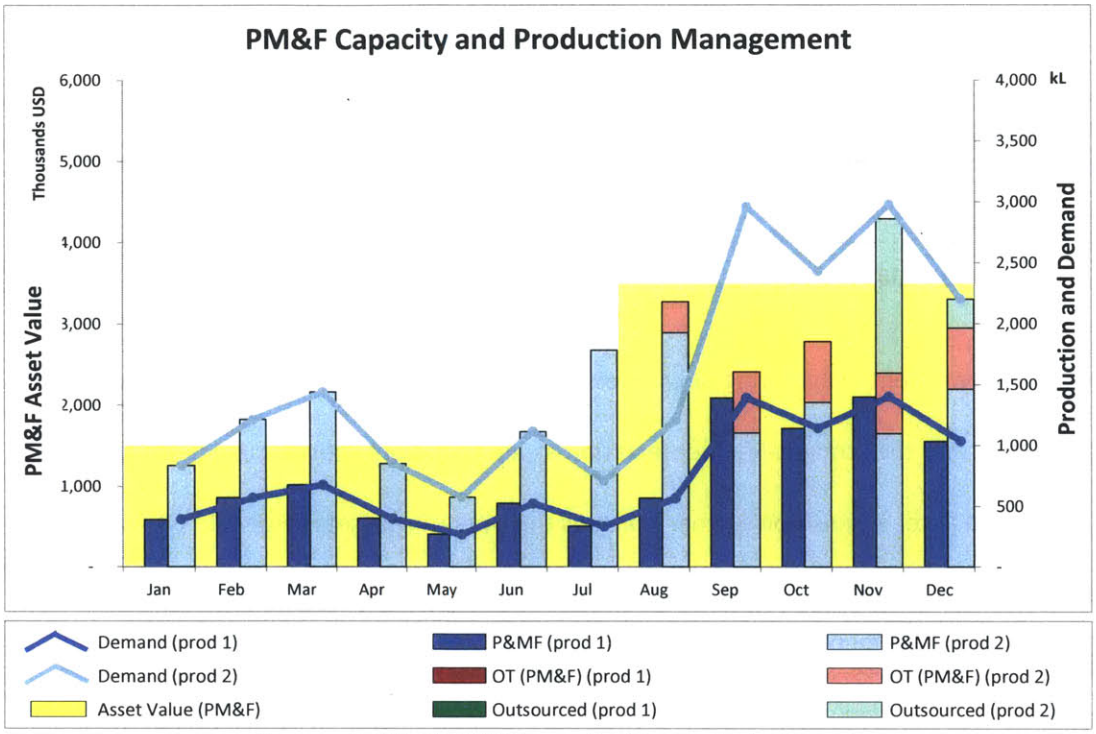

Figure 4-12. PM&F Capacity Upgrade in Year 5

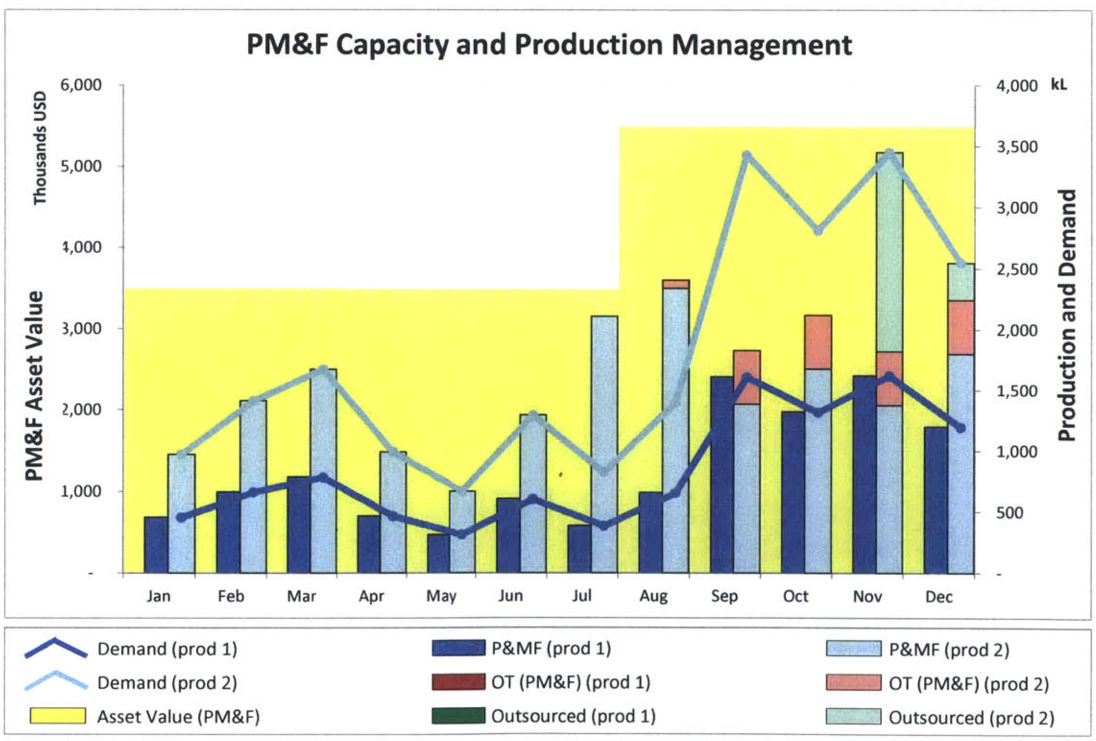

Figure 4-13. PM&F Capacity Upgrade in Year 8

We observed similar capacity upgrade behaviors for PCK to those for PM&F and illustrated them in Figure 4-14 and Figure 4-15: The 1st capacity upgrade only takes place in the September of Year 8, and the 2nd upgrade in the October of Year 10. We do not illustrate for Storage as there is no upgrade observed within the time frame.

An interesting finding is that even though the capacity utilization in certain earlier periods goes to 100%, the model doesn't suggest asset acquisition until a later time.

For example, before the 1st capacity upgrade for PM&F in the 5th year, there were at least 5 consecutive periods each year where utilization rate reaches 100% from Year 1 to Year 5. Similarly, in each year prior to the 2nd capacity upgrade, utilization rate for the peak season reaches 100% and lasts for 5 consecutive periods as well.

The reasons for such postponed asset acquisition might be two-folds. Firstly, the cost calculations from either outsourcing or overtime might be more preferable than the double impact on OAVA from acquisition in both the asset value increase and the asset depreciation as an operational expense. Secondly, the demand can be fulfilled by outsourcing or overtime, making asset acquisition not necessary.

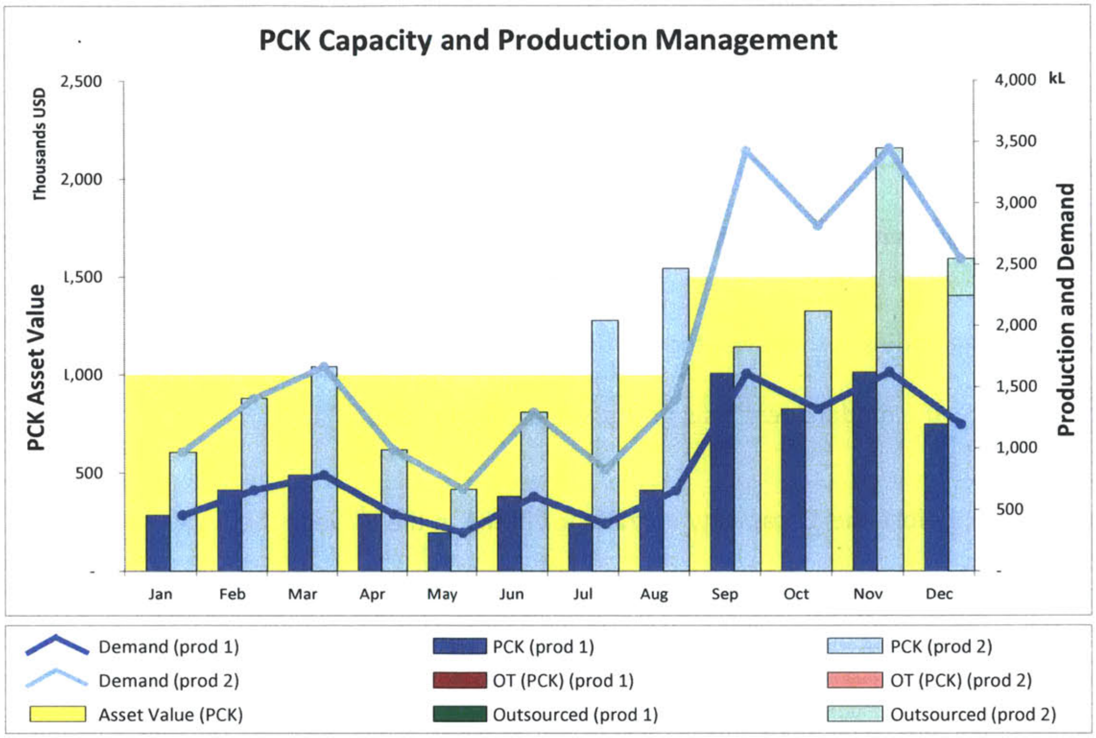

Figure 4-14. PCK Capacity Upgrade in Year 8

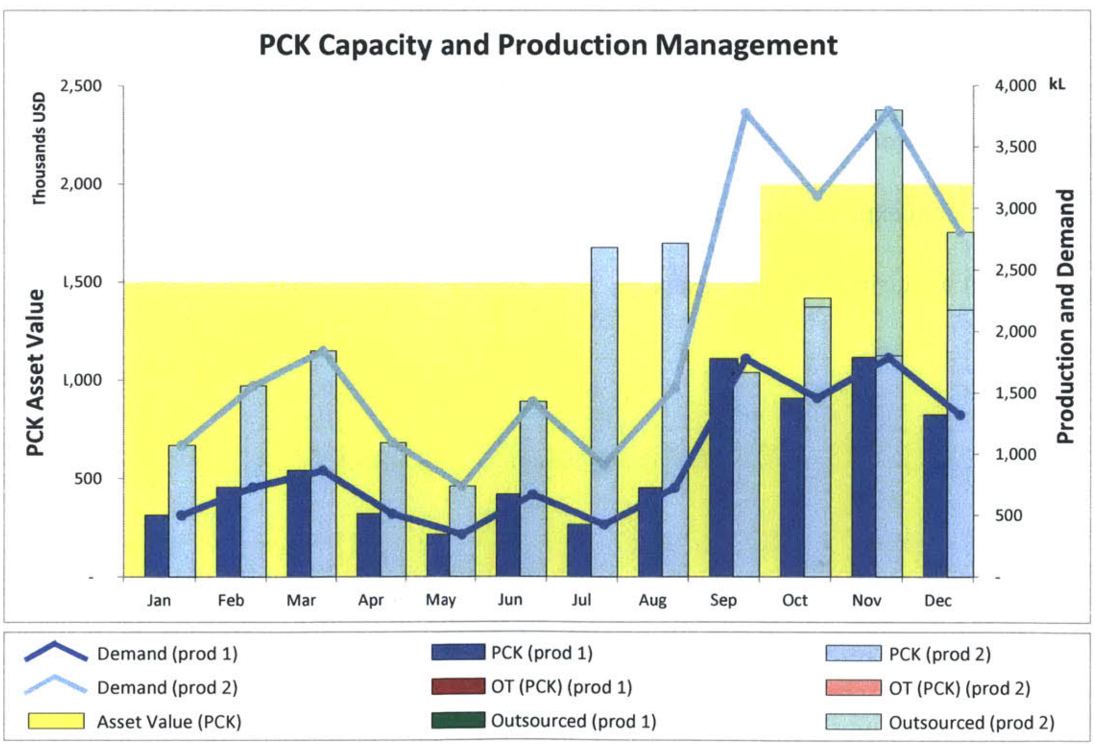

Figure 4-15. PCK Capacity Upgrade in Year 10

4.4.2 Outsourcing

With a 40% markup to the production cost, our model shows that outsourcing is not pursued more than 3 months in a row and will be enabled only after applicable overtime capacity, which is entitled a 25% markup, is pursued. Figure 4-16 shows the capacity and production management for PM&F in Year 7 with the green columns indicating the outsourced volume and pink columns the overtime production volume.

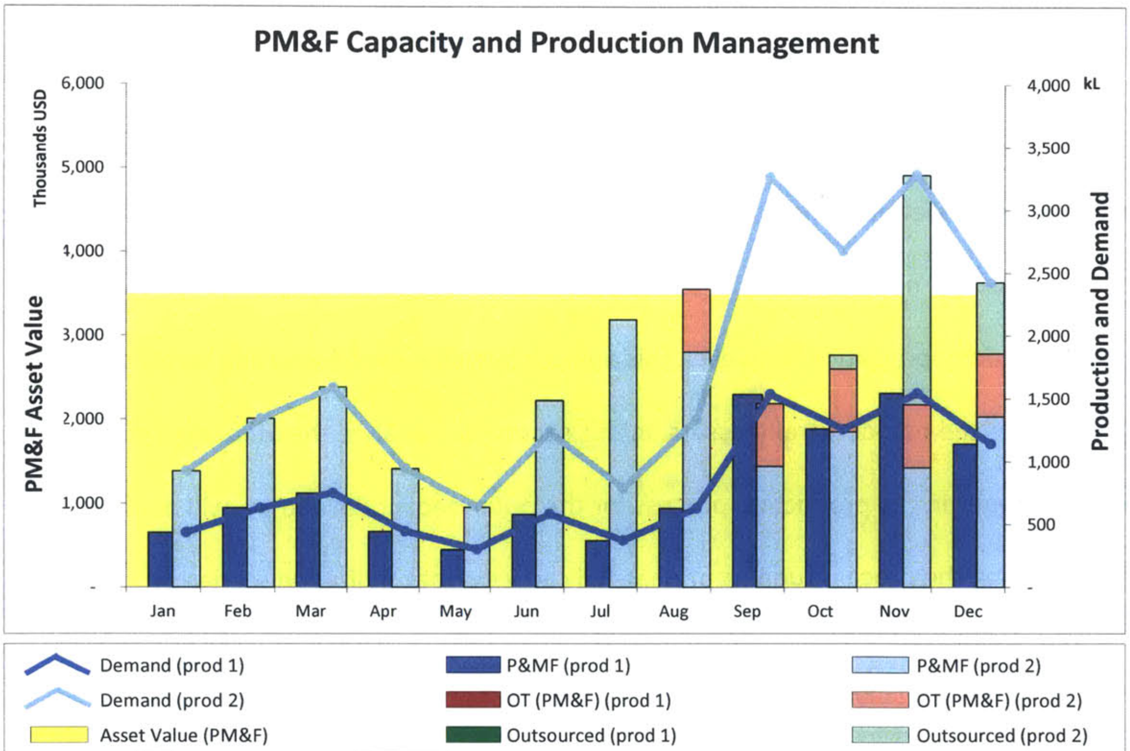

Figure 4-16. PM&F Capacity and Production Management in Year 7

Since outsourcing takes over the end-to-end production process from raw materials to finished goods, which go through PM&F and PCK in series, once outsourcing is pursued, the same amount of products will be outsourced for both stages. Therefore, overtime cannot replace either outsourcing production stage and is not an applicable alternative even though its cost is lower.

4.4.3 Overtime

The results from our model show that the 25% markup makes overtime a preferable alternative to other capacity increase options. Therefore, the model suggests pursuing this option during the peak season (August to December) each year throughout the 10-year time horizon of our research scope.

4.5 Remarks on Asset Utilization

Upper management leaders usually have different perspectives of what the approach should be concerning asset utilization. In the past, operations managers would actively strive to run their processes at near-full capacity to keep the lowest cost per unit possible and make the best return on depreciation. However, this approach implies ever increasing levels of inventory for the non-constraint assets. In this section, we analyze the utilization of the different stages in the production process for the optimized model and we will contrast it against having the process running at near-full capacity (max utilization scenario).

On the one hand, the optimal scenario maximizes NPV OAVA over the 10-year horizon, regardless of the utilization for either stage in the production process. On the other hand, for the maximum asset utilization scenario, we set the objective function to maximize the asset utilization rate. However, in an effort to keep the model linear, we did not use the asset utilization as a ratio but used the sum of overall consumed capacity instead.

In figure 4-17 we contrast the difference between the optimal and the maximum utilization line configurations.

	Optimal	Max Utilization	vs Optimal	vs Optimal (%)
Average Utilization (PM&F)	79%	100%	21%	26%
Average Utilization (Storage)	25%	99%	74%	291%
Average Utilization (PCK)	66%	72%	6%	9%
Holding Cost	$ 1,583,940	$ 90,427,290	$ 88,843,350	5609%
Manufacturing Cost	$ 851,769,273	$ 909,856,895	$ 58,087,622	7%
Outsourcing Cost	$ 55,372,450	$ -	-$ 55,372,450	-100%
Overtime Cost	$ 52,295,046	$ 41,777,161	-$ 10,517,885	-20%
Depreciation	$ 8,791,694	$ 5,400,027	-$ 3,391,667	-39%
Proxy Capacity Value	$ 4,395,847	$ 2,700,014	-$ 1,695,833	-39%
Inventory Value	$ 1,055,960	$ 60,284,860	$ 59,228,900	5609%
10Y NPV OAVA	$ 123,127,204	$ 16,576,701	-$ 106,550,503	-87%

Figure 4-17. Optimal Scenario vs. Maximum Utilization

We can see that for the optimal scenario neither stage goes beyond 80% utilization, which matches Goldratt and Cox (1992)'s idea that utilization is not an accurate measure for a system's overall performance.

Contrastingly, for the max utilization scenario, the utilization rate for the first stage is 100%, while for packaging it is well above the optimal solution. The total production cost (manufacturing, outsourcing and overtime costs) is lower than in the optimal solution, since in-house resources are less expensive. Nevertheless, the OAVA for this scenario drops by over $317k USD or 258% when compared to the optimal solution, thus confirming that utilization alone cannot judge the system's performance as a whole. This drop in the OAVA is driven by a significant increase in holding cost. The preference to make production in-house in order to maximize utilization drives in-house manufacturing cost to increase 15%, while completely disregarding the possibility for outsourcing.

4.6 Executive Recommendations

Two major managerial implications can be derived from our data analysis.

First of all, out of the many internal and external production resources, as well as future asset investment, there are a variety of resource configurations that can help drive the corporate objective based on different demand patterns. Therefore, a strategized combination of these resources is critical in accomplishing the objective, which, in this research, is the optimal net present value of OAVA. Following the outputs of our model, which give recommendations to the overall capacity management in the short and long term, the company can get the highest OAVA.

Additionally, the master production schedule, the resulting inventory levels, and the recommended timings for external resources and asset acquisition are important takeaways from our model. They serve not only as the guidance of the company's day-to-day operations, but also as the quantitative analysis necessary to communicate with stakeholders across different functional teams with potentially conflicting interests.

"Let the future tell the truth, and evaluate each one according to his work and accomplishments. The present is theirs; the future, for which I have really worked, is mine."

Nikola Tesla

5. Conclusion

5.1 Insights

This research aimed to establish a strategic plan to meet customers' demand in a highly volatile demand environment. In addition to fulfilling demand, and thus minimizing lost sales, the strategy would also make the best use of operating assets in terms of OAVA. Following the data analysis, we identified 3 main insights:

Firstly, when several products compete for the same resource in the production process, priority should be given to the one with the highest ratio of value to processing time. Inventory should be built out of products with lower ratios, since holding it will have less impact on the company's financial bottom line. This holds true as long as the profit margin for the products is similar.

Secondly, having enough capacity to meet demand at all times could be financially counterproductive, especially when dealing with a drifting demand pattern. We must look into the possible future demand and adjust accordingly. Sometimes it is to work overtime, outsource and build inventory; others it is to expand capacity.

Thirdly, a capacity increase in a bottleneck resource across the production process will yield an increase in the system's output as a whole, while potentially switching the bottleneck status to another resource. For this reason, management executives must make capacity-increase decisions based on solid analysis and keep an ongoing effort to continuously know the constraints of their production process.

5.2 A Link to the Future

Our optimization model handles a simplified version of reality. Managers should not assume that the outcome of this simulation is a perfect predictor of the future. It is a well-known fact that the further the planning horizon, the more difficult it is to foretell; therefore, planners should do further tweaks to the model to better assess the reality of their environment. Additionally, the mathematical model has some opportunity areas that could be further developed, particularly in the areas of equipment valuation and depreciation.

As computational power continues to grow in the future, solving increasingly complicated mathematical models will become easier. Planners need to develop the sensibility to determine what the depth of the analysis should be and what factors are better left overlooked. Tweaking the model could improve the precision of the outcomes, but while we should not compromise the integrity of the model, we must also keep a low level of complexity such that the actual users won't be discouraged from using it.

As we stated earlier, the problem addressed in this research is not restricted to the agrochemical industry. Rather, the insights can be applied across virtually every industry that deals with a similar problem, be it a manufacturing company or a service provider.

"It's amazing what you can accomplish when you do not care who gets the credit"

Harry S. Truman

6. References

The following are the references used during the elaboration of this project. The list is sorted alphabetically by the author's last name:

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