The Role of Demand Uncertainty in Materials Selection: A Case Study on Aluminum Recycling

by

Hashem H. Dabbas

Submitted to the Department of Materials Science and Engineering in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Science

at the

Massachusetts Institute of Technology

June 2007

Signature of Author:______________________________
Department of Materials Science and Engineering
May 21, 2007

Certified by:______________________________
Randolph E. Kirchain, Jr.
Assistant Professor of Materials Science and Engineering
Thesis Supervisor

Accepted by:______________________________
Caroline A. Ross
Professor of Materials Science and Engineering
Chairman, Departmental Undergraduate Committee

The Role of Demand Uncertainty in Materials Selection: A Case Study on Aluminum Recycling

by

Hashem H. Dabbas

Submitted to the Department of Materials Science and Engineering
on May 21, 2007
in Partial Fulfillment of the Requirements for the Degree of
Bachelor of Science

Abstract

Aluminum is a versatile material that is used frequently in transportation and packaging, two industries with substantial recent growth. The increase in demand for aluminum, however, has outpaced the growth of primary aluminum production. One way to meet this shortfall is the use of secondary, or recycled, materials which provides both economic and environmental benefits. The increased use of secondary materials is limited by numerous factors; one such factor of concern is uncertainty. One form of uncertainty that all producers face is consumer demand; this will be the focus of this study. The two stage recourse optimization model presented in this thesis aims to provide batch planners with a tool to effectively manage raw materials in an uncertain demand environment. This model enhances existing research by increasing the number of demand scenarios considered by an increase in the model's resolution. The two metrics evaluated are scrap purchased and production cost. The batch planning process is affected by a number of assumptions about factor inputs including the model resolution, salvage value, coefficient of variation, scrap cost and compositional constraints. Results show that understanding the influence of these factors provides producers with the insight and ability to effectively manage and mitigate the effects of demand uncertainty in a cost minimization framework.

Thesis Supervisor: Randolph E. Kirchain, Jr.
Title: Assistant Professor of Materials Science and Engineering

Contents

List of figures

List of tables

Acknowledgements

I am grateful to Professor Randy Kirchain for providing me with the opportunity to engage in such an interesting research project. Professor Kirchain helped me combine my interest in economics with the engineering skills I have acquired at MIT and allowed me to add value to a project with tremendous practical applications. I could not have conducted this research without the remarkable guidance and help of Gabrielle Gaustad, who I cannot thank enough for the time she spent with me on this project. Gabby's invaluable suggestions, viewpoints and insights have played an instrumental role in streamlining the whole research process and making this a truly enjoyable and stress free experience. I would not be the person I am today without the continued love and support of my family, who I am forever indebted to. Last but not least, I would like to thank my friends, who have always been there for me, and who have made my experience at MIT an unforgettable one.

1 Introduction

1.1 Aluminum and Society Background

Aluminum is one of the most commonly used materials in our daily lives; in the United States alone, approximately 6,100 MT were consumed in 2006. It began to be industrially produced after 1886 when Hall and Heroult discovered the ability to isolate aluminum via electrolysis[2]. Aluminum and its alloys exhibit numerous versatile properties that enable their use for a broad spectrum of applications. In addition to being a good conductor of heat and electricity, aluminum is lightweight, malleable, ductile and corrosion resistant[3]. Figure 1 provides a graphical representation of the US domestic aluminum consumption by sector in 2006.

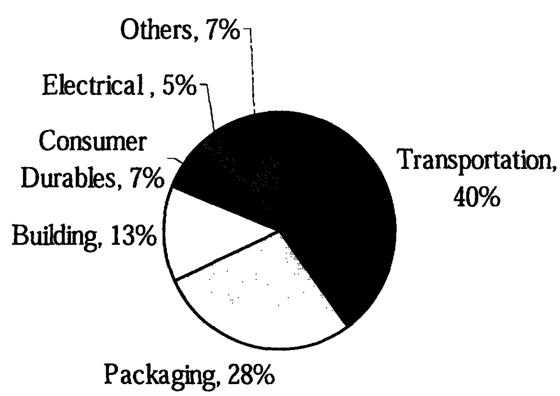

Figure 1 Domestic Aluminum Consumption by Sector (2006)[4]. The transportation and packaging industries were the lead consumers of aluminum in 2006.

The transportation industry was the largest consumer of aluminum and its alloys in 2006. The production and manufacture of ships, buses, automobiles, trailers, railroad and subway cars in addition to aerospace applications and mobile homes fall under this category, with automobiles comprising the majority. Forty years ago, the average American and European vehicle contained about 25 kg of Aluminum; today, that value has reached over 150kg of Aluminum per vehicle[5]. Figure 2 provides a schematic of the various components of a modern automobile that are aluminum based, resulting from Aluminum's versatility and desirable mechanical properties.

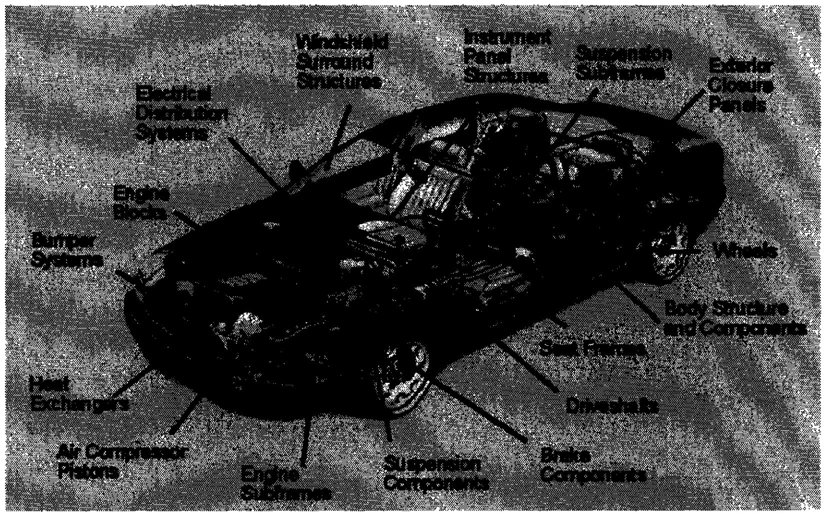

Figure 2 Aluminum Components in Modern Automobile [5]. Today, aluminum comprises over 150kg of a typical vehicle's weight.

Moreover, the lightweight nature of aluminum has played a fundamental role in the enhancement and growth of the global aviation industry. The International Aluminum Institute estimates 80% of an aircraft's weight to be aluminum-based, with a typical Boeing 747 jumbo jet containing 75,000 kg of aluminum[6].

The packaging industry follows transportation as the largest domestic consumer of aluminum. This category comprises such products as beverage cans, food containers and household and institutional foil[7]. The Can Manufacturers Institute reports than in 2004, aluminum can shipments exceeded 134 billion, led by beverage cans which amounted to almost 100 billion of those shipments[8]. Aluminum foil, meanwhile is a light, strong, flexible and durable material that is commonly used for both household and industrial applications.

The third largest domestic consumer of aluminum: building and construction, is the largest consumer of aluminum in most other countries[7]. Aluminum's high strength to weight ratio allows it to be used in the form of architectural sheet and extrusions. Aluminum is also used in such applications as curtain walling, window frames, siding and roofing, greenhouses, staircases, heating and air-conditioning systems, scaffolding and ladders amongst other uses[7].

The breakdown of domestic aluminum consumption by industry has been somewhat steady over the past 15 years, as shown in Figure 3. The use of aluminum in packaging, construction and electrical appliances has been relatively consistent since 1975. Much of the increase in overall aluminum production is brought about by an increase of aluminum use in the transportation sector. It is evident that despite year-over-year fluctuations, domestic aluminum consumption has exhibited an upward trend over the past 30 years. As the world population increases past 6.5 billion people, an increase in aggregate demand for aluminum products is to be expected, acting as a major obstacle for the sustainability of this highly versatile material.

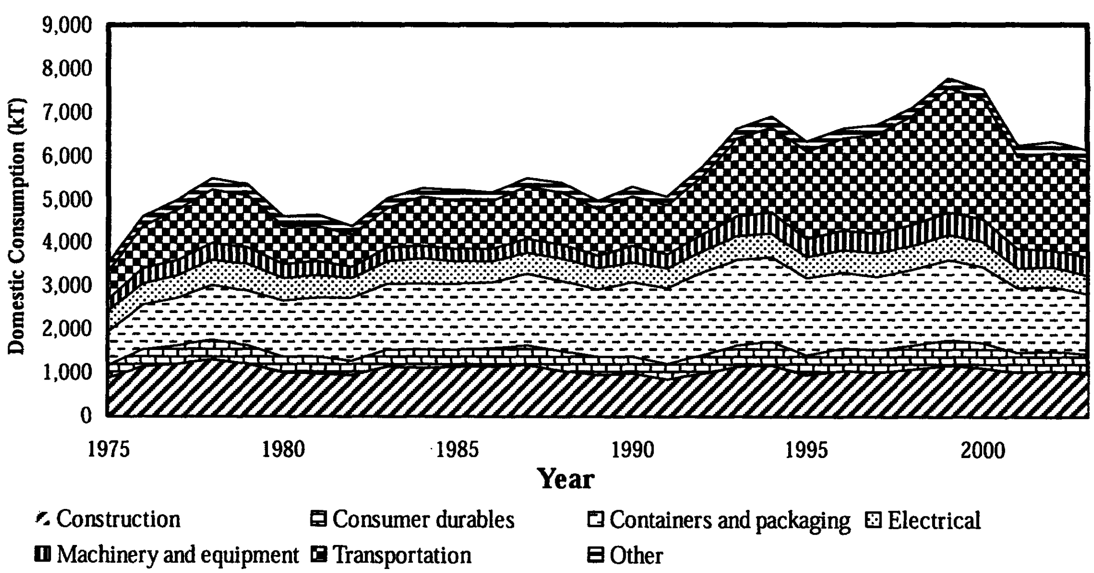

Figure 3 Domestic Aluminum Consumption by Sector (Historical)[4]. The general trend is that of increasing aluminum consumption, highlighted by growth in the transportation industry.

At the beginning of the 20th century, global aluminum consumption was approximately one thousand tons; a century later that number had jumped to 32 million tons[2]. This rate of increase in domestic aluminum demand has greatly outpaced the rate of increase in primary aluminum supply as is seen in Figure 4, thereby further complicating the materials selection process. A natural choice to satisfy the excess demand of aluminum would be to augment and expand the usage of secondary materials.

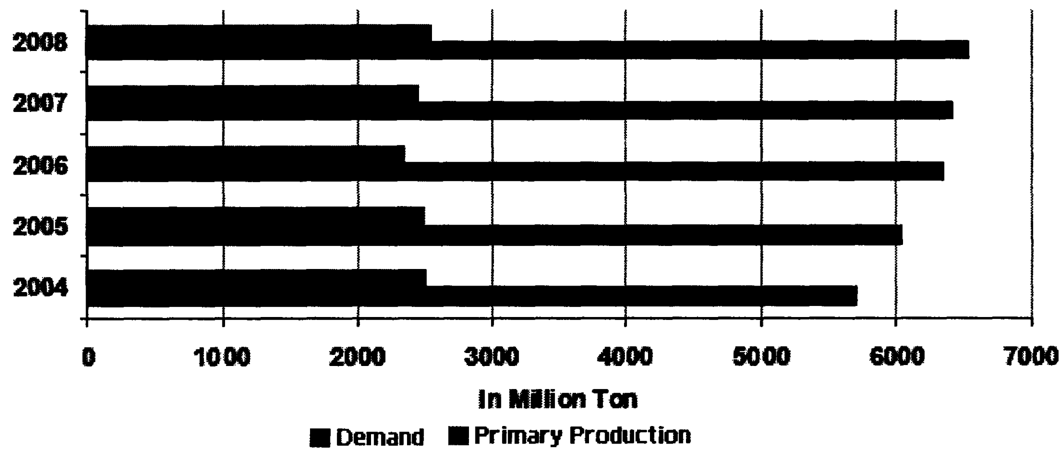

Figure 4 US Aluminum Demand and Primary Production from 2004-2008E [9]. Primary production of aluminum is equivalent to just over one third of domestic aluminum demanded.

1.2 Materials Selection

Current estimates[10] conclude that there are over 40,000 useful metallic alloys including 1,200 wrought and cast aluminum alloys in existence, not accounting for composite materials, plastics, semiconductors and other nonmetallic materials. This wide array of available building blocks at an engineer's disposal makes the selection of appropriate materials a vital decision in the production processes faced by firms globally. Fundamentally, the inherent motivation behind the materials selection process lies in optimizing the properties of the product while simultaneously minimizing cost – a task of balancing numerous countervailing forces that engineers have to face on a daily basis.

The materials selection process takes into account the desired mechanical and structural capabilities of the material, its availability, and potential secondary uses. Other factors that play a role in the decision making process include ease of shaping and processing, reliability, and the environment the materials will be used in[10]. Ashby's materials selection charts[11] provide a quantitative tool to group the desired mechanical properties of various materials and facilitate selection based on the structure-property relationships.

The nuances of the materials selection process are clearly exhibited in the varying constituents for typically aluminum based products. In the transportation domain, for example, Boeing's new 787 airplane is said to be a pioneer in the aviation industry – transforming the bulk of an airplane's weight from being aluminum to composite materials which are lighter weight and thus provide better fuel economy. Similarly, in the packaging industry, Aluminum beverage cans face stiff competition by both plastic and glass bottles. These competing products further augment the interplay between desired properties and keeping production costs controlled.

The cost minimization constraint acts as a major roadblock for profit-maximizing firms that aim to increase profit margins by controlling costs. Therein lies the principle stimulus behind using secondary materials. These recycled, or scrap, materials provide both economic and environmental advantages over their primary counterparts. From an economic perspective, scrap is typically less expensive to obtain than primary material and alloying elements, yet can provide similar properties[7].

The increase in recovery and recycling of secondary materials will have a major impact on the long term sustainable use of light metals in general, and aluminum in particular. For many metals, the energy required in the fabrication of primary raw materials far exceeds the burden that is necessary to process them out of scrap materials. This environmental incentive for recycling is especially compelling in the case of aluminum whose primary production requires up to ten times more energy than its secondary production[12]. In fact, recycling 1 kg of aluminum can save up to 8 kg of bauxite, 4 kg of chemical products and 14 kW of electricity [2].

1.3 Secondary Production & Recycling

In the year 2000, the recycling rate of aluminum was estimated to be only 36% [7], where the recycling rate is defined as:

$$\frac{\text{(Consumption of Old Scrap + Consumption of New Scrap)}}{\text{Apparent Supply of Scrap}} \times 100\% \qquad (1)$$

Even though the aluminum can industry recycling rates are higher than the aluminum industry's overall average, the last decade has shown a troubling decrease in recycling rates, as exhibited in Figure 5.

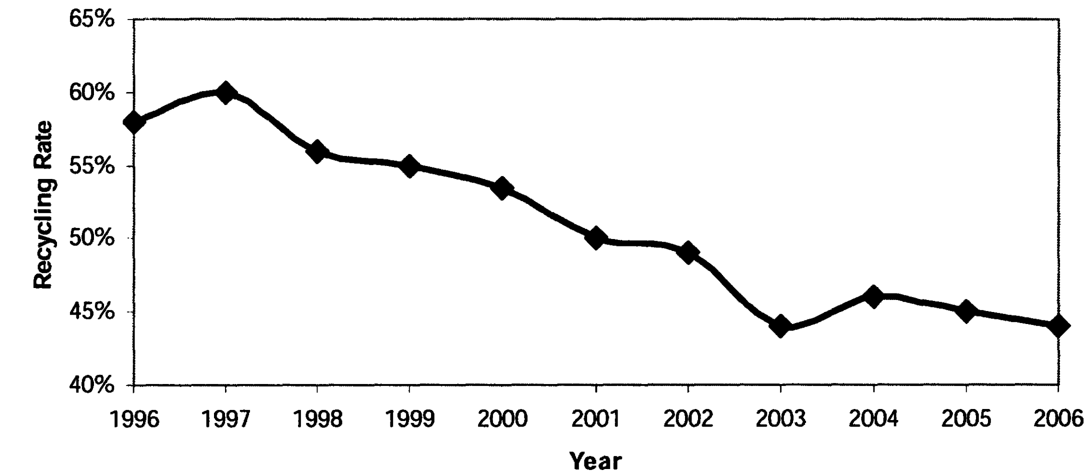

Figure 5 Aluminum Can Recycling Rates [13]. The trend over the last decade has been one of decreasing recycling rates.

Recycling efficiency can be defined as the aggregate sum of scrap that is recycled over the aggregate sum of aluminum that could be collected and reused. USGS estimates[7] indicate that the recycling efficiency of aluminum in the year 2000 is close to 60%. It may be somewhat puzzling that despite scrap being less expensive than primary aluminum, in addition to being a feasible necessity for its long term sustainable use, less than 2/3 of the aluminum that is eligible to be recycled is being used in secondary production. One possible explanation behind this lack of optimal use of recycled aluminum is related to the various multidimensional uncertainties faced by aluminum producers, which will be discussed hereafter.

1.4 Barriers to Aluminum Recycling: Uncertainty

The aluminum market is rich with a wide array of uncertainties that hinder optimal decision making ability with regards to production and use of secondary materials. Key uncertainties include the availability and composition of scrap in addition to the volatility of both prices and demand for aluminum products.

1.4.1 Price

Figure 6 Fluctuations in Aluminum Prices since 1920 [4]. The year to year change in aluminum prices has been volatile and exhibits sharp peaks and valleys. Figure 6 exhibits the year-to-year change in price of aluminum since 1920 in 1998 dollars. This dramatic variation in price may be attributed to unstable supply and demand of aluminum that acts as a major obstacle for aluminum producers in planning and preparing for future production cycles.

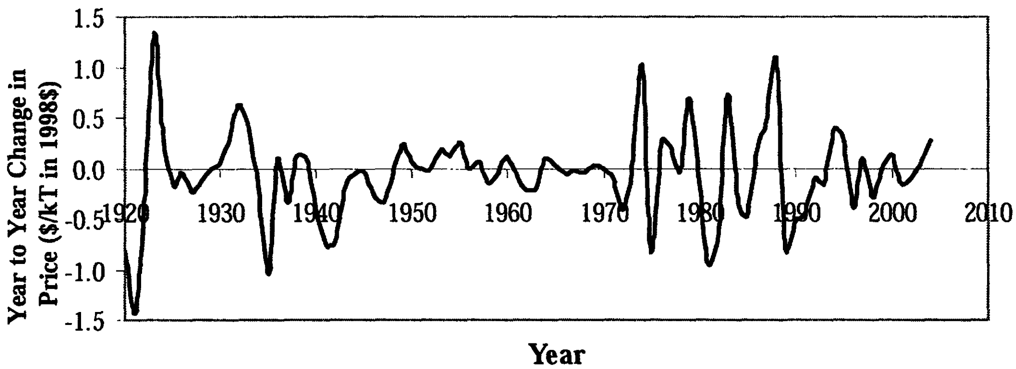

Figure 6 Fluctuations in Aluminum Prices since 1920 [4]. The year to year change in aluminum prices has been volatile and exhibits sharp peaks and valleys.

1.4.2 Availability

Uncertainty in the availability of aluminum scrap is significantly affected by the variation in the end-of-life of different products. This has a profound effect on the quantity of aluminum that can be recycled on a year to year basis, and thus the amount of scrap that is available for use is not a steady value. The volatility in geographic availability of scrap is exhibited by variations in local prices of scrap, plotted in Figure 7.

Higher prices tend to be associated with the cost of transporting the scrap from its collection site or location. These geographic variations bring to light the price and availability uncertainties that hamper increased scrap purchasing and usage.

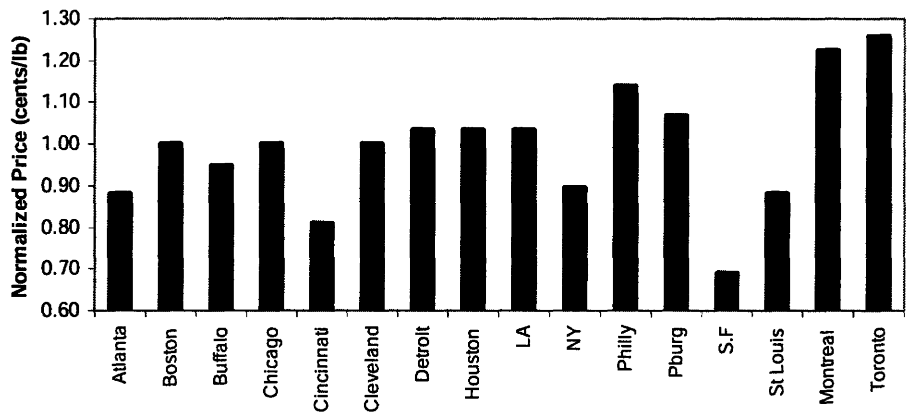

Figure 7 Normalized Scrap Prices across various locations [14]. Scrap access and availability in key North American cities plays a major role in determining scrap prices.

1.4.3 Composition

The volatility associated with end-of-life products shapes the variation in aggregate compositions of scrap materials on an annual basis. Certain processing at end of life, for example shredding, can contribute to the build up of undesirable compositional additions. The metal yield of aluminum from the melting process is unquestionably a function of the aluminum based products undergoing recycling. These compositional uncertainties are the basis behind why aluminum scraps are not identical, and thus hinder the viability of replacing one scrap type with another.

1.4.4 Demand

Demand uncertainties associated with a dynamic market play a central role in causing inefficiencies in the metal alloy production process as well. This is particularly true in the aluminum market where consumer demand has traditionally been volatile[15].

Apparent consumption is defined as primary aluminum production plus net exports, and is plotted in Figure 8. In a 15 year time span, aluminum apparent consumption ranges from 5000kT to close to 8000kT, thus making the task of predicting future consumption an extremely daunting task.

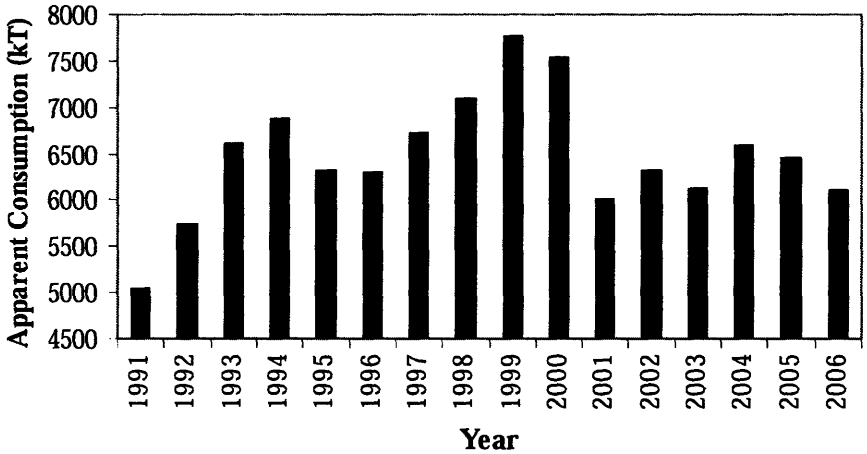

Figure 8 US Apparent Consumption of Aluminum over time[4]. No direct trend is observed, highlighting the difficulty of predicting future aluminum consumption.

A longer term variation is shown in Figure 9, which plots year to year changes in domestic aluminum produced since 1920.

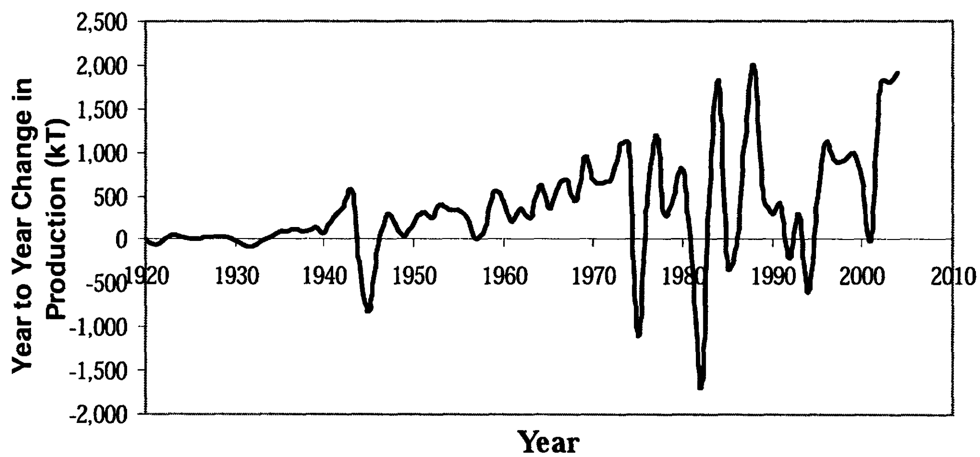

Figure 9 Fluctuations in domestic Aluminum Produced since 1920 [4]. The year to year changes in aluminum production are extremely volatile, relating to inconsistent demand.

These remarkable variations in aluminum produced are further affected by fluctuations in demand for industries that commonly use aluminum. Demand for aluminum is mired by competition from lower cost substitutes that offer similar properties. This further highlights the need to manufacture aluminum products at lower costs and clearly enhances the potential added value of using secondary materials.

Although some peaks and valleys in Figure 9 appear to parallel those of the US economy as a whole, the fluctuations in price and production of aluminum do not appear to be cyclical in nature. Rather, a common theory relating to these inefficiencies in supply chain management is given by the Bullwhip effect[16]. This theory states that the most dramatic variations in demand are noticed by the operators furthest away from the customer, who in this case would be the aluminum producers. The bullwhip effect is believed to be caused by inaccurate and inefficient demand forecasting, order batching, price fluctuations and rationing.

The magnitude and scope of the bullwhip effect is clearly observed in both Figure 6 and Figure 9, adding a further obstacle in the use of secondary materials. The fundamental constraint for scrap usage, from a demand perspective, is that scrap used in the production of aluminum alloys must be purchased before the demand for these alloys is known. Thus, the bullwhip effect complicates the purchasing decisions of materials producers who need to preorder scrap whilst overcoming significant projected demand volatilities.

Given these uncertainties, the ability of a firm to position itself in such a manner to hedge against these variations becomes of tremendous potential added value. In the automotive industry, for example, where much of aluminum scrap is obtained, studies[17] have shown that through strategic alloy choice, material reuse rates, production costs and variability can be dealt with effectively. More generally, by being well-hedged, a firm can actively engage in profit-maximizing operational activities involving scrap pre-purchasing, while ensuring a consistent cash flow and minimizing vulnerability to fluctuations in market demand.

2 Problem Statement and Overview

The goal of this study is to establish a methodology that examines the effective implementation of efficient raw materials management by specifically considering uncertainty in consumer demand for alloys. The financial benefits and specific economic incentives associated with incorporating secondary materials in the materials selection process and utilizing scrap in production will be examined by a two-stage recourse model, with a case study focusing on aluminum.

The results of the study aim to assess the relationship between demand uncertainty and batch mixing decisions, focusing on such factors as purchasing decisions and production costs. This will be conducted by modifying an existing model[15, 18] to enhance the resolution of the outcomes and applications, through expanding the number of demand scenarios considered. The objective of this case study is to characterize scenarios that optimize the use of aluminum scrap in various production settings, in addition to clearly identifying the effectiveness of this optimization to minimize costs in specific production processes and conditions.

Sensitivity analyses will be run to accurately identify any assumptions that may affect the scrap pre-purchase decisions and/or production cost. These assumptions include 1) the resale or salvage value of scrap, 2) demand variability (reported as the coefficient of variation), and 3) the cost of scrap relative to the cost of primary materials. Also, the impact of differing demand resolutions and scenarios on versatility of different scraps and their pre-purchase amount will be evaluated. Finally, the compositional constraints of different elemental components of aluminum alloys will be analyzed via shadow pricing to assess potential compositional modifications aimed at further optimizing the scrap hedging behavior.

The hypothesis that is to be investigated is that recourse modeling can act as an effective tool in providing insight to batch planners. These planners operate under a cost minimization framework which includes combining primary and secondary materials in the production of alloys. This framework is complicated by the presence of demand uncertainty, which the model aims to assess and manage efficiently. This research intends to demonstrate that increasing the resolution of a two stage recourse model leads to an enhancement in the batch planning decisions that can be utilized by producers.

3 Methodologies

3.1 Recourse Modeling

Optimization is a tool used to attain a solution to a complex problem involving numerous interrelated variables. The optimization process aims to maximize (or minimize) an objective function that is subject to various constraints[19]. One mechanism that is commonly employed to simplify the optimization considerations is that of linear programming. Broadly defined, a linear program is a mathematical tool in which the objective function is linear in the unknowns and where linear equalities and inequalities are employed to represent the constraints[19]. Linear programming is a technique that has commonly been used in the optimization of various production processes[20-23].

Optimization via linear programming becomes increasingly complex when the constraints are probabilistically altered, thereby introducing ambiguity to the core problem[24]. A multi-step recourse model is broadly defined as an optimization tool that assists in the decision making processes given uncertain, or stochastic final outcomes[25, 26]. Intuitively, it can be thought of as an "action-reaction" coupled decision making process[27]. An action is taken prior to stochastic knowledge, with the respective reaction being the recourse undertaken to satisfy all the constraints, given the stage one decisions, once knowledge of the stochastic outcomes is available.

In the model examined within this thesis, the fundamental trade-off between primary and secondary materials is two fold. The primary material is available to be purchased at all times, yet is sold at a higher cost than scrap. Scrap, meanwhile, needs to be purchased prior to demand being known, and thus the outcome of scrap pre-purchase decisions are subject to the uncertainties in demand discussed earlier. A schematic representation of the recourse model is presented in Figure 10. The blue squares in the figure represent decision nodes, while the yellow circles represent uncertain outcomes.

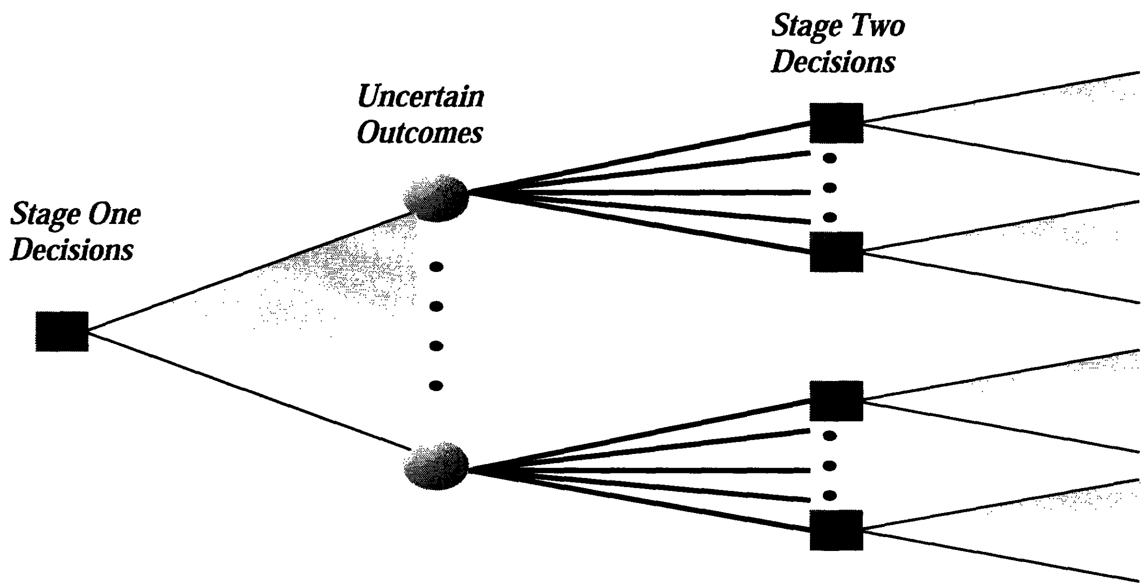

Figure 10 Schematic Representation of Recourse Model Strategy[1]. The two-stage recourse model relies on decisions taken prior to demand being certain, and results in stage two decisions taken after demand is known.

Given the uncertain nature of demand, the stage one decision is comprised of scrap pre-purchases. At a time *t* later, demand becomes known, and the producer meets the demand by combining the scrap pre-purchased with primary material as needed. Excess scrap pre-purchased is sold at a discounted rate given by the salvage value, which acts as a proxy for carrying cost.

Mathematically, the recourse model optimization problem[15] can be described using the objective function given in Eq. 2.

$$f\ (C,D^1)\ + g\ (C,p,D^2) \qquad (2)$$

The contribution from stage 1 is given by the function *f*(.) while that from stage 2 is given by the function *g*(.). C represents the cost vector whose constituents from both stage 1 and stage 2 decisions combined must be minimized in this linear optimization. D^1 maps the stage one decision parameters, D^2 does the same for stage two decisions, and p reflects the probabilities of the decision outcomes.

Thus, the overarching objective function of the recourse model is to minimize:

$$\textit{Scrap Cost} + \textit{Primary Cost} - \textit{Salvage Value} \tag{3}$$

given the uncertain nature of demand and the built-in compositional constraints. This minimization can be more precisely be decomposed into two components associated with each decision making stage.

The stage one effect takes into account the cost of the scrap pre-purchased, given by Eq. 4:

Stage One Effect: $$f\,(C,D^1) = \sum_s C_s D_s^1 \tag{4}$$

The stage two effect (Eq. 5), however, takes into account both the amount of primary material needed to be purchased to meet the demand and compositional constraints built into the model, in addition to the value of excess scrap that was pre-purchased but unused. If the amount of scrap pre-purchased in stage 1 does not meet the demand, the producer needs to purchase primary material to alleviate the shortage. This represents an added cost to the producer given that the price of primary aluminum is higher than scrap. Similarly, if more scrap is purchased than required, the producer will have to sell the excess scrap at a discount rate, given by the salvage value. More generally, the salvage value can be considered to be the carrying cost of inventory from one production cycle to another. In this model, however, the salvage value represents the resale value of excess scrap, making this simulation a closed loop after only two stages.

These two nuances of the cost minimization formula shed light on the "penalties" faced by the producer resulting from pre-purchasing either too little or excessive scrap.

Stage Two Effect: $$g\,(C, p, D^2) = \sum_{p,f,z} C_p P_z D^2_{pfz} - \sum_{s,z} SC_s P_z R_{sz} \qquad (5)$$

More clearly stated, the objective function is to *minimize*:

$$\sum_s C_s D^1_s + \sum_{p,f,z} C_p P_z D^2_{pfz} - \sum_{s,z} SC_s P_z R_{sz} \qquad (6)$$

such that: $$D^1_s \leq A_s \qquad (7)$$

The amount of scrap pre-purchased for each scenario is given by:

$$R_{sz} = D^1_s - \sum_f D^1_{sfz} \qquad (8)$$

Given the various built in constraints as well as the probabilistic nature of the model, D^1_s, D^1_{sfz}, D^2_{pfz} are the variables solved for in such a manner to minimize costs. These variables represent the amount of scrap pre-purchased, amount of scrap used and amount of primary material purchased, respectively.

The condition that scrap must be pre-purchased is enforced by Eq. 9, which states that at the time of production, no more scrap can be used than was initially purchased:

$$\sum_f D^1_{sfz} \leq D^1_s \qquad (9)$$

The production constraint for each scenario z is given by Eq. 10 which includes mass balance and emphasizes that the amount produced must meet or exceed the total demand:

$$\sum_s D^1_{sfz} + \sum_p D^2_{pfz} = B_{fz} \geq M_{fz} \qquad (10)$$

In addition to demand specifications, compositional constraints associated with each alloying element c, must be met. These constraints are used in the determination of the production portfolio, specifically the amount of aluminum scrap, primary, and alloying elements required to meet the compositional specifications:

$$\sum_{s} D^{1}_{sfz} U_{sc} + \sum_{p} D^{2}_{pfz} U_{pc} \leq B_{fz} U_{fc} \tag{11}$$

$$\sum_{s} D^{1}_{sfz} L_{sc} + \sum_{p} D^{2}_{pfz} L_{pc} \geq B_{fz} L_{fc} \tag{12}$$

From these equations, it becomes increasingly clear that both the price spread between primary and secondary materials as well as the salvage value of scrap will greatly influence the optimal solutions. Thus, sensitivities for both these variables will be conducted and evaluated.

The variables used in the linear programming model are defined[15] below:

R_{sz} = Residual amount of scrap s unused in scenario z

S = 1 – discount on the value of unused scrap materials

C_s = unit cost ($/T) of scrap material s

C_p = unit cost of primary material p

D^1_s = amount (kt) of pre-purchased scrap material s

P_z = probability of occurrence for demand scenario z

D^2_{pfz} = amount of primary material p to be acquired on demand for the production of finished good f under demand scenario z

A_s = amount of scrap material s available for pre-purchasing

D^1_{sfz} = amount of scrap material s used in making finished good f under demand scenario z

B_{fz} = amount of finished good f produced under demand scenario z

M_{fz} = amount of finished good f demanded under demand scenario z

U_{sc} = max. amount (wt. %) of element c in scrap material s

L_{sc} = min. amount of element c in scrap material s

U_{pc} = max. amount of element c in primary material p

L_{pc} = min. amount of element c in primary material p

U_{fc} = max. amount of element c in finished good f

L_{fc} = min. amount of element c in finished good f

3.2 Previous Work

There currently exists[15, 27] a deterministic two-stage recourse model that maps the behavior of scrap purchase and usage based on a limited set of demand scenarios and volatilities that was developed within the MIT Materials Systems Laboratory. The existing model represents demand via a discrete probability distribution consisting of five distinct probability scenarios; though demand scenarios would be more accurately represented by a continuous probability curve, discrete probability scenarios provide increased computational efficiency. One of the main objectives of this study is to enhance the existing model by increasing the number of quantized demand scenarios. This enhancement of the model's resolution is aimed at obtaining a more realistic and broad uncertainty environment.

3.3 Aluminum Case Study

Once the recourse model methodology has been established, it is difficult to visualize the results it may have on batch mixing decisions. Therefore, a case study on aluminum recycling will be presented. The profound role aluminum plays in today's society as well as the various sources of demand uncertainty outlined earlier make aluminum an ideal candidate to be evaluated in this recourse methodology. Given the design parameters, the compositional constraints, and the demand uncertainties, the two-stage model provides an optimal solution of specific scrap purchases to meet the probability-weighted expected demand.

Aluminum is typically used in the alloy form, which is comprised of pure aluminum combined with dozens of possible alloying elements. Alloying is a tool used by engineers to enhance aluminum's properties based on their desired use[3]. In order to keep the case study small computationally, only six of the major alloying elements will be tracked: silicon, manganese, iron, copper, zinc and magnesium. The 2006 year average prices[28] for these primary materials is listed in Table 1. Since much of aluminum scrap is obtained from end-of-life vehicles and their compositions are publicly available, seven sources of automotive aluminum scrap are used and presented in Table 1. These scrap sources include: brake, transmission, co-mingled media scrap, heat exchanger, bumper, body sheet, and all aluminum engines.

Table 1 Prices of Raw Materials[28]

Primary Elements	$ / Ton	Scrap Materials	$ / Ton
P1020	2,646	Brake	1,984
Silicon	1,690	Transmission	1,984
Manganese	3,610	Media Scrap	1,984
Iron	520	Heat Exchanger	1,984
Copper	6.830	Bumper	1,984
Zinc	3,200	Body Sheet	1,984
Magnesium	2,000	All Al Eng. & Trans.	1,984

Variations in prices of different aluminum scrap from end-of-life vehicles is not publicly available, and thus, the prices of the various scrap types are set to be equal to one another. In the base case, the scrap price is chosen to be 75% of the price of the primary aluminum. This price spread between primary and secondary aluminum may affect the scrap pre-purchasing decisions and as such, sensitivity analyses of the scrap price will be evaluated.

In addition to being an abundant source of aluminum scrap, compositional data of recycled aluminum from end-of-life vehicles is widely available[15]. Table 2 presents the average weight percent of the tracked alloying elements in each scrap type. Metal yield for these scraps was assumed to be 100% for simplification.

Table 2 Average Composition of Automotive Scrap Materials[15]

Raw	Average Composition (wt %)					
Materials	Si	Mg	Fe	Cu	Mn	Zn
Brake	1.54	1.23	0.40	0.62	0.14	0.12
Transmission	10.30	0.21	0.90	3.79	0.28	2.17
Media	4.88	0.64	0.53	1.00	0.11	1.00
Heat Exchange	2.88	0.21	0.44	0.68	0.59	0.20
Bumper	0.39	0.78	0.38	0.32	0.09	0.75
Body Sheet	0.47	1.34	0.21	0.57	0.19	0.07
All Al. Eng & Trans.	8.61	0.30	0.68	2.69	0.27	1.26

These various elements act as the foundation behind the compositional constraints of using secondary aluminum in various alloys. In the aluminum case study, two aluminum alloys will be considered: 380 and 390. The chemical specifications of the alloying elements in each alloy is presented in Table 3. Included are upper and lower bounds for the weight percent of the alloying elements- thereby establishing a range of accepted compositions in each alloy. The particular scraps and alloys used represent commonly used materials in the automotive industry as per studies conducted by Gorban[29].

Table 3 Finished Goods Chemical Specifications[15]

	Si		Mg		Fe		Cu		Mn		Zn	
	Max	*Min*	*Max*	*Min*	*Max*	*Min*	*Max*	*Min*	*Max*	*Min*	*Max*	*Min*
380	9.50	7.50	0.10	0.00	2.00	0.00	4.00	3.00	0.50	0.00	3.00	0.00
390	18.00	16.00	0.65	0.45	1.30	0.00	5.00	4.00	0.10	0.00	0.10	0.00

By comparing the compositions of the various scrap types with the alloys to be evaluated, it is clear that there are discrepancies in the average compositions of alloying elements. These discrepancies will constrain and limit the use of certain types of scrap given the two cast alloys under consideration. The magnitude of the compositional constraints for each type of alloying element will be evaluated to assess which are the most highly constraining.

3.4 Discrete Probability Distributions

One of the unique additions to this work that is lacking in other production decision-making models is the consideration of alloy demand uncertainty and/or volatility. Although demand would more effectively be represented via a continuous probability distribution, a discrete distribution is assumed so as to take advantage of computational efficiency of linear optimization methods[27]. This simplification in the demand profile is aimed at minimizing computational memory and time needed to run the model. In this case study, it is assumed that both alloys have identical demand profiles, which are shown graphically in Figure 11.

(a)

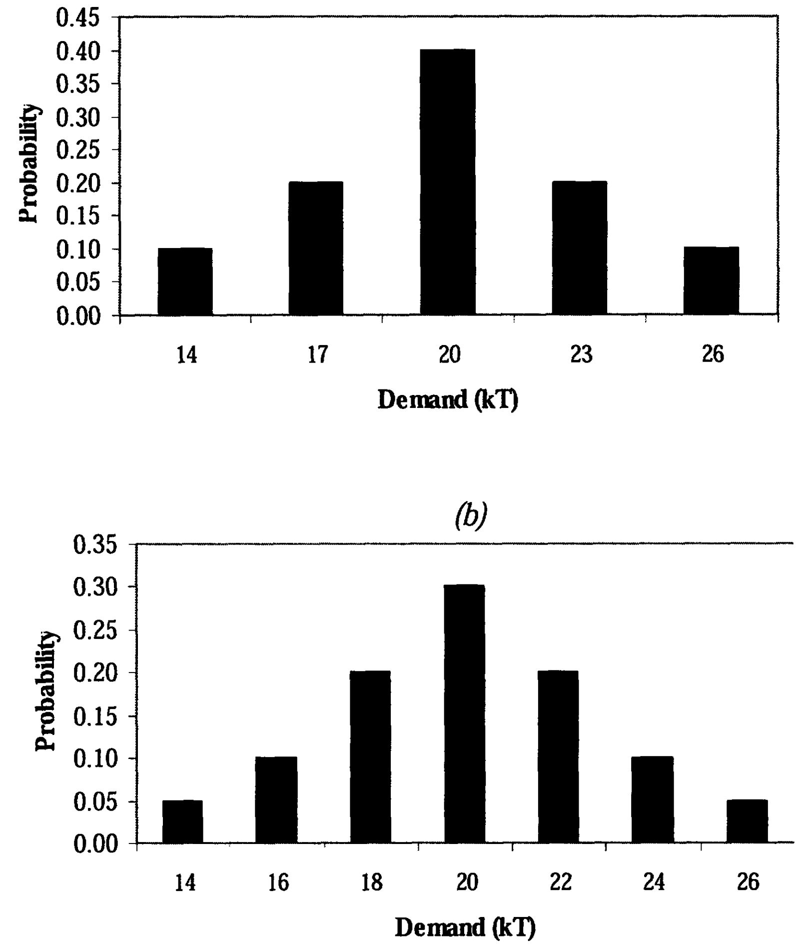

Figure 11 Modeled Discrete Probability Distribution representing possible finished alloy demands: (a) Limited Case, (b) Expanded Case

For both the 380 and 390 alloys, the mean demand is set to 20kT with a 30% probability of occurrence. The other six demand scenarios provide for a symmetric demand profile which has a base coefficient of variation of 14%. The coefficient of variation (COV) is the standard deviation divided by the mean (given by Eq. 13); this is a way to normalize the variation of alloys with different average demands. The coefficient of variation in demand will inevitably affect the production costs and hedging ability of producers, and as such, sensitivity analyses of this variable will be conducted.

$$COV = \frac{\sigma}{\mu} \tag{13}$$

It is imperative to note that in this study, the demand profile consists of seven unique demand scenarios. As was mentioned earlier, previous research[27] has been conducted using a limited set of five demand scenarios. The increase in resolution presented in this study, represents a closer approximation to continuous demand probability profiles. This enhancement will influence the scrap pre-purchasing decisions as well as the production costs and will be presented hereafter.

4 Results and Discussion

The fundamental objective of this modeling effort described in this thesis is to specify a breakdown of the optimal scrap pre-purchasing decision under a cost minimization framework that takes into consideration a wide array of variables. The principle addition of this study to existing theory is the encapsulation of demand uncertainty in the cost minimization framework. Using a base case salvage value of 95%, coefficient of variation of 14% and scrap prices fixed at 75% of the cost of primary materials, values for production cost and total scrap purchased are obtained for both the limited and expanded cases. For the limited case, described earlier, the amount of scrap purchased in stage one is 37.61 kT, resulting in a total production cost of $83.39M. Meanwhile, the higher resolution expanded case results in a production cost of $83.31M and scrap purchases of 38.49 kT. This initial output shows that increasing the resolution of the model led to an increase in scrap purchased and a resultant decrease in production cost.

The outputs of the model are sensitive to a broad set of factors including variations in salvage value, coefficient of variation of demand, scrap cost and versatility. Sensitivity analyses of these factors are presented hereafter, and provide the model's user with the ability to enhance the cost minimization process by manipulating these considerations. Additional sensitivity information relating scrap purchasing with the compositional constraints is obtained by analyzing shadow prices.

4.1 Salvage Value

One assumption that has an impact on both the scrap purchasing decision as well as the resultant production cost is the salvage value. As explained earlier, the salvage value is used as a proxy for the carrying cost; it is a way to simulate a closed loop process in a two stage model. In effect, the salvage value acts as the penalty for purchasing excess scrap, as in a two stage model this excess scrap will be sold after demand is realized. The greater the salvage value, the higher the resale value of excess scrap and thus the lower the effective carrying cost. Similarly, the lower the salvage value, the greater the discount the excess scrap must be sold for, the larger the penalty paid.

Analogous with this theoretical framework, Figure 12 exhibits the effect of changing salvage value on the amount of scrap purchased. Using a base case of 95% and varying from 88-98%, the amount of scrap purchased exhibits a clearly increasing trend with increasing salvage value. This finding can be attributed to the fact that increasing the salvage value reduces the risk of having too high a hedge, given by the amount of scrap purchased.

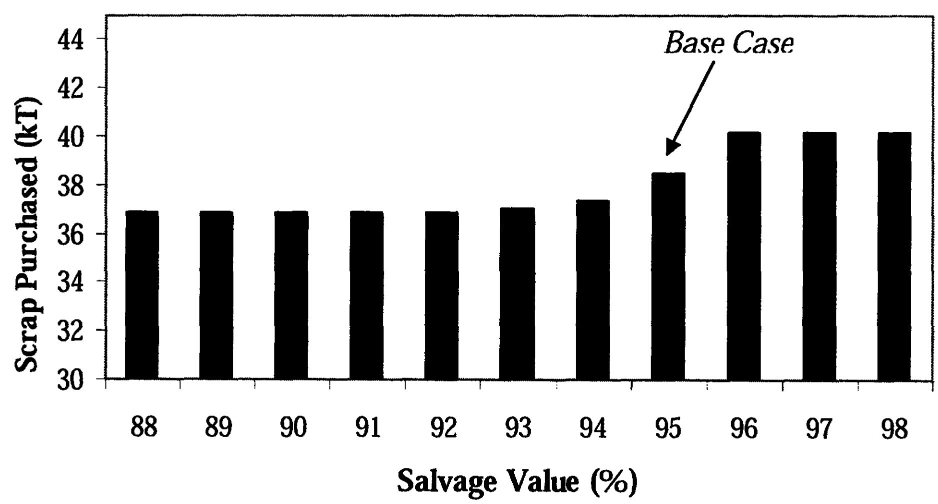

Figure 12 Scrap Purchased as a function of Salvage Value. Scrap purchased is held constant over a range of salvage values, but increases when salvage value is greater than 93%.

It is interesting to note, however, that over some ranges of salvage values, the amount of scrap purchased is held constant. Had the base case been a salvage value of 91%, varying this to any value between 88% and 93% would not have had an impact on the amount of scrap purchased. Whereas with a base case of 95%, varying this to either 94% or 96% will in fact result in significant changes in scrap purchasing. The 8.5% jump in scrap purchased between a salvage value of 93% and 96% underlines the importance of obtaining a relatively accurate estimation of the salvage value in order to identify the optimal amounts of scrap to pre-purchase with a cost minimization framework.

As the salvage value increases, the greater the amount of scrap purchased, and in turn the lower the production cost, as seen in Figure 13. As explained in earlier sections, the production cost is equivalent to the cost of scrap purchased plus the cost of primary material purchased once demand is realized, minus the revenue from selling excess scrap.

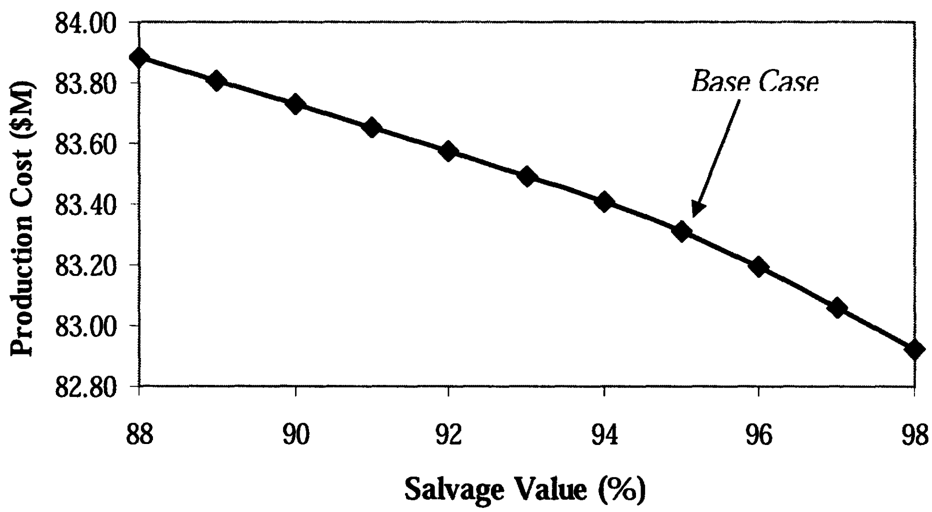

Figure 13 Decreasing production cost as a function of increasing salvage value. The higher the salvage value, the higher the resale value of excess scrap and thus the lower the production cost.

The trend observed in Figure 13 is a direct result of increased scrap purchased, due to higher resale value of excess scrap. The higher the resale value of excess scrap, the lower the penalty of purchasing scrap, and thus the greater the motivation to increase scrap pre-purchasing. Ignoring the compositional constraints in the alloying process, the greater the scrap purchased, the less primary material needs to be purchased once demand is realized. The price difference between scrap and primary implies that as more scrap is purchased relative to primary material, the larger the potential savings due to the lower effective cost.

It is imperative to note that the data presented in the last two figures used the expanded probability distribution of demand as described by Figure 11(b). When comparing the total scrap purchased and production costs of the expanded case with the limited case, we notice the same overall trend. As salvage value increases, the amount of scrap purchased increases and in turn so does the production cost.

Figure 14 presents the effect of a larger range of salvage values on the amount of scrap purchased in both the expanded and limited case. Although both the limited and expanded cases exhibit the same overall trend, the rate of increase in scrap purchased as a function of increasing salvage value is greater in the expanded case than in the limited case. Additionally, almost throughout the whole range of salvage values depicted in this figure, the amount of scrap purchased in the expanded case is equal to or greater than that in the limited case. This observation may imply a convex behavior relating scrap purchased and uncertainty.

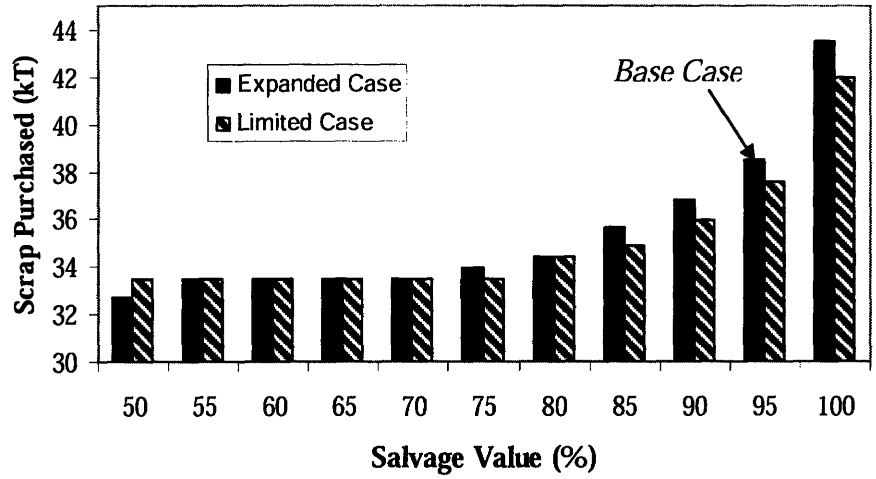

Figure 14 Increased scrap purchased as a function of salvage value for both the expanded and limited models. Increasing the resolution of the model keeps scrap purchased either equal to or greater than scrap purchased in the limited case.

Based on the hedging behavior outlined above, the increased scrap purchased in the expanded case leads to a lowering of the production cost. As the salvage increases, however, the gap in production cost between the expanded and limited cases decreases, as shown in Figure 15.

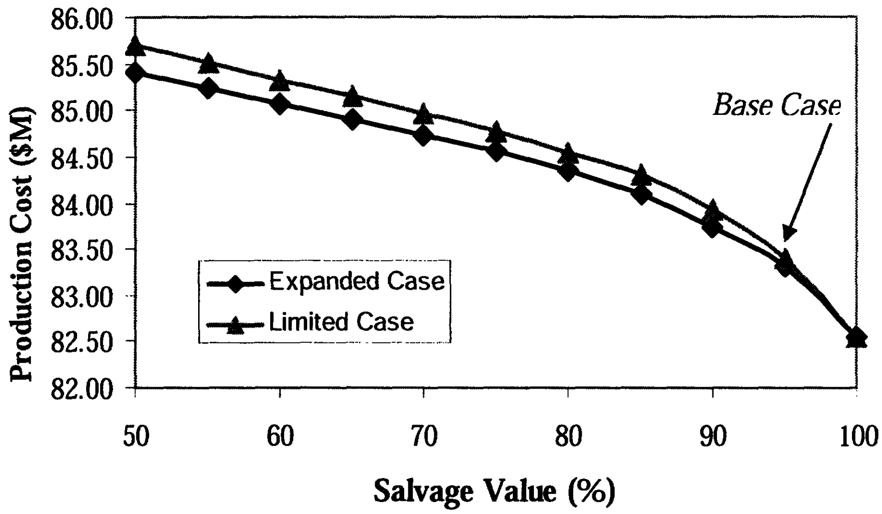

Figure 15 Decreased production costs as a function of increasing salvage value. Increasing the resolution of the model has a clear effect of decreasing the cost of production relative to the limited case.

Recall that due to the price differential, having scrap in inventory is viewed as a hedge against uncertainty in demand. The higher resolution case implies greater uncertain demand scenarios being realized than the limited model, and thus there is a greater need to hedge against this added resolution. Moreover, as the salvage value increases, the effective cost of hedging decreases, thereby strengthening the motivation to hedge and thus increasing the scrap purchased. The rationale of increasing hedging with increased uncertainty is in line with the fundamental objective of minimizing total production cost, and may help rationalize the differences observed in purchasing decisions using both the limited and expanded models.

Once the salvage value reaches the unrealistic value of 100%, the production cost using both the limited and expanded cases is identical. A salvage value of 100% represents an effective zero carrying cost of excess scrap, and thus the production costs using cases of varying resolution will converge at this point. Thus, the increase in resolution of the model will lead to an increase in the hedging, leading to greater scrap purchases and lower costs of production.

4.2 Coefficient of Variation

The data above is conducted using a coefficient of variation equal to 14% in both the limited and expanded cases. Increasing the demand uncertainty, given by the coefficient of variation, is another factor that will impact the scrap purchasing behavior. Figure 16 Increased scrap purchased as a function of increasing coefficient of variation. Scrap purchased acts as a hedge against increased uncertainty. Figure 16 Increased scrap purchased as a function of increasing coefficient of variation. Scrap purchased acts as a hedge against increased uncertainty. Figure 16 below is a representation of the change in scrap purchased as a function of coefficient of variation.

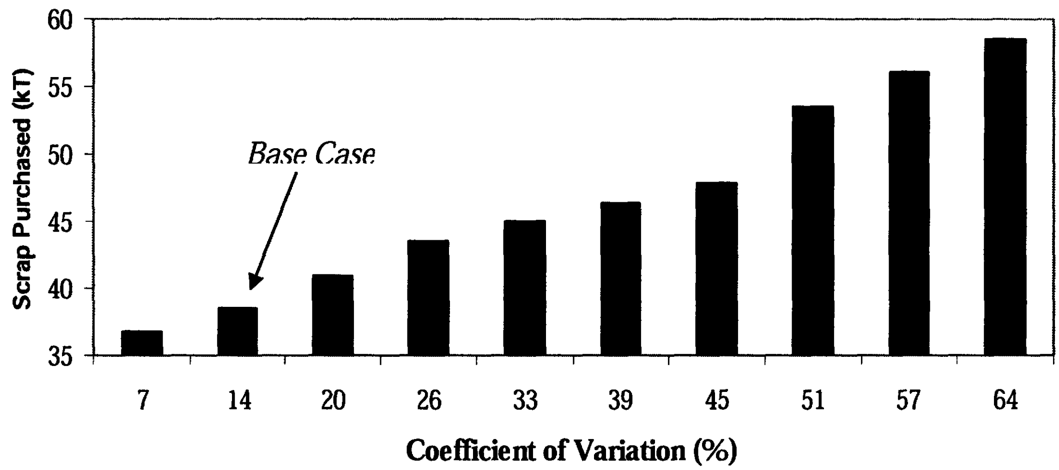

Figure 16 Increased scrap purchased as a function of increasing coefficient of variation. Scrap purchased acts as a hedge against increased uncertainty.

The amount of scrap purchased increases with increasing demand uncertainty. Although at first glance, this may appear to be counterintuitive, this behavior can again be characterized by examining the fundamental reasons why hedging occurs. Due to the arbitrage arising from the price differential between primary and secondary materials, purchasing scrap is used as a production tool against increased demand uncertainty. It is essential to mention that this type of hedging behavior is aimed at managing the risk associated with demand uncertainty and does not necessarily manage other forms of uncertainty mentioned earlier.

Although scrap pre-purchasing can help to somewhat marginalize the effect of demand uncertainty, it does not completely eliminate it. Figure 17 shows the increase in production costs associated with increasing demand uncertainty. This increase in costs can be attributed to non-optimal scrap purchasing. At greater demand uncertainty levels, the amount of scrap purchased may be either too low or too high relative to the actual demand. If too little scrap is purchased, the producer pays a penalty associated with the difference in price between primary and secondary materials. Similarly, if the amount of scrap purchased is too large, the penalty paid by the producer is associated with the difference between the resale value of excess scrap and the original price, determined by the salvage value.

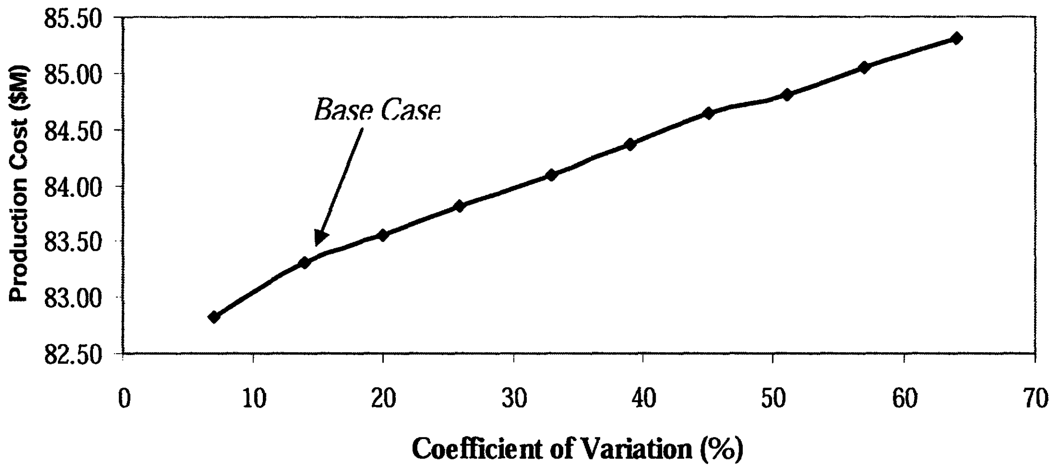

Figure 17 Increased production cost as a function of increased coefficient of variation. Uncertainty complicates the scrap purchasing process and thus leads to increases in production costs.

Thus, as demand uncertainty increases in magnitude, predicting the actual demand becomes increasingly difficult which leads to higher production costs that the producer bears.

4.3 Scrap Cost

The main driver for scrap purchasing relies on the price differential between scrap and primary materials. As mentioned earlier, obtaining specific scrap prices is a non-trivial task, and thus, for this study, scrap is assumed to be some percentage of the primary aluminum price. The base case of scrap cost equaling 75% of the primary cost is in line with aggregate scrap prices[14].

Figure 18 presents the change in scrap purchased as a function of changing scrap prices relative to primary, using the expanded resolution model. The higher the scrap cost, the lower the scrap purchased. Decreasing the size of the price differential between primary and secondary materials lessens the benefit of using scrap as a substitute for primary aluminum. Because the scrap cost is measured relative to the primary material, an increase in the scrap cost is analogous to a decrease in the cost of the primary. Thus, the higher the cost of scrap, the less scrap purchased.

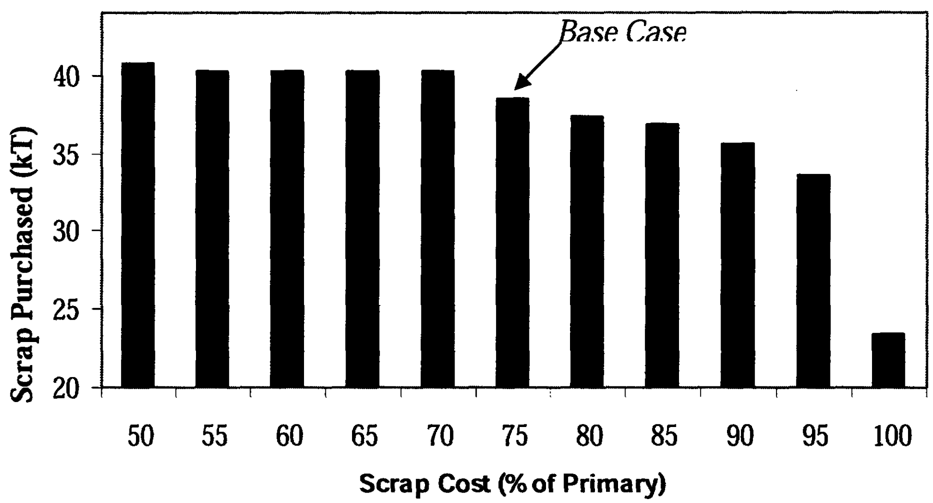

Figure 18 Decreasing amount of total scrap purchased with increasing cost of secondary materials (as compared to primary aluminum). Interestingly, scrap materials are still used even when costs are equivalent.

Figure 18 exhibits a decreasing trend, with the largest drop-off in scrap purchased arising between 95% and 100%. The amount of scrap purchased when scrap and primary material are equivalent in cost is non-zero. This behavior is highly dependent on the chemical compositions of both the scrap materials as well as of the alloys. It seems intuitive that when scrap and primary material are of equal cost, only primary material would be purchased, however, some of the scrap aluminum in this case study contains alloying elements that are needed in the alloying process of cast alloys 380 and 390 evaluated here. Though the scrap is equal in price to the primary aluminum, it is still less expensive than many of the alloying elements.

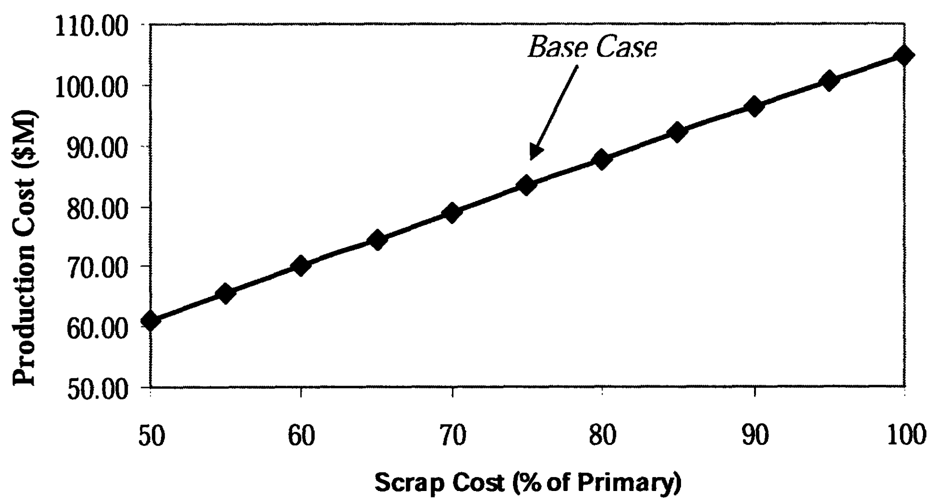

Figure 19 Increased production cost as a function of increasing scrap cost. As the cost of raw materials increases, the total cost of production increases as well.

Total production costs increase linearly with increasing scrap costs as shown in Figure 19 above. Given the mix of primary and secondary aluminum that is needed in the production of the alloys, an increase in the price of the raw materials will inevitably lead to an increase in the total production cost.

4.4 Scrap Usage by Alloy

Based on the chemical compositions of both the alloys as well as the scraps employed in the model, a study on the versatility of scraps can be conducted. Figure 20 presents the amount of scrap purchased for each alloy. From this figure, it is clear that brake and bumper scrap are the predominant components of the 390 alloy, where transmission and heat exchanger scraps are used in the 380 alloy. These results are in line with the chemical compositions outlined in Table 2 and Table 3.

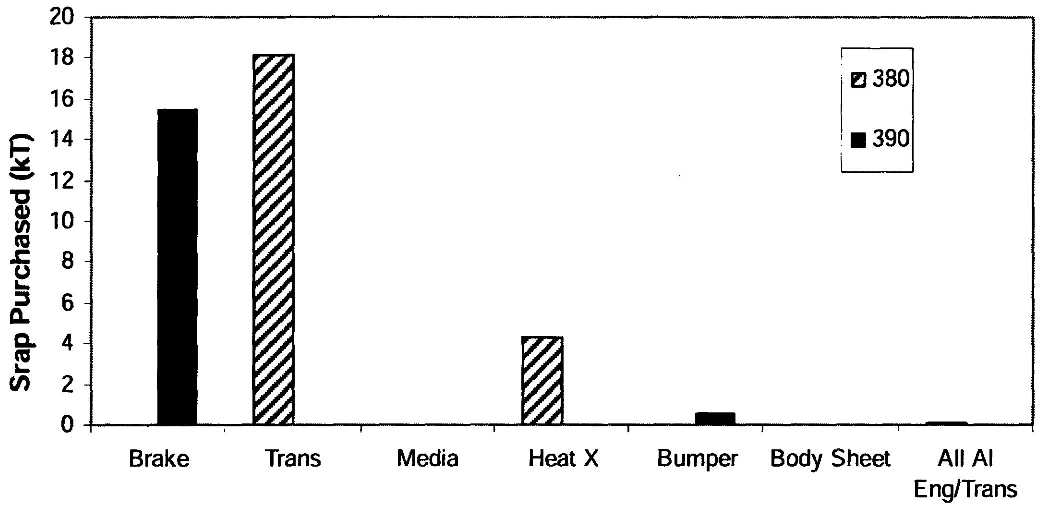

Figure 20 Scrap usage by alloy. Alloy 380 primarily uses transmission and heat exchanger scraps, while alloy 390 predominantly uses brake and bumper scraps.

Brake scrap contains 1.23 wt% magnesium, which is above the maximum magnesium threshold for the 380 alloy. Thus, this scrap type is predominantly used in the production of the 390 alloy. Similarly, the transmission and heat exchanger scraps contain higher zinc and manganese content, respectively, than the maximum threshold for the 390 alloy and thus are predominantly used in the 380 alloy.

When comparing the limited and expanded cases, the scrap break downs exhibit similar results, as seen in Figure 21. The 4 main scrap types used in both the limited and expanded cases were brake, transmission, heat exchanger and bumper. In the expanded case, more transmission scrap was purchased than in the limited case. Meanwhile, less brake and heat exchange was purchased, with the amount of bumper scrap being purchased being almost equal. However, the increase in transmission purchased outweighs the decrease in brake and heat exchange purchased, implying that the total amount of scrap purchased in the expanded case was greater than in the limited case.

This result is consistent with the trend observed in Figure 12, using a salvage value of 95% as the base case.

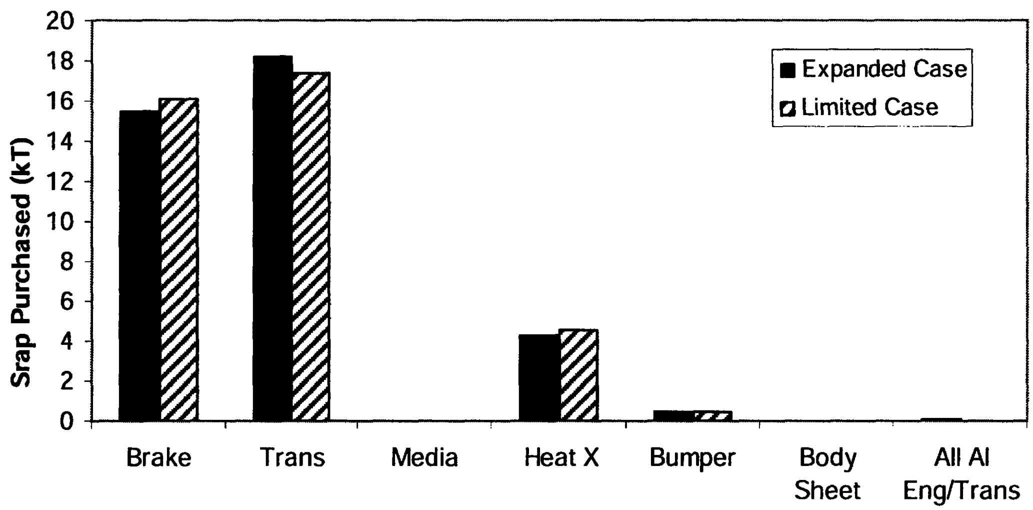

Figure 21 Comparison of overall scrap purchased for both the expanded and limited demand resolution cases shown by scrap type.

4.5 Shadow Prices

A powerful set of results that emerge from linear optimization solutions can provide a way to quantify the sensitivity of the optimal result to changes in assumptions. Among these sensitivity parameters are what is known as "shadow prices".

In this context, the shadow price is defined as the increase in savings (or further reduction in cost) associated with relaxing one of the constraints by one unit as expressed by equation 14. Each shadow price has a range of validity associated with it.

$$SP_{\text{Constraint}} = \frac{\delta(\text{Production Cost})}{\delta(\text{Constraint})} \tag{14}$$

Table 4 lists the binding compositional constraints as well as the resultant savings associated with relaxing them. For the maximum compositional constraint for magnesium in alloy 380, relaxing the constraint by unit would result in cost savings of $1777 per ton. Similarly, for the minimum compositional constraint for copper in alloy 390, decreasing the constraint by one unit would lead to a cost saving of $13 per ton. It is clear from the table that relaxing the same constraints results in greater savings in the 390 alloy than the 380 alloy. This is consistent with the compositional specifications of the alloys presented in Table 3.

Table 4 Binding shadow prices for compositional constraints

Element	Shadow Price ($/T)	Alloy	Max/Min
Mg	1776.96	390	Max
Mg	888.48	380	Max
Cu	13.21	390	Min
Fe	10.65	390	Max
Cu	6.61	380	Min
Fe	5.33	380	Max
Si	4.88	390	Max
Si	2.44	380	Max

Although six alloying elements are considered and listed in Table 2, only four of those elements are binding and act as constraints in the model. These elements are magnesium, copper, iron and silicon. From Table 4, it is clear that magnesium composition acts as the most binding constraint meaning it is the element that limits the potential scrap consumption the greatest, from a compositional perspective.

Aside from copper, all of the binding constraints are associated with the maximum specifications of these elements. The consequences for being out of specification are non-symmetric, as having lower content that the minimum is better than having higher content than the maximum. If the elemental composition of the scrap is lower than the minimum required in the alloy, the pure alloying element can be added to compensate for the missing weight percent. However, if the elemental composition of the scrap is greater than the maximum allowed in the alloy, this will limit the amount of that specific scrap that be used for that specific alloy.

Because of the relatively high magnesium content in the scraps, and the relatively low maximum specification for magnesium in the alloys, this element acts as a major limitation to increasing scrap purchasing. On the other end of the spectrum, the maximum specification for silicon in both alloys is rather high compared to the content in the scrap materials and thus it is not a major obstacle to scrap usage.

The minimum composition of copper in both alloys, however, is rather high, and of the 4 binding elements, it is the only one where the minimum composition is a binding constraint. The weight percent of copper in the various scrap types is relatively low compared to the range of copper required for the alloys and thus acts as a limit to scrap use and purchasing. Additionally, it can be noted that the price of the copper alloying element is much greater than the other alloying elements [28] and as such tends to be the only alloying element where the minimum composition acts as the binding constraint.

Manganese and zinc are not binding mainly because the weight percent of these two elements in the alloys is well within the acceptable range for both alloys. Thus, relaxing either the minimum or maximum constraints by one unit will not affect the scrap purchased and thus will have no impact on the production cost. As evidenced above, compositional specifications play a paramount role in the materials selection process as a whole, and in scrap purchasing and usage in particular.

Thus, although the use of secondary materials reduces overall production costs, the stochastic nature of demand complicates the batch planning process faced by producers. The purchasing decision of optimal amounts of scrap is affected by numerous factors including model resolution, salvage or resale value of excess scrap, the coefficient of variation of demand, scrap cost and compositional constraints. These factors may vary depending on producer-specific scenarios. Nonetheless, understanding the relationship between these considerations and the resultant optimal scrap purchased provides producers with the ability to proactively mitigate the effects of demand uncertainty. The sensitivity analysis presented also allows producers to translate the optimal decisions presented to their specific production inputs.

5 Conclusions

Recently, the growth of aluminum demand has greatly outpaced its primary production, leading to perceived shortages in the aluminum market and sky-rocketing prices. One tool that can be employed to help marginalize this problem and increase sustainability is the use of secondary or recycled aluminum, which can offer both environmental and economic benefits. Increased use of recycled aluminum is limited by a number of factors; one of which is the many forms of uncertainty encountered by producers. One form of uncertainty that is evaluated in this study is the demand for finished alloys which is typically extremely volatile and difficult to predict.

The recourse model presented in this research is aimed at managing the demand uncertainty faced by batch planners in the production process. Previous research conducted on this subject has shown the benefits of using this type of model; this study's specific unique addition is an increase in the demand scenario resolution of the model. The two primary metrics evaluated using this model are the amount of scrap purchased as well as the overall production cost. These two metrics are sensitive to numerous assumptions on the input factors that impact the scrap purchasing decisions.

Increasing the model resolution resulted in an increase in the scrap purchased and a subsequent reduction in production cost. The increased resolution expanded case more closely models the realistic continuous probability distribution function than the limited case and allows the producer to understand the optimal solutions more effectively as well as better manage the uncertainty, as hypothesized. Meanwhile, increasing the salvage value led to an increase in scrap purchasing and a reduction in production cost. In the model the salvage value represents the resale value of excess scrap and acts as a proxy for carrying cost. Increasing the salvage value reduces the risk of being too heavily hedged, characterized by purchasing too much scrap. By decreasing the penalty of having excess scrap, the production cost exhibits a decreasing trend as salvage value increases.

A similar trend is observed when assessing the sensitivity of the model with respect to increased demand uncertainty given by the coefficient of variation. Increasing the coefficient of variation results in the need for increased hedging to mitigate the added uncertainty, which in turn leads to an increase in scrap purchased. Nonetheless, uncertainty is inherently costly and as such, as uncertainty increases, predicting the realized demand becomes increasingly difficult and will thereby lead to increases in production costs.

Increasing the cost of scrap relative to primary will lead to a decrease in the scrap purchased and a resultant increase in production cost. As the price differential between primary and scrap materials, the incentive to purchase scrap decreases. Similarly, as the price of raw materials increases, the overall production cost will increase as well.

From a compositional perspective, it was found that given the mix of scraps and alloys under consideration, manganese and zinc were non-binding constraints. This would indicate that an increase in these elements in the scrap materials would not adversely affect the optimal amount of scrap purchased or production cost. On the other end of the spectrum, magnesium was the largest binding compositional constraint in magnitude for both the 380 and 390 alloys. Through the utilization of the compositional shadow prices to understand the cost savings associated with relaxing various specification constraints, producers have the ability to target elemental considerations that will have the largest possibility to further decrease costs.

Overall, this model provides producers with a tool to effectively implement an efficient raw materials management strategy while considering demand uncertainty. Although increasing the model resolution results in a small decrease in the computational efficiency, this negative is far outweighed by the positive benefits of having increased number of demand scenarios. Specifically, this benefit provides producers with more comprehensive and realistic insights on how to manage demand uncertainty in a cost-minimizing materials selection framework.

6 Future Work

Future studies in this field may focus on further modifying the model's resolution. Although this research compares the cases of five and seven discrete demand scenarios, further insight may be obtained by increasing the resolution to include nine or eleven scenarios. This may help in assessing how the trend of decreasing production costs due to increased demand scenarios behaves at larger resolutions. At some point, the positive trade-off between decreased computational efficiency and increased insight to model behavior will shift; quantifying at what resolution this takes place would be beneficial to the modeler.

Moreover, it may be useful to further examine the effect of increased uncertainty on the batch planning process. Although it was believed that added uncertainty would lead to increased hedging, this trend may be asymptotic where an additional unit of hedging may not lead to increased risk mitigation.

Further, the sole form of uncertainty considered in this study was demand based. As mentioned earlier, price and compositional uncertainty are two supply-side factors that will have a direct impact on the batch planning process. Engineering new models that consider these sources of uncertainty may assist in obtaining a more comprehensive decision making mechanism. A dual model that considers multiple forms of uncertainty may provide deeper insight on the dynamic interplay between supply and demand that a batch planner is faced with.

This study was simplified to focus on two cast alloys, which have unique compositional constraints. As mentioned earlier, however, there exist over 1,400 different wrought and cast aluminum alloys that are categorized by their chemical compositions. Wrought alloys can be broken up into 2XXX, 3XXX, 4XXX, 5XXX and 6XXX categorizations, with each group defined by distinguishable compositional constraints. Running this model with wrought alloys from the different series will affect the role of compositional constraints on the scrap purchasing process.

Although this model used aluminum as a case study, it can be expanded and applied to other industries that have established recycling mechanisms such as the steel, glass and plastics markets. These industries will undoubtedly have differing recycling rates and price differentials between primary and secondary materials, which as shown earlier will impact the production costs. Because demand uncertainty is a facet of production that affects all industries, enhanced recycling arising from mitigating risk may prove to be an effective tool to minimize production costs across a wide array of production processes.

The results of this study showed that only 4 of the scraps were used by the two alloys considered. By expanding the scope of the model and evaluating differing alloys, it may be possible to assess the versatilities of the different scraps. Moreover, running the model with scraps from different sources, for example secondary materials obtained from aerospace or packaging industries, may yield differing results and versatilities when compared to the automobile data set.

References

1. Gaustad, G. *Raw Material Usage Strategies Under Conditions of Uncertain Alloy Demand.* in *135th TMS Annual Meeting and Exposition.* 2006. San Antonio, Texas.
2. Institute, I.A., *The Aluminum Industry's Sustainable Development Report.* 2003: London.
3. Hatch, J.E., *Aluminum: Properties and Physical Metallurgy.* 1984: ASM International. 424.
4. Plunkert, P., *Mineral Commodity Summaries: Aluminum.* 2007, U.S. Geological Survey.
5. Moore, D.M., *Environment & Life Cycle Benefits of Automotive Aluminum.* 2001, Alcan: Toronto.
6. Institute, I.A., *Aluminum for Future Generations.* 2005: London. p. 7.
7. Plunkert, P., *Aluminum Recycling in the United States in 2000.* 2000, U.S. Geological Survey.
8. Institute, C.M., *2004 Annual Report & Can Shipments Report.* 2004: Can Manufacturers Institute. p. 24.
9. RNCOS, *US Aluminum Market,* in *Online Business Research.* 2006, RNCOS.
10. Kutz, M., *Handbook of Materials Selection.* 2002, New York: John Wiley & Sons.
11. Ashby, M., *Materials Selection in Mechanical Design.* 1999: Butterworth-Heinemann. 502.
12. R. Quinkertz, G.R., D. Liebig, *A Scenario to Optimize the Energy Demand of Aluminum Production Depending on the Recycling Quota.* Resources, Conservation and Recycling, 2001. **33**(3): p. 217-234.
13. Institute, C.R., *Aluminum Can Recycling Statistics.* 2006, Containter Recycling Institute.
14. Market, A.M., *Nonferrous Metal Scrap Prices,* in *American Metal Market.* 2007.
15. Gaustad, G.L., P.; Kirchain, R., *Raw Material Usage Strategies Under Conditions of Uncertain Alloy Demand.* TMS: The Minerals, Metals & Materials Society, 2006. **4**: p. 891-896.
16. Lee, H.L., *The Bullwhip Effect in Supply Chains.* Sloan Management Review, 1997. **38**(3): p. 93-102.
17. A. Cosquer, R.K., *Optimizing The Reuse of Light Metals from End-of-Life Vehicles: Lessons from Closed Loop Simulations.* TMS: The Minerals, Metals & Materials Society, 2003. **AA3**.
18. Preston Li, R.K., *Modeling Scrap Sourcing Decisions Given Uncertain Demand.* TMS: The Minerals, Metals & Materials Society, 2005: p. 849-855.
19. Luenberger, D.G., *Linear and Nonlinear Programming.* 2003, Norwell, MA: Addison-Wesley.
20. Granot, D., *A generalized linear production model: A unifying model.* Mathematical Programming, 2005. **34**(2): p. 212-222.
21. Florian, M., *Deterministic Production Planning: Algorithms and Complexity.* Management Science, 1980. **26**(7): p. 669-679.

22. Dekker, R., *Applications of maintenance optimization models: a review and analysis.* Reliability Engineering and System Safety, 1996. **51**: p. 229-240.
23. Castillo, E., *Building and Solving Mathematical Programming Models in Engineering and Science.* Journal of Applied Mathematics and Stochastic Analysis, 2002. **15**(4): p. 389-391.
24. Manne, A., *Linear Programming and Sequential Decisions.* Management Science, 1959. **6**(3): p. 259-267.
25. Willem K Haneveld, M.v.d.V., *Stochastic integer programming: General models and algorithms.* Annals of Operations Research, 2004. **85**: p. 39-57.
26. Birge, J., *Introduction to Stochastic Programming.* Springer Series in Operations Research. 1997, New York: Springer.
27. Li, P.P.-C., *Strategies For Aluminum Recycling: Insights From Material System Optimization,* in *Materials Science and Engineering.* 2005, Massachusetts Institute of Technology: Cambridge, MA. p. 185.
28. Survey, U.S.G., *Mineral Commodity Summaries.* 2007, U.S. Geological Survey.
29. Gorban, L., *An In-Depth Analysis of Automotive Aluminum Recycling in the Year 2010.* SAE transactions, 1994. **103**(5): p. 17-35.