Quantitative Purchasing Structure for Ferrous Scrap

by Andrew Stefanek

B.S. in Electrical Engineering, May 2009, Marquette University
M.S. in Systems Engineering, December 2015, Johns Hopkins University

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Praxis directed by

Amirhossein Etemadi
Assistant Professor of Engineering and Applied Science

Ebrahim Malalla
Visiting Associate Professor of Engineering and Applied Science

The School of Engineering and Applied Science of The George Washington University certifies that Andrew Barry Stefanek has passed the Final Examination for the degree of Doctor of Engineering as of December 4, 2018. This is the final and approved form of the Praxis.

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Andrew Barry Stefanek

Praxis Research Committee:

Amirhossein Etemadi, Assistant Professor of Engineering and Applied Science, Praxis Co-Director

Ebrahim Malalla, Visiting Associate Professor of Engineering and Applied Science, Praxis Co-Director

Timothy Blackburn, Professorial Lecturer of Engineering Management and Systems Engineering, Committee Member

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Dedication

The author wishes to thank his family for the support and encouragement they constantly provide as it continues to motivate me each and every day. None of this would have been possible without the H.O.P. I am truly, truly blessed for being surrounded by such an amazing and wonderful family. I am so grateful for them and look forward towards continuing this journey of life with them. Mom, Dad, John, Catherine and Alex, Megan and Trevor and Noah – Love you all!

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Abstract of Praxis

Quantitative Purchasing Structure for Ferrous Scrap

The majority of steel manufacturers within the United States have employed electric arc furnaces (EAFs), which melt raw materials, for the production of steel. The raw material used in EAFs is referred to as steel, or ferrous, scrap. There are many different grades of ferrous scrap, which are classified by the following attributes: size, density, and chemistry weight percentages of residual elements. Methods currently applied to assess the price of ferrous scrap employ qualitative measures. Furthermore, the largest unknown when procuring ferrous scrap is the chemistry weight percentages of residual elements. This attribute is the most critical to the steel manufacturer as it affects the quality of steel. The goal of the research conducted for this praxis was to create a pricing model that predicted the value-in-use price of ferrous scrap per supplier using a quantitative purchasing structure. The solution to this problem was attained through a pricing model. As this research was applied, the pricing models developed during this research are readily available for use within the steel industry. Results from the pricing models displayed a significant improvement in predicting the value-in-use ferrous scrap price over the current procurement process used by the steel manufacturer.

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Chapter 1 – Introduction

The steel industry has been around for centuries, and when steel entered into mass production, it quickly became essential to the creation of modern civilization. There is always demand for this product as the world is in a constant state of development. According to Statista (2018) in 2017, 82 million metric tons of steel were produced within the United States alone. Up until the middle of the 20th century, steel was made using natural resources, specifically: coal, iron ore, and limestone. It was around this time when truncated mills, or mini mills, came into existence and provided a new method to make steel. Rather than using natural resources as their primary ingredients to create steel like integrated steel mills had done previously, mini mills use recycled steel instead. While the mini mills offer a cheaper and more efficient method to create steel, a persistent problem plaguing them is the variability of the weight percentage per residual element in the recycled scrap.

1.1 Background

Recycled steel, also known as ferrous scrap, occurs in many shapes and sizes. For a small portion of the available steel that can be recycled, its chemistry is known. However, the majority of the steel recycled within the United States is generated from obsolete products that have reached the end of their useful life and whose chemical composition is unknown. An automobile is an example of a product which has reached the end of its useful life and can be recycled. Recovering the steel from the automobile so that it can be recycled is not an intuitive process as the vehicle consists of many other components other than steel. Suppliers of ferrous scrap are

responsible for ensuring these unwanted components are removed prior to delivering the ferrous scrap to the mini mill. The process for recovering steel from a vehicle at the end of its useful life is depicted in Figure 1-1. Unfortunately, the processes to remove these components containing residual elements which are detrimental to the quality of steel are not always effective.

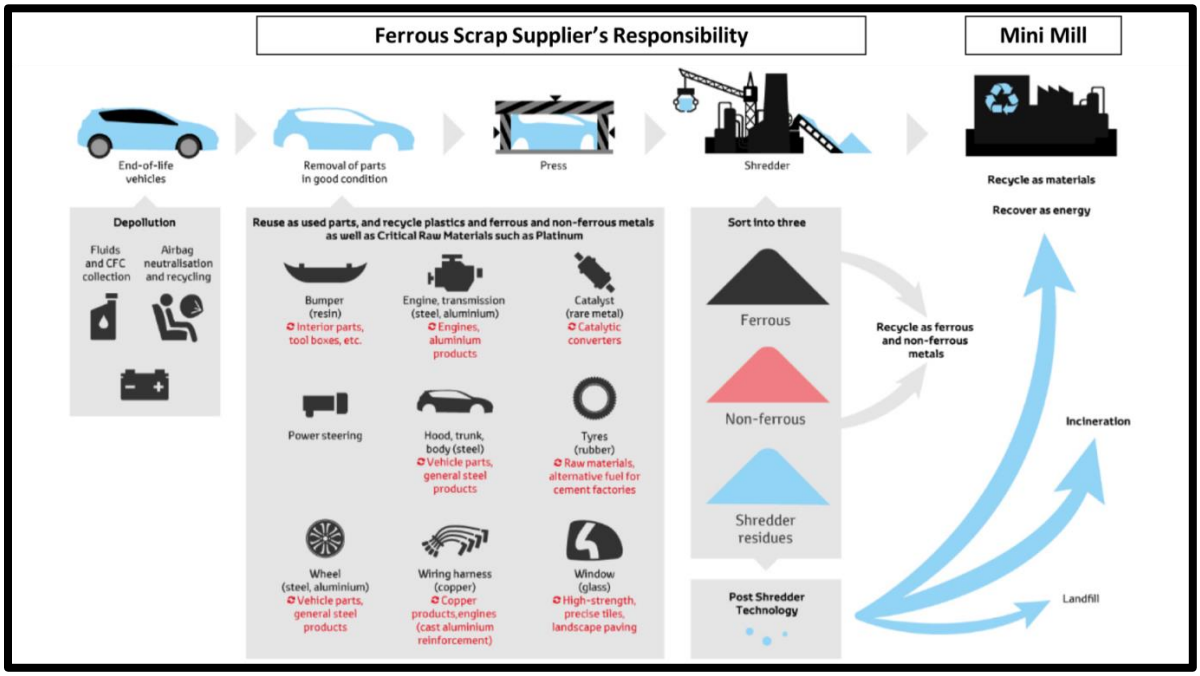


Figure 1-1: Vehicle Recycling (Toyota, 2018)

Guidelines have been published by the Institute of Scrap Recycling Industries, Inc. (ISRI) relative to the maximum allowable percentages of residual alloying elements contained within recycled steel to be considered acceptable for use in an EAF. ISRI states that "any deviations from the general classification of iron and steel scrap may be consummated by mutual agreement between buyer and seller" (Institute of Scrap Recycling Industries, 2018). Although, these percentages are not currently

considered when ferrous scrap prices are negotiated within the United States. This is an issue because these residual elements can cause a heat, which is the term used to describe the liquid steel contained within a furnace prior to it being poured out, to be wasted or downgraded. The ferrous scrap entered into the furnace has a direct impact on the chemistry of the liquid steel resulting in a heat to be wasted, downgraded, or within specification meaning the liquid steel satisfies the identified chemistry requirements. This process is shown in Figure 1-2.

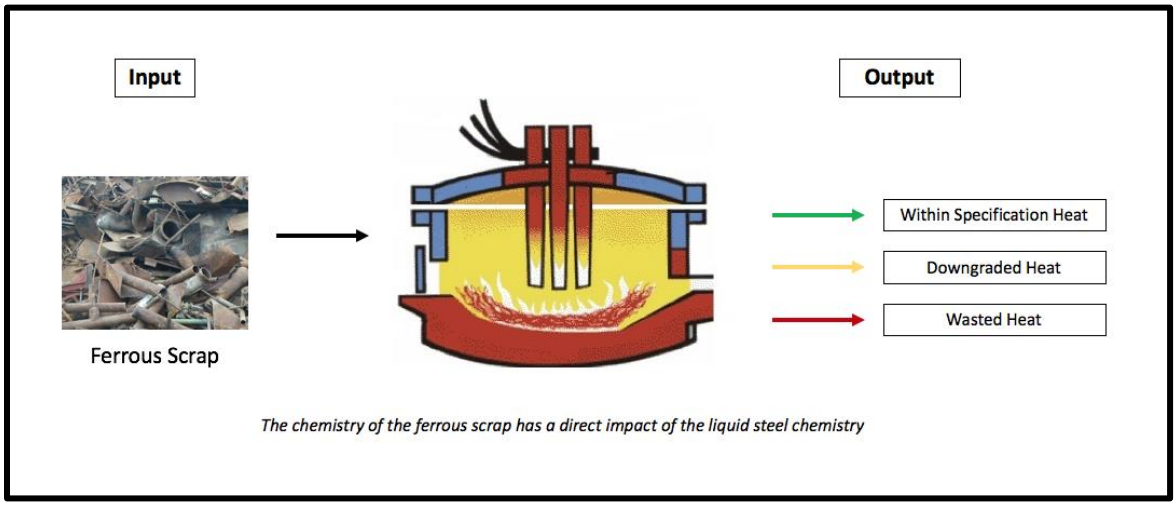


Figure 1-2: Potential Heat Outcomes

The process of melting ferrous scrap into liquid steel to create a heat is displayed in Figure 1-3. If a heat cannot be saved it is labeled as wasted and poured out on the ground to be disposed. Wasted heats are not sold as the steel cannot be used for any application. Moreover, a heat is downgraded if the liquid steel does not satisfy the chemistry requirements of the final steel product. Downgraded heats are saved and sold at a discounted price as the steel created from them is of lower

quality. Furthermore, downgrade heats have potential to create inventory issues for the mini mill because finding a customer can be difficult as the number of potential buyers is reduced since the steel's application is now limited.

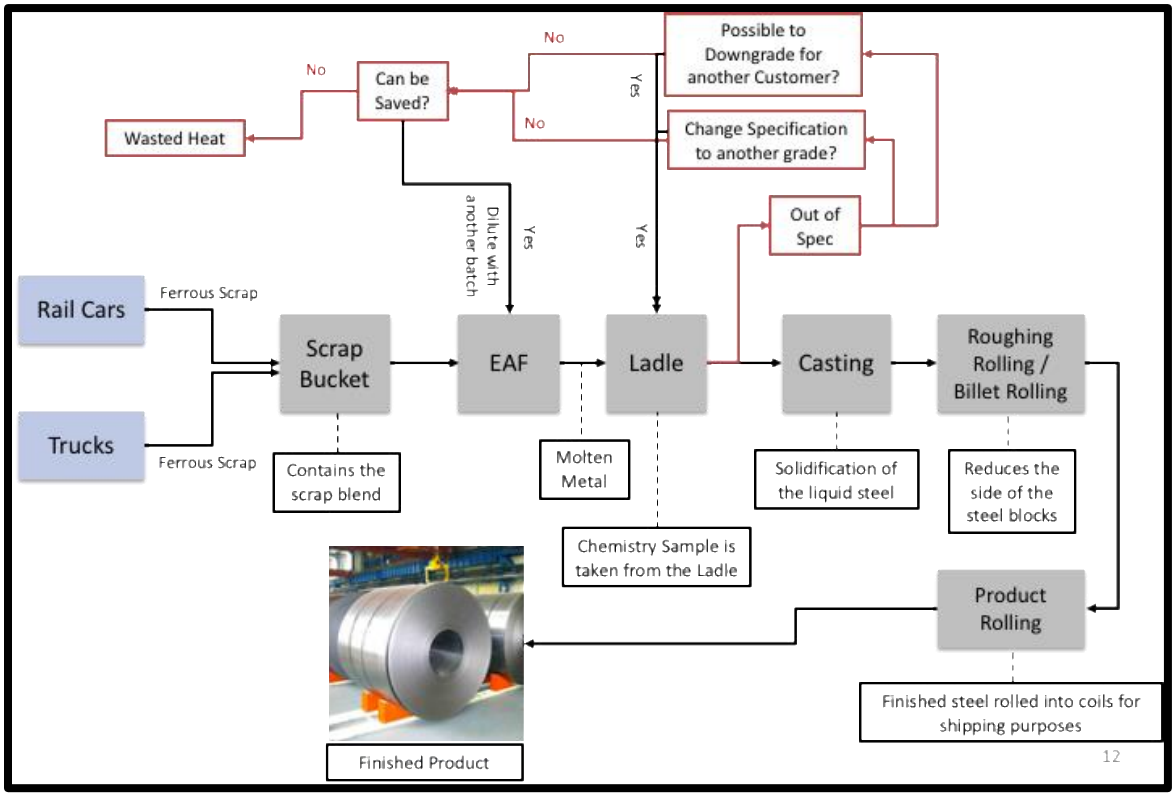


Figure 1-3: Converting Ferrous Scrap into a Heat

1.2 Problem Statement

Steel manufacturers who recycle steel (i.e. ferrous scrap) rely on an arbitrary pricing structure that does not consider the quality of the ferrous scrap or suppliers' historical contributions to wasted and downgraded heats when purchasing scrap, consequently reducing profits.

The phrase “garbage in, garbage out” is extremely relevant in the steel industry today. Within the past few decades, this industry has evolved its manufacturing processes to employ an electric arc furnace (EAF) to generate steel in a more efficient fashion. The EAF is able to create steel cheaper and faster than previously used furnaces, however a problem encountered with this method is the quality of the ferrous scrap used to make steel. Ferrous scrap can contain elevated levels of residual alloying elements, which are detrimental to the quality of the final steel product. This problem is incredibly difficult to manage from the perspective of the steel manufacturer as they lack the appropriate insight needed to determine its quality. However, the steel manufacturer is culpable regarding this lack of insight as they do not request this information from the ferrous scrap supplier.

1.2.1 Ferrous Scrap

There are a plethora of ferrous scrap grades and they are categorized by the following attributes: size, density, and chemistry. A list of the grades of ferrous scrap is located in Appendix A. The chemical composition of ferrous scrap can vary significantly from grade to grade and have considerable deviations within a grade. These deviations in chemical composition of ferrous scrap are a major issue for steel manufacturers as this problem directly contributes to wasted and downgraded heats. Compounding this problem is all of these different grades of ferrous scrap are melted together based on a recipe, which is designed to fulfill the chemistry requirements of the final steel product. The steel manufacturer attempts to optimize this recipe with the goal of generating the highest quality steel product for the lowest cost. This

approach can lead to issues because producing steel for the lowest cost might require a certain grade of ferrous scrap that might be cost-effective to use, but contains elevated levels of residual elements. Using ferrous scrap that has elevated weight percentages of residual alloying elements is problematic because these elements are detrimental to the quality of steel.

1.2.2 Wasted and Downgraded Heats

Elevated levels of residual elements contained within ferrous scrap are the most critical factors of whether a heat is wasted, downgraded, or within specification of the chemistry requirements levied against the liquid steel. The process of converting ferrous scrap into a heat resulting in the finished steel product, downgraded heat, or wasted heat is depicted above in Figure 1-3.

If the heat is within specification, the chemistry requirements of the liquid steel are satisfied and the steel is sold at full price. The heat is considered downgraded if the chemistry requirements were not met for the desired steel grade, but it was possible to change the specification to a lower steel grade. The steel manufacturer must sell the final steel product of a downgraded heat at a reduced price due to the lower steel grade. In the United States, the steel manufacturer loses approximately $10 per net ton on downgraded heats. The average weight of a heat produced is 175 net tons.

Finally, there are wasted heats to the detriment of a steel manufacturer's profits. A heat is considered wasted if it cannot be saved; consequently, it is poured out and recorded as a complete loss. A wasted heat costs a steel manufacturer located in the

United States $80,000, which does not account for labor costs required to produce either the heat or the subsequent downtime. The steel manufacturer incurs an additional cost of $10,000 per hour of downtime for each wasted heat as well as an associated profit loss of $10,000 per hour for a net loss of $20,000 per hour. Thus, not only does the ferrous scrap represent a large percentage of the overall cost in the steel production process but it also has the ability to negatively impact profits for a steel manufacturer.

1.2.3 Steel Manufacturer and Suppliers

In the steel industry, during the purchasing process, all of the different grades of ferrous scrap are treated as if they had the same chemical composition. This is a flawed assumption because the majority of ferrous scrap recycled is from obsolete products, e.g. end-of-life vehicles, which contain significant variability of the weight percentages present relative to residual elements. Steel manufacturers are aware that the majority of ferrous scrap they purchase has a percentage of residual elements, they are just uncertain of how much. Rather than confronting this problem directly with the suppliers, the steel manufacturers have decided to buy raw material high in carbon content (e.g. pig iron), which is used to dilute the ferrous scrap they purchase from suppliers. Unfortunately, the dilution process is not always effective as wasted and downgraded heats are still experienced.

In addition to diluting the ferrous scrap, majority of steel manufacturers attempt to address the variability in chemical composition of ferrous scrap through scrap optimization software. These models calculate the amount and grades of ferrous

scrap to be used per heat, effectively creating a recipe. Some of the simpler models create a couple of recipes based on experience; whereas, the more advanced ones are based on production requirements, scrap steel properties, and consider scrap market prices and availability. While some of these models are helpful, the majority of them suffer from a shortcoming relative to how the price of ferrous scrap is weighted in the model. The problem is the model weighs the price higher than the chemical composition of the ferrous scrap. The lowest priced scrap is chosen to the maximum extent possible while it potentially has the highest weight percentages of residual elements. Providing more weight to the price of ferrous scrap rather than the weight percentages of residual elements contained within ferrous scrap is not advisable as these elements increase the probability of producing wasted or downgraded heats.

Suppliers could help to alleviate this uncertainty regarding the chemical composition of the ferrous scrap for the steel manufacturer by measuring its chemistry and implementing better controls over shredding the scrap at their yards. However, suppliers are not incentivized to do either of the previously mentioned tasks. All of the risk inherent in the chemical composition variability of ferrous scrap is transferred to the steel manufacturer due to this lack of incentive. This paradigm is counterproductive for the steel manufacturer as the supplier is currently incentivized to ship the lowest quality of ferrous scrap possible to expand their margins, and hope the steel manufacturer does not correlate their mediocre ferrous scrap back to them. Therefore, the steel manufacturer is only able to reduce the risk of wasted and downgraded heats via their relationship with the supplier hoping for consistency in the chemical composition of ferrous scrap they provide, the reputation of the

supplier, and allowance of a generous margin of error when selecting the charge to blend.

1.2.4 Purchasing Structure

In the United States, the three main characteristics steel manufacturers use when determining the price of ferrous scrap are the following: the reputation of the supplier, quantity, and transportation costs. While these are reasonable factors to use when determining the price of ferrous scrap, they do not help the steel manufacturer determine the value-in-use price of a supplier's ferrous scrap. If the internal buyers of the steel manufacturer were to ask whether the ferrous scrap provided by supplier X was worth 10% more than the quoted price, the employee being asked the question would most likely use the reputation of the supplier as the basis for his or her answer. The use of a qualitative measure, which is the deciding factor, to answer a question that affects profits is suboptimal. Therefore, the arbitrary pricing structure currently used in the steel industry must be updated to remove its qualitative qualities.

The procurement process for ferrous scrap is vital to the operations of mini mills where ferrous scrap is used as it represents 85% of the overall in steel production costs (Liu et al., 2005). The current pricing structure used by steel manufacturers for ferrous scrap does not account for the variability in chemical composition of the ferrous scrap. This is a problem the United States steel industry must solve because its advantage as being the largest producer of ferrous scrap will not last forever. Eventually, ferrous scrap will have to be purchased from foreign

markets where US steel manufacturers will have even less insight into the chemical composition of ferrous scrap.

1.3 Thesis Statement

The thesis statement for this praxis is as follows:

Developing a pricing model that is driven by historical heat chemistry and accounts for the market price of ferrous scrap helps to mitigate the impact of wasted and downgraded heats, thus resulting in increased profits.

1.4 Research Objectives

The steel industry has been extensively researched since its inception many centuries past. There are many facets of the industry that have been investigated, such as: evolving the manufacturing processes to generate steel within the shortest timeframe possible, identifying residual alloying elements most detrimental to the steel's quality, and developing optimized ferrous scrap recipes for electric arc furnaces. The research conducted for this praxis related to aggregating historical steel industry financial and chemistry data, which originated in the United States, to develop predictive models used to facilitate a quantitative purchasing structure for ferrous scrap.

As stated previously, in the steel production process the cost of raw materials represents 85% of the overall cost (Liu, Pan, Meng, & Cui, 2005). The raw material used in electric arc furnaces to produce steel is ferrous scrap. If there are elevated levels of residual elements present within the ferrous scrap used, then steel manufacturers are more likely to experience wasted and downgraded heats. The profits of a steel manufacturer are impacted in two areas when wasted or downgraded

heats are experienced. First, by overpaying for the ferrous scrap used to create the heat. Second, they either have to pour out the heat, which is a complete loss of revenue, or sell the final steel product that was created from the downgrade heat at a reduced price, minimizing their profit margin. The goal of this praxis is to create a quantitative purchasing structure to predict the value-in-use price of ferrous scrap per supplier.

The value-in-use price represented the recommended or "true" price that considers the variation of residual elements in the ferrous scrap as this factor directly related to wasted and downgraded heats. The steel manufacturer preferred to pay more for scrap with elevated levels of residual elements but had a tight range relative to the chemical composition as they had more certainty in the amount of wasted heats that would be produced, which resulted in lower overall cost. This price ensures the steel manufacturer does not overpay for ferrous scrap and maximizes their profits, hence the "true" price that should have been paid.

1.5 Research Goals

Steel manufacturers currently have no insight into the chemical composition of the ferrous scrap nor request this information from the supplier during their procurement process. This increases the risk exposure of the steel manufacturer as they trust but do not verify the chemical composition of the ferrous scrap they purchase. Although, the steel manufacturer does record the chemistry of each heat produced and tracks all of the ferrous scrap delivered. Aggregating historical financial and chemistry data from the steel manufacturer, allowed for the ability to

leverage past performance behavior to determine the value-in-use price of ferrous scrap per supplier. Thus, the approach to developing a quantitative purchasing structure was to use historical financial data and leverage historical heat chemistry to correlate suppliers who contributed ferrous scrap to wasted and downgraded heats.

Correspondingly, the research goals of this praxis are as follows:

- Identify the factors that result in variations of ferrous scrap quality
- Determine how to leverage the historical ferrous scrap procurement and heat chemistry data provided by a steel manufacturer to identify statistical trends that serve as the basis of a purchasing structure
- Develop and provide a model that can be used by the internal buyers of a steel manufacturer

1.6 Research Questions and Hypotheses

In this praxis, the research question answered is the following:

1) What is the relationship between profits and purchased quantities of ferrous scrap that contain increased percentages of residual elements?
2) What are the factors a steel manufacturer can use to predict the value-in-use ferrous scrap price per supplier?

The research question identified above leads to the following corresponding hypotheses:

H_1: When steel manufacturers leverage historical heat chemistry to determine the value-in-use ferrous scrap price per supplier, profits are increased.

H_2: A steel manufacturer can use the following factors: historical weight percentages of residual elements, market price, and material weight to predict the value-in-use ferrous scrap price per supplier.

1.7 Scope of Research

The United States is currently the largest producer and consumer of ferrous scrap annually (Statista, 2018). The geographical scope of this praxis research effort was the United States ferrous scrap market because it is the largest. Concentrating on the US ferrous scrap market also helped to minimize dynamic global economic factors (e.g. tariffs) when this research was conducted as these factors are unpredictable and outside the scope of this research effort. Additionally, transportation costs were not considered in the quantitative purchasing structure because they are outside the scope of the research conducted for this praxis. Thus, the problem solved in this research focused on predicting the value-in-use ferrous scrap price per supplier by their contributions to wasted and downgraded heats as well as residual elements present in these respective heats.

1.8 Research Limitations

The scope of this research effort was bound by a very aggressive timeline. A desire to develop a real-time system which provided ferrous scrap prices in real-time based on the most recently recorded heat chemistry was rescinded due to time limitations.

1.9 Summary of Praxis Organization

The praxis in organized in the following structure:

- **Chapter 2** is the literature review, which provides research previously conducted on the ferrous scrap market relative to the supply, consumption, recycling process, and pricing. Furthermore, optimal pricing schemes are reviewed to determine their applicability to these research problems.
- **Chapter 3** details the methodology used to conduct this research and the models used for analysis. The majority of this chapter explains the techniques used and reasons why they were applied in support of the solutions to the hypotheses.
- **Chapter 4** contains the results of the research based on the methods described in the previous chapter. This chapter provides the results generated from the data analysis and models developed. A description and analysis of the results is provided.
- **Chapter 5** comprises of the summary of the research and respective findings. Moreover, suggestions were provided for future research efforts.

Chapter 2 – Literature Review

The literature review commenced with an Internet search on the following three phrases: “ferrous scrap”, “chemistry of ferrous scrap”, and “pricing structure for ferrous scrap”. As the literature survey progressed and the abstracts from journal articles, conference proceedings, web pages, books, and reports were reviewed, the initial search terms were expanded.

Once the initial research papers were identified, an iterative process was implemented to obtain the identified papers and evaluate the associated reference list contained within each paper to further locate potentially relevant sources and if they were of value, obtain them. As the search continued, it was observed that some key works were repeated in several of the papers’ reference list. Special emphasize was placed on these papers and additional efforts were made to ensure these works were acquired for this collection.

As previously stated, an effective technique to discover key works is through leveraging reference citations within relevant research papers. This iterative search was conducted using the extensive online database resources of Johns Hopkins University and The George Washington University. Thus, many of the referenced papers could be traced directly to the respective journal’s website where they were originally published.

2.1 Introduction

The steel industry started with iron ore, coal, and limestone as the primary ingredients to produce steel. Over the past couple of decades, recycling steel to create new steel has been the process used as it is more cost-efficient and effective than mining for virgin resources. As the process of recycling steel to produce new steel becomes more prevalent, it is critical the chemistry of the ferrous scrap is known prior to melting. The grade of ferrous scrap is known prior to being melted, however there are large variations within these grades. This presented a problem for the steel manufacturer because all of the ferrous scrap must be melted prior to knowing whether the chemistry requirements levied against the liquid steel are satisfied.

There is no lack of research published on the steel industry as this business has been studied since the mid-1800s, which was before steel was being mass produced. While this industry has been thoroughly researched and its market evolution well-documented, there still appears to be a gap in the body of knowledge relative to a quantitative purchasing structure for ferrous, or steel, scrap. This literature review will provide an overview of the techniques employed to obtain ferrous scrap, chemical composition of the various ferrous scrap categories, and applicable pricing strategies to the steel industry.

2.2 Ferrous Scrap

The process of recycling ferrous scrap has become increasingly important as regulation in America and other developed countries are placing greater emphasize on preserving the environment. These policies help to preserve natural resources, and force

businesses to conduct themselves in a responsible manner that is respectful of the environment rather than harming it for the sake of a profit. The production of steel has to be conducted in a sustainable fashion to ensure the natural resources (i.e. iron ore, coal, and limestone), which are finite, are available for future generations. Furthermore, not all ferrous scrap can be recycled as a percentage of it is lost due mainly to rust. The steel industry will cease to exist when all of the natural resources are consumed. Therefore, an emphasis must be placed on the recycling of ferrous scrap as it is vital to the steel industry's long-term survival.

The World Steel Association (2017) identified some significant statistics relative to the environmental advantages of recycling steel: over 1,400 kg of iron ore, 740 kg of coal, and 120 kg of limestone are saved for every 1,000 kg of steel scrap made into new steel. The European Commission (EC) has taken notice of these statistics and has promoted the recycling of ferrous scrap to increase steel independence ((EC (European Commission), 2014); (Sevigne-Itoiz, Gasol, Rieradevall, & Gabarrell, 2014)). The EC plans to achieve steel independence by increasing the annual amount of ferrous scrap recycled, which would translate to a decrease in imports relative to of the following raw materials: iron ore, coal, and limestone. Additionally, using recycled ferrous scrap to produce steel conserves more energy than other steel manufacturing techniques and reduces the worldwide waste burden by roughly 280 million tons of ferrous scrap annually (Janke, Savov, Weddige, & Schulz, 2000).

Soderholm and Ejdemo (2008) noted that while it is difficult to estimate the overall steel recycling ratio, previous studies have suggested the amount of ferrous scrap recycled is in the sixty to seventy percent range. Janke and colleagues (2000) previously

confirmed Soderholm's and Ejdemo's (2008) observation as their research relative to the steel recycling ratio provided the following results: the world occurrence of obsolete scrap in 1994 was 272 million tons, which represented 70% of the manufactured steel products in 1974. Basson (2017) further reinforces Janke's and colleagues's (2000) and Soderholm's and Ejdemo's (2008) research efforts by noting that the United States, who is the largest producer and consumer of ferrous scrap, has increased the proportion of ferrous scrap used in crude steel production from 71.7% in 2015 to 72.1% in 2016. Thus, it is encouraging these independent research efforts align with the expected annual steel recycling ratio as it provided evidence ferrous scrap will be used into the foreseeable future.

2.2.1 Furnaces

The two furnaces capable of consuming ferrous scrap are: Electric Arc Furnaces (EAFs) and Basic Oxygen Furnaces (BOFs). Ferrous scrap is the primary raw material used in EAFs to make liquid steel. When the steel making process is facilitated by an EAF, it is dependent on the supply of ferrous scrap. This is not the case when a BOF is used during the steel manufacturing process as this furnace relies more on natural resources, such as: iron ore, coke, and limestone. The BOF faces a metallurgical maximum proportion of ferrous scrap to pig iron. Thus, the total metallic input of a BOF averages to be approximately 25 percent ferrous scrap (Houck, 1994).

In his article, *American Scrap: An old-school industry globalizes*, Seabrook (2008) stated that in 2006, two out of every three tons of steel made in the U.S. originated from recycled steel, up from one ton in ten in 1980. This achievement would not have been

possible without the United States embracing the EAF to generate steel using ferrous scrap as the primary ingredient. Janke and colleagues (2000) identified in their report, *Scrap-based Steel Production and Recycling of Steel*, not only are EAFs more effective at producing steel but are also more efficient at conserving energy as compared to BOFs. Their report further defines the possibilities and limitations of recycling ferrous scrap, emphasizing the effect ferrous scrap has on the final steel product when using an EAF in the steel manufacturing process. Figure 1, below, depicts the scrap flow in steel production when using a BOF or an EAF.

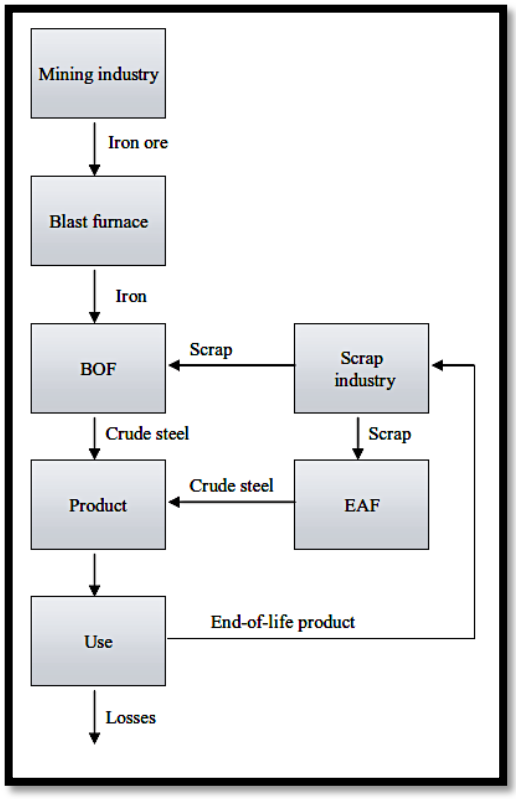


Figure 2-1: Scrap Flows in Steel Production (Soderholm & Ejdemo, 2008)

2.2.2 Categories of Ferrous Scrap

Ferrous scrap is classified in one of the three categories: home scrap, prompt scrap, and obsolete scrap. Home scrap is an unavoidable by-product of the steel production operation, thus referred to as home scrap. As an example, in the production of a steel sheet, the rough edges of the sheet must be trimmed. These pieces of trim are usually immediately recycled within the mill to produce more steel, otherwise they are sold. The chemical composition of this ferrous scrap is known since it is created during the steel production phase, which increases its value if sold.

Whereas home scrap is a by-product of the steel production operation, prompt scrap is a by-product of the steel fabrication operation. As an example, in the fabrication of an automobile fender from a steel sheet, the excess material must be trimmed. These pieces of trim are sold back to the steel mill so that they can be recycled to produce more steel. This type of scrap can be recycled shortly after it is created, and like home scrap receives a premium value because its chemical composition is known. The amount of prompt scrap typically available is minimal as it usually consists of steel shavings.

Finally, there is obsolete scrap which consists of iron or steel products that have been recycled at the end of their useful lives. Janke and colleagues (2000) observed that the chemical composition of obsolete scrap fluctuates widely depending on the following two factors: origin and degree of processing. Examples of products where obsolete scrap is obtained include the following: automobiles, steel cans, home appliances, aged buildings, railroad cars, and other electric appliances. Soderholm's and Ejdemo's (2008) studies showed that in 2004 the US steel industry recycled more steel from scrapped automobiles than was used in the domestic production of new vehicles. It is evident that the quantity of obsolete scrap in circulation dwarfs the combined amount of home and

prompt scrap available. Thus, steel manufacturers are more likely to encounter scrap in which they have minimal insight into its chemical composition.

Figure 2, below, clarifies the nomenclature used for the categories of scrap previously defined.

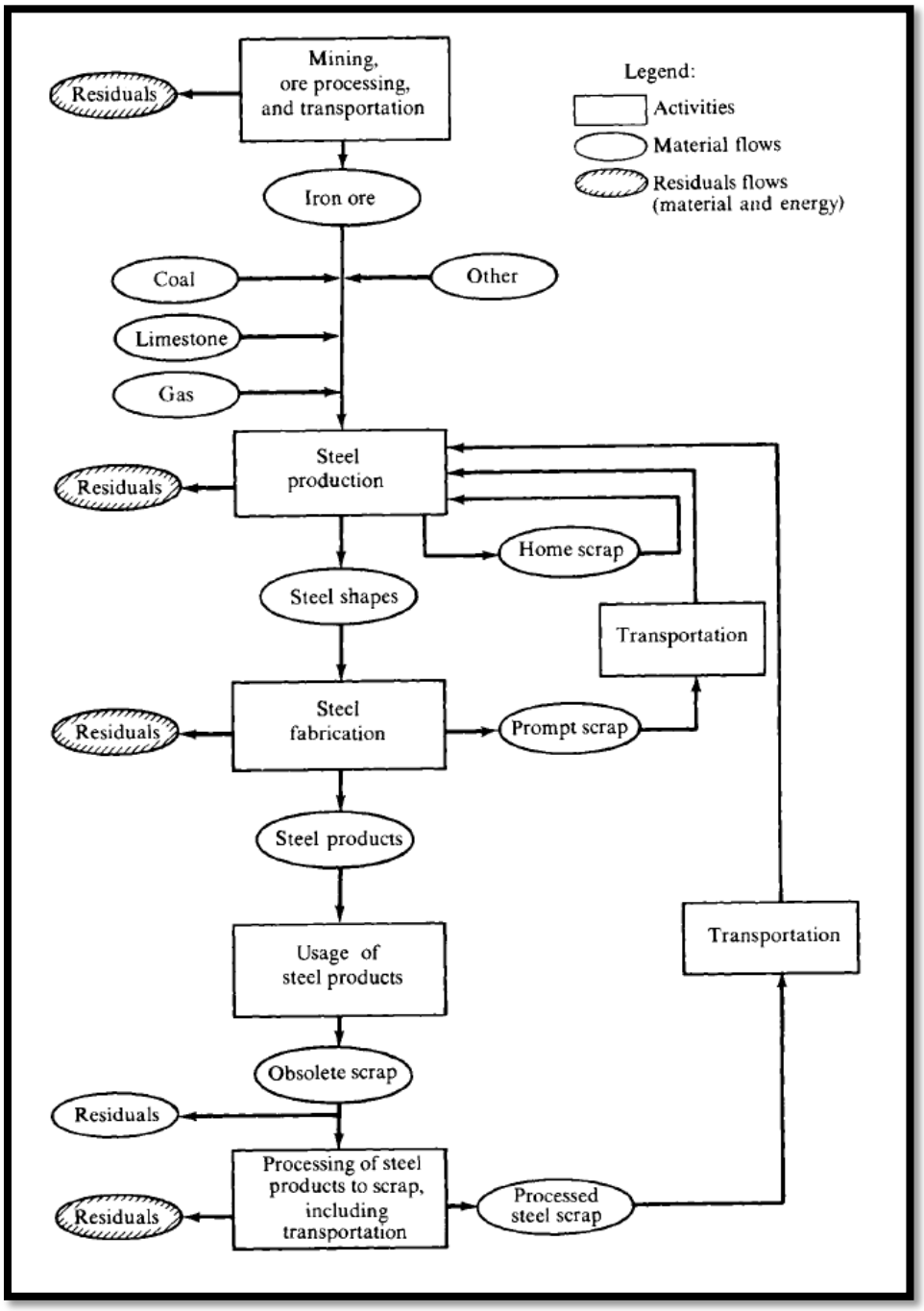


Figure 2-2: Steel Supply System Displaying Recycling Loop (Sawyer, 2016)

2.3 Chemical Composition

Steel can be recycled indefinitely as it does not degrade during the melting process, which is the greatest advantage of using it as a resource. However, certain residual elements contaminate the steel and occasionally prevent it from being recycled. Some studies have identified the need to pay due diligence to issues related to ferrous scrap quality if a sound material for steel production is to be achieved (Nakajima et al., 2013; Reck, Chambon, Hashimoto, & Graedel, 2010; Nakajima, Takeda, Miki, Matsubae, & Nagasaka, 2011; Nakamura et al., 2012). Von Gleich and colleagues (2004) demonstrated through their research impurities, such as: copper, nickel, and tin remain alloyed in steel because they are nobler than iron and not volatile. Von Gleich et al. (2004) research showed when two metals are in direct contact with one another galvanic corrosion can occur since metal is electrically active, thus the base metal (i.e. iron) corrodes more easily than copper alloys. The base metal contributed electrons to the more noble metal creating an electric circuit, which resulted in the nobler metal (i.e. copper, nickel, and tin) being preserved while the base metal (i.e. iron) was corroded. Nakajima and colleagues (2011) extended von Gleich's and associates' (2004) work by investigating technologies and the thermodynamic potential to reduce the copper content in steel. Unfortunately, Nakajima and colleagues (2011) results showed removing this impurity, copper, from liquid steel is hardly possible.

Janke and colleagues' (2000) studies showed the limits of the methods used to purify scrap (i.e. remove residual elements) and discussed how various alloying elements unintentionally introduced into the EAF negatively affect the chemistry of the liquid steel. Nakajima and colleagues (2013) confirmed through their experiments that alloying

elements (i.e. copper, chromium, nickel) are likely to be unintentionally introduced into ferrous scrap, especially those originating from highly complex products, e.g. consumer vehicles, when they are recycled. Ohno and colleagues (2014) verified Nakajima and colleagues (2013) findings by performing a material flow analysis to determine the unintentional flows of alloying elements from end-of-life vehicles into an EAF. Ohno's and colleagues' (2014) research revealed that 8% of the ferrous scrap metal entered into an EAF is alloying elements that were unintentionally introduced. These results are understandable as the majority of ferrous scrap recycled originated from products that did not consist solely of steel, but rather co-existed with other metals. This is why residual elements are so prevalent when recycling ferrous scrap.

2.3.1 Residual Alloying Element Analysis

It is well-known within the steel industry residual elements, specifically: copper and tin, present issues when recycling ferrous scrap as they negativity effect the chemistry of liquid steel. Furthermore, there are additional residual alloying elements that intrude into liquid steel. Studies have been conducted which used a technique that allowed for an assessment on the impact residual alloying elements, such as: manganese (Nakajima, Yokoyama, & Nagasaka, 2008), chromium (Johnson, Schewel, & Graedel, 2006), nickel (Reck, Muller, Rostkowski, & Graedel, 2008), and molybdenum (Nakajima, Yokoyama, Matsuno, & Nagasaka, 2007) had on the chemistry of the liquid steel. It is important to note, these studies considered each element separately and did not account for the total accompanying flow of impurities, or other alloying elements. Although, there are notable exceptions, Daigo and colleagues (2010) and Reck and associates (2010) applied this

method to simultaneously considered the residual alloying elements of: chromium and nickel contained in stainless steel. Therefore, all of this research confirmed Daigo and colleagues (201 there are residual alloying elements other than copper which are detrimental to the chemistry of liquid steel.

2.3.2 Residual Elements Detrimental to Steel Quality

Copper is one of the most undesirable elements in steelmaking, thus steel manufacturers must account for its presence and suppliers must separate as much of this element as possible prior to delivering the ferrous scrap to the steel mill. Recycling processes currently do adhere to specific methods when copper contamination is found within ferrous scrap. Daigo and colleagues (2005) and Nakamura and colleagues (2012) confirmed issues with the quality of recycled steel which were attributed to copper contamination. Both sets of researchers were able to study this effect by estimating the flow of copper that supplements steel materials. Nakajima and colleagues (2011) also verified the adverse effects copper has on the chemical composition of steel materials and noted that copper tends to accumulate during the life of a steel product. Furthermore, von Gleich and colleagues' (2004) article, *Sustainable Metal Management*, showed that excessively high copper concentrations prevent a significant amount of scrap from being recycled.

Tin is another residual element that has an equally undesirable impact, like copper, on the quality of ferrous scrap. Both copper and tin harden steel during manufacturing, which is detrimental to the quality of the steel. These residual elements are also known to accumulate in steel over the course of its life and, from a long-term perspective, preclude

the use of recycled ferrous scrap. This fact is on full display in the construction industry where the maximum potential amount of raw material available to be recycled is reduced mainly due to these two elements. Tailoka and associates (2003) studied a method of removing tin by chlorination in air. Fortunately, their results confirmed it was feasible to separate tin from ferrous scrap when implementing this technique. While Tailoka's and associates' results are positive, tin is still detrimental to the quality of the steel product if it is not identified and treated.

While copper and tin are two surrogate variables used by stakeholders concerned with the quality problem inherent within ferrous scrap, they are only two of the five main deleterious metallic impurities (Sawyer, 2016). Silver et al. (1970) had studied how steel properties are affected by trace metallic nonferrous contaminants, and their results found the following elements: copper, chromium, molybdenum, nickel, and tin to be exceptionally detrimental to the quality of steel. Due to these residual elements, the steel manufacturers are forced to dilute the charge with relatively low impurity level iron (i.e. pig iron) to ensure the liquid steel produced meets its chemistry requirements. This dilution process helps to reduce the amount of wasted and downgraded heats, but it also increases the overall steel production cost. Furthermore, this process could be eliminated if the steel manufacturer knew the chemical composition of the ferrous scrap prior to it being melted.

2.3.3 Scrap Recipe

Prior to the various grades of ferrous scrap entering the furnace, they are first combined together in a scrap bucket based on a scrap recipe. The importance of the scrap recipe is well-known within the steel industry as this topic has been researched since the

1950s starting with Fabian (1958). This recipe defines the amount of ferrous scrap by grade to be included in a scrap bucket, which will be emptied into an EAF so that the ferrous scrap can be melted to create a heat. The goal of the scrap recipe is to satisfy the chemical requirements to achieve the final steel product and mechanical requirements resulting from the design and operations of the EAF. As shown in Figure 1-2, ferrous scrap is directly related to whether a heat is downgraded, wasted, or within specification (i.e. meets its chemistry requirements), so ensuring the scrap recipe minimizes the residual elements per heat is vital.

While the criticality of this topic cannot be stressed enough, the closest research has come to resolving this problem has been to identify the most cost-efficient blend. Mazumdar and Evans (2010) stated in their book, *Modeling of Steelmaking Processes*, the majority of steel manufacturers optimize their scrap recipe to minimize production costs. As noted in section 1.2.3, this is not always wise because cheaper ferrous scrap might contain elevated levels of residual elements and would be used more frequently based on this recipe, potentially increasing the probability of encountering additional wasted and downgraded heats. Therefore, it is essential steel manufacturers leverage historical chemistry data of heats to determine which suppliers' ferrous scrap contains elevated levels of residual elements and which suppliers' ferrous scrap to melt together in an effort to decrease the number of wasted and downgraded heats produced.

2.4 Ferrous Scrap Pricing

One factor that highly impacts the price of most steel products, which is true for ferrous scrap, is its availability. If the demand for the product is high but the supply is

low the price will increase, and the price will decrease if the demand is low and the supply is high. The demand for ferrous scrap is derived from the demand for steel mill and foundry products, which are affected by the general business cycle. If steel demand is weak then the demand for scrap will be low and prices will drop because of a fairly low own-price elasticity of supply in the short-term (Soderholm & Ejdemo, 2008). The demand for steel products affects the short-term pricing of ferrous scrap. However, in the long-term, market forces appear to push the price back to the value of the commodity. Research conducted by Barnett and Crandall (1986) confirmed that the supply of ferrous scrap available to purchase correlates to its price.

Obtaining clean data on the ferrous scrap recycling industry is notoriously challenging, which increases the difficulty in determining an accurate figure on the supply of scrap. This is partially due to the nature of the product as scrap is a by-product of garbage and it is rarely counted in a precise manner. Developing countries only add to the problem as they rarely, if ever, count scrap at all. Even when it is possible to count scrap, such as out of a shipping container, there are additional problems. These issues are encountered because shipping containers filled with steel scrap usually contain mixtures of many different metals, some of which have never been precisely tabulated (Minter, 2013). In his book, *Junkyard Planet: Travels in the Billion-Dollar Trash Trade,* Adam Minter (2013) identified another major problem in obtaining accurate recycling numbers, which was due to false declarations of mixed metals to governments for the purposes of tax evasion. Unfortunately, the amount of ferrous scrap available to be recycled is an elusive number to obtain which increases the difficulty of assigning a price to ferrous scrap. Additionally, three other factors that also contribute to the price of ferrous scrap

are: distance between supplier and consumer, grade of ferrous scrap, and timing of demand over the year (Gruver & Giarratani, 2005).

2.4.1 Market Price

There are resources available to help steel manufacturers negotiation the price of ferrous scrap, one of which is the American Metal Market (AMM) who has been the metals authority since 1882. AMM publishes a composite scrap price per grade at the beginning of each month which is based on an average calculated from quotations that are collected from stakeholders within the steel industry. AMM's reporters rely on information furnished by participants who are involved in or aware of the buying and selling of ferrous scrap. These contributors consist of representatives on both sides of the contracts, such as: producers, consumers, traders, and brokers.

Metal Statistics, Iron Age, and Bureau of Labor Statistics also provide figures on the composite price of ferrous scrap. Unfortunately, the prices published by each of these entities do not align as expected. This discrepancy reflects the competitive nature of the ferrous scrap market within the United States, which consists of approximately: 3000 suppliers, 50 brokers, and 110 mini-mills. The structure of this market forces each ferrous scrap deal to be highly customized resulting in a unique price. Furthermore, other factors causing each trade to be bespoke are: the cost of obtaining the scrap, insurance needed to ship the scrap, and freight charges. Ohno and colleagues (2014) observed in their research that while residual elements affect the chemical composition of ferrous scrap, this factor is rarely considered in negotiations as ferrous scrap is classified and traded almost exclusively based on its weight.

2.4.2 Movement of the Market Price

In the literature review, the movement of ferrous scrap prices has shown the following characteristics: United States prices correlate to European prices and the existence of annual cyclic trends. Both of these features are examined in this section.

Figure 2-3, below, displays the development of ferrous scrap prices in the United States and Europe since 1999. This figure indicates the ferrous scrap prices in these two world regions move together in a fairly consistent manner barring some short-term deviations. This correlation was confirmed through research conducted by Albertson and Aylen (2006). The dataset they used to verify this relationship comprised of quarterly ferrous scrap prices during the years of 1977 to 2005. Their results showed the cointegration of ferrous scrap prices between the United States and Europe. Albertson and Aylen (2006) acknowledged that while the price of ferrous scrap may diverge in the respective local market due to seasonal patterns, the price will realign over the long-term because of market forces.

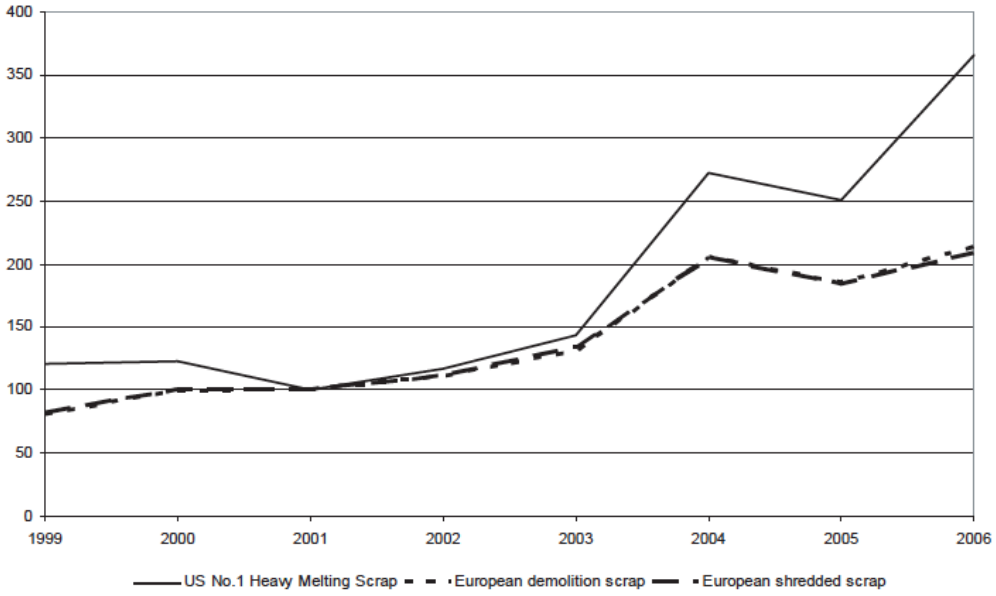


Figure 2-3: Price Development of US and European Steel Scrap (Soderholm & Ejdemo, 2008)

Ferrous scrap prices appeared to be cointegrated between the United States and European markets, whereas ferrous scrap market trends seem to follow a strong seasonal pattern with prices rising systematically in the autumn and winter and then falling back again during the spring and summer quarters. Marcus and Kirsis (1994) were the first researchers to identify this pattern. Albertson and Aylen (1996) and Evans (2006) analysis both confirmed that ferrous scrap prices experience seasonal trends due to the effect of climatic condition on transportation expenses, at least in the United States. This is understandable as the transportation routes are greatly affected in the US during the winter season due to the freezing over of the Great Lakes, snow, and flooding. The severe weather experienced in the US during the winter season disrupts the flow of ferrous scrap from the suppliers' sites to steel mills, causing an increase in the ferrous scrap price due to higher transportation

costs. While seasonal patterns appear to have an effect on the price of ferrous scrap in the United States, this factor was not considered in the quantitative purchasing structure because transportation costs are outside the scope of the research conducted for this praxis. Furthermore, the problem solved in this research does not focus on the price of ferrous scrap by season rather it was addressed by suppliers' contributions to wasted and downgraded heats as well as residual elements present in the suppliers' ferrous scrap.

Albertson and Aylen (1996) discovered some evidence to indicate a different trend relative to the volatility of the ferrous scrap composite price over the course of the year. This cyclical ferrous scrap market trend showed scrap prices tending to drop at the end of the calendar year when inventories are depleted, and subsequently rebounding at the beginning of the following year as inventories are replenished. Fenton (2004) argued this high volatility of ferrous scrap prices can, to some extent, be countered by steel manufacturers increasing their inventory to absorb price differentials. Although, the suppliers may hold on to their higher quality (i.e. low percentage of residual elements) ferrous scrap until the market price increases in an attempt to obtain the optimum price for their scrap. If a steel manufacturer adhered to Fenton's advice, in an act to absorb price differentials of ferrous scrap, the steel manufacturer might unknowingly purchase large amounts of ferrous scrap contaminated with elevated levels of residual elements. Thus, the steel manufacturer would have a false sense of beating the high volatility in ferrous scrap prices because while they might have circumvented the volatility issue, they have potentially increased the amount of wasted and downgraded heats they will produce effectively

erasing the profit margin they thought was secured using Fenton's approach. While steel manufacturers might not be able to counter the volatility of ferrous scrap prices by increasing their inventory, but by knowing the suppliers who consistently provide them ferrous scrap with elevated levels of residual elements will help them determine which suppliers will receive less than or only market price when the price of ferrous scrap changes unpredictably.

2.5 Optimal Pricing Strategies

The next step in the literature review was to research and evaluate different pricing strategies across multiple domains and identify the best aspects of each methodology. These aspects were leveraged to influence the creation of the models used to predict the value-in-use price of ferrous scrap. The industries reviewed in this section are the following: insurance, fine wine, rentals, perishable goods, and oilfield services.

2.5.1 Insurance

The insurance pricing structure used by Spedicato et al. (2018) focused on performing price optimization per an individual's premium. Similarly, the quantitative pricing structure for ferrous scrap calculated the value-in-use price per supplier. Spedicato et al. (2018) applied an innovative methodology which used the following factors: customer behavior and the market environment to optimize the premium quoted to prospective customers. Both of these factors are pertinent to the value-in-use ferrous scrap price. Customer behavior was accounted for by the suppliers' propensity to contribute ferrous scrap to wasted and downgraded heats. Market environment was considered through the composite market price for ferrous scrap, which was provided by

the American Metal Market. The ferrous scrap composite market price used in the research for this praxis, which was provided by American Metal Market, was calculated by aggregating quotes and purchase orders for ferrous scrap within a geographical region located in the United States. Furthermore, the ferrous scrap composite market price was used as a predictor in the models developed for the quantitative purchasing structure for ferrous scrap. The impetus to determine the optimized price differs between the insurance and steel industry as well as the customer context (i.e. the insurance company targeted prospective customers, whereas the steel manufacturer is the customer), however the factors used in the insurance pricing structure are related to the quantitative purchasing structure for ferrous scrap.

Spedicato and associates (2018) built 5 models to predict the optimized premium, two of which used machine learning techniques (i.e. Random Forest and Neural Networks). Their results showed that the machine learning techniques used in their research (i.e. Random Forest and Neural Networks) may offer higher accuracy and discrimination power over classical logistic regression techniques relative to the prediction of an optimized premium per prospective customers. One aspect of the approach used to discern whether the machine learning techniques used in the research conducted by Spedicato et al. (2018) provided an advantage over traditional methods was the use of a performance metric (i.e. ability to best predict the optimized premium), which was related to a performance metric (i.e. ability to best predict the value-in-use price) used to compare the models built for the quantitative purchasing structure for ferrous scrap.

2.5.2 Fine Wine

One pricing strategy used to predict the price of fine wine is based on a hypothesized relationship between certain predictor variables (i.e. critic ratings) and previous wine prices. The methodology normally employed to test the strength of these relationships is linear regression. This pricing strategy of predicting a wine price based on the relationship of a qualitative factor does not differ much from steel manufacturers who negotiate the price of ferrous scrap based on a supplier's reputation (i.e. critic rating), which is not a recommended approach.

Yeo et al. (2015) leveraged historical price data to predict the price of fine wine. The factor they used to predict the fine wine price were previous profits obtained from wine sold over the course of a 2-year period. Thus, the factor used in the pricing strategy to predict the price of fine wine that was common in the prediction of the value-in-use price of ferrous scrap was profits. While Yeo et al. (2015) solely relied on previous profits that spanned a 2-year time period to predict the price of fine wine, the research conducted in this praxis used the profits lost due to wasted and downgraded heats as one of the predictors to calculate the value-in-use price of ferrous scrap. Furthermore, one of the key issues Yeo et al. (2015) faced was that some of the wines were traded infrequently and hence lacked sufficient price data which made predicting the price of the respective fine wine difficult. A similar issue was encountered when predicting the ferrous scrap price as some suppliers were not active across the entire dataset. Thus, time series analysis was not applicable as the data used to predict a respective supplier's value-in-use ferrous scrap price was based on their contributions to wasted and downgraded heats and the residual elements present in these heats.

Furthermore, the research conducted by Yeo and colleagues (2015) consisted of applying commonly used financial models (i.e. Autoregressive Moving Average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH)), as well as a machine learning technique (i.e. Gaussian process regression) to sparse historical price data to predict the fine wine price and compared their results. Their results, which are displayed in Figure 2-4, in terms of mean square error, where higher values are indicative of worse performance, showed the performance of this machine learning technique (i.e. Gaussian process regression) was not much better than those generated from the simpler prediction models.

Method	*MSE*
Predicting 0	3.65×10^{-5}
ARMA(1,1)	3.92×10^{-5}
GARCH(1,1)	7.95×10^{-5}
Gaussian Process Regression (optimal)	3.40×10^{-5}

Figure 2-4: Fine Wine Model Comparison (Yeo et al., 2015)

The evaluation technique used by Yeo et al. (2015) to compare the performance of the financial models and the machine learning technique employed in their research was an error metric (e.g. Root Mean Square Error). The concept of using error metrics, which calculate the square difference between the predictions and actual values, was applicable to the research conducted in this praxis as it provided a technique to compare the performance of the models built for the quantitative purchasing structure for ferrous scrap.

2.5.3 Rentals

A challenge faced by hosts of short-term rentals pertained to determining the optimal nightly rental price. The pricing strategy employed by hosts of rental units used historical data (i.e. rental listings) which was comprised of criterion (e.g. number of bedrooms, number of beds, number of bathrooms, nightly price for the rental, etc.) similar to their listing and then calculated an average price from this criterion. The average price calculated was used by the hosts as their new list price. Devlin (2018) implemented a machine learning algorithm (i.e. K-Nearest Neighbors) to automate the process of calculating the optimal nightly rental price which ensured the hosts selected an affordable price while maximizing their potential revenue. Devlin's (2018) results displayed the usefulness of applying a machine learning technique (i.e. k-nearest neighbor) to calculate the optimized price for short-term rental units.

The construct of the pricing problem experienced by hosts of short-term rentals was similar to the one encountered by steel manufacturers as they must obtain the value-in-use ferrous scrap price if they want to maximize their potential revenue. The concept used by hosts of short-term rentals, which consisted of using historical listings with similar criterion as their listing and then calculated an average price from this information, to determine their nightly rental price appeared to have applicability for calculating the value-in-use price of ferrous scrap. In the context of the research conducted for this praxis, the concept of using suppliers with similar criterion (i.e. residual element levels and composite market price) and calculating an average price from this information was investigated. Therefore, this concept has potential to help steel manufacturers calculate the value-in-use price of ferrous scrap

by leveraging historical data to identify patterns relative to residual elements provided by suppliers as well as market prices.

2.5.4 Perishable Goods

Markdown pricing is a strategy widely used by perishable goods, sporting goods, and apparel suppliers for revenue management. The purpose of markdown pricing is to clear excess inventory before the expiration date of the goods. Wang et al. (2016) developed a markdown pricing model to evaluate the trade-offs between revenue for the food supplier and the consumer utility (i.e. fair price perception) relative to the perishable food price. The markdown pricing concept was related to the steel industry even though ferrous scrap is a raw material rather than a perishable good. When the market price of ferrous scrap is low, suppliers are attempting to clear their inventory of ferrous scrap containing increased percentages of residual elements. When the market price of scrap is high, suppliers prefer to sell their inventory of ferrous scrap containing low percentages of residual elements in an attempt to maximize the price received for this higher quality scrap. Thus, ferrous scrap suppliers are constantly attempting to clear their inventory and their quoted price for ferrous scrap was not based on an expiration date but rather the date when the market price of ferrous scrap increased.

The results produced by Wang et al. (2016) indicated that if the retailer sacrificed a small amount of revenue, they saw high returns in terms of consumers' aggregated utility. An increase in the consumers' aggregated utility translated into a long-term relationship with the consumer and resulted in greater overall revenue. Wang's and colleagues' (2016) results provided evidence to support the claim that consumer utility is an important factor when determining the markdown price. Unfortunately, majority of the

time ferrous scrap suppliers attempt to maximum their revenue without considering the consumer utility from the steel manufacturer's perspective since they are not incentivized to do so as described in section 1.1.3. Therefore, the factor of consumer utility was not incorporated into the models used for the quantitative purchasing structure for ferrous scrap due to the lack of incentive respective of the supplier to create a long-term relationship with the steel manufacturer.

2.5.5 Oil and Gas Industry

The oil and gas industry requires unique and highly-engineered components, and these components account for a significant percentage of company's cost who provides products and services to this industry. Similarly, raw materials (i.e. ferrous scrap) account for a major percentage of a steel manufacturer's costs. The prices of these specialized components used within the oil and gas industry are often negotiated with suppliers during the procurement process. Likewise, the prices of ferrous scrap are negotiated with suppliers during the procurement process. In the purchasing structure used within the oil and gas industry, conflicts arise during the price negotiation of the specialized components because information on the cost to manufacture the product is minimal or non-existent which leaves the buyer with only the prices quoted by the supplier. This aspect of the oil and gas industry's purchasing structure differs with the steel industries as the market price of ferrous scrap is available. Nevertheless, if a company only has a supplier's quoted price as a reference point, the supplier has an incentive to quote the price higher to ensure a substantial profit margin is realized even as the buyer attempts to negotiate a lower price.

Research was conducted by Mealer and Park (2013) to address the problem of predicting the cost of a diverse array of specialized components used within the oil and gas industry through the use of a should-cost model. Mealer and Park (2013) developed the should-cost model based on aggregate historical financial data, which was obtained from a global provider of products and services to the oil and gas industry, to predict the prices these specialized components should cost. This information provided leverage for the provider's (i.e. buyer's) procurement personnel in price negotiations, which was critical because the only piece of data the procurement personnel usually had for these negotiations was the supplier's quoted price. The analysis conducted by Mealer and Park (2013) showed their model was able to remove the reliance on quotes provided by the supplier and strengthen the provider's (i.e. buyer's) negotiation position by predicting the should cost price of specialized components used within the oil and gas industry.

The purpose of the should-cost model was to predict the price of specialized components procured by a provider of products and services to the oil and gas industry and provide a tool to assist in price negotiations. The concept of the should-cost model was related to the research conducted for this praxis as aggregate historical chemistry and financial data was used to predict the value-in-use price of ferrous scrap per supplier. Thus, the should-cost model was adapted for the research conducted in this praxis to help address the question of whether a supplier's ferrous scrap was or was not worth their quoted price and to strengthen the steel manufacturer's position when prices of ferrous scrap are negotiated.

2.6 Decision Support Analysis

The last step in the literature review was to investigate the applicability of the decision support analysis method in the context of determining the value-in-use price of ferrous scrap. The decision support analysis provided an organized method to examine alternatives required for a decision (Pandolfini, 2018). The alternatives examined in the decision support analysis pertained to the useful information obtained from the historical chemistry and financial data, which was used in the research for this praxis, relative to determining the value-in-use price of ferrous scrap. The intent of this analysis was to inform the decision makers (i.e. internal buyers for the steel manufacturer) of the relative merits of the alternatives free of unintended bias, which is not the case when using arbitrary weighting schemes. Thus, the decision support analysis method was applicable to the research conducted for this praxis as it provided a means to determine the value-in-use price of ferrous scrap.

The technique used to evaluate the decision support analysis model was based on the principle of maximum information entropy (Jaynes, 1985; Jaynes, 1978; Jaynes, 2003), which is an extension of the centuries past principle of indifference. The premise of this principle is: for a system with n states, the principle asserts, when no further information is available, each of the n states is equally probable.

The first step executed in the process to create a decision support analysis model was to define the evaluation factors. Once the evaluation factors were identified, the essential considerations related to the factor were enumerated to construct atomic statements. For each factor, a state table was created. The state tables were constructed by forming a series of sentences which were built from the

atoms. The compound sentences created from the state tables fell into two general areas: those which were logically permitted in the state space and those which were outside of this space and not permitted. This ensured the responses inputted into the state tables were logical and rational since a score was not computed if they were outside of the state space.

Once the 6 state tables were constructed, the value-in-use ferrous scrap price with respect to all of the evaluation factors as defined by the decision support analysis was calculated. Subsequently, this price was then compared to a quantitative metric, which was the actual price paid by the steel manufacturer for ferrous scrap, to enable an assessment of the model's ability to predict the value-in-use ferrous scrap price.

2.7 Conclusion

The literature review process confirmed the problem mini mills, steel manufacturers who use electric arc furnaces to produce new steel, encounter when using and determining the price of ferrous scrap, which is the high variability in its chemical composition. The variability of the chemical composition of ferrous scrap has shown to deviate substantially between grades and occasionally within a grade. Residual elements were the cause of this variability and are known to be detrimental to the quality of steel. In particular, the 5 residual elements most deleterious to the quality of steel identified were: copper, chromium, molybdenum, nickel, and tin. Moreover, various grades of ferrous scrap with different chemical compositions are melted together based on a scrap recipe to produce new steel. This combination of ferrous scrap was directly correlated to

whether a heat was wasted, downgraded, or within specification (i.e. the chemistry requirements of the liquid steel are satisfied). Wasted and downgraded heats are terrible for steel manufacturers as costs are incurred and profits are lost when these heats are experienced. The chemical composition of ferrous scrap is known to be affected by residual elements, unfortunately this factor is rarely considered in price negotiations as ferrous scrap is classified and traded usually based on the quantity purchased, supplier's reputation, and transportation costs. Therefore, a critical factor, chemical composition of ferrous scrap, which affects the outcome of a heat, is not considered when ferrous scrap prices are negotiated.

The supply and demand forces of the global market for ferrous scrap had an effect on its market price, which is apparent in the cointegration of ferrous scrap market prices between the United States and Europe. Economic issues have also shown to have an impact on the market price of ferrous scrap. However, the research conducted for this praxis concentrated on the United States ferrous scrap market because it is the largest and the focus on this geographical region minimized the effects of dynamic global economic factors (e.g. tariffs) when predicting the value-in-use price of ferrous scrap since these economic factors are unpredictable. Additionally, these global economic factors were outside the scope of this research effort.

The literature review process concluded with the evaluation of different pricing strategies across multiple domains in which the best aspects of each methodology were identified. These aspects were leveraged to influence the creation of the models used to predict the value-in-use price of ferrous scrap. During this phase of the research, another method was found to have applicability in determining the value-in-use ferrous scrap

price which was decision support analysis. Thus, this literature review confirmed the direction of the solution provided in this praxis by helping to focus on the gaps present in determining the value-in-use ferrous scrap price and how to address them via different pricing models.

Chapter 3 – Methodology

"The best predictor of future behavior is past behavior" – Mark Twain

The research conducted for this praxis was designed to develop a model capable of predicting the value-in-use price of ferrous scrap per supplier. In this chapter, the methodologies used to solve the research questions are defined and consisted of two phases. Phase I detailed the analysis conducted on the steel manufacturer's dataset, thus turning data into information. Statistical analysis was used to verify the residual elements contributions to wasted and downgraded heats.

Phase II consisted of developing models that were used to predict the value-in-use price for ferrous scrap per supplier. The information produced in Phase I was used in these models. Phase II concluded with an assessment of the models using a quantitative validation metric, which was the previously paid ferrous scrap prices by the steel manufacturer to suppliers. This assessment was conducted via a comparison of the value-in-use ferrous scrap prices generated by the models against the quantitative validation metric.

3.1 Phase I: Correlating Wasted and Downgraded Heats to Suppliers

The steel manufacturer, who provided the dataset, annually procured and produced over 2 million tons of ferrous scrap during this time period. The dataset consisted of over 39,000 heats, which was comprised of the liquid steel chemistry, and procurement information for ferrous scrap. Once the data was interpreted, wasted and downgraded heats were identified and subsequently correlated to suppliers.

Statistical analysis was used to verify the contributions of each residual element had on wasted and downgraded heats, and the portion each residual element was present across all of the wasted and downgraded heats.

3.1.1 Interpretation of the Dataset

The dataset from the steel manufacturer was provided in a Microsoft Excel file, which consisted of 5 sheets with each sheet containing numerous fields. Interpreting how the data was structured by historical heat chemistry and annual ferrous scrap procurement information was essential prior to conducting analysis. To aid in this comprehension process, it was important to appreciate why the steel manufacturer was collecting this data in the first place and how it was used.

The steel manufacturer confirmed the use cases in which they used the dataset. The first use case related to their customers. For this use case, the data was used as evidence to prove the chemistry requirements of the heat were satisfied. Hence, the data provided confirmation that the liquid steel contained in the heat was within desired specifications. The second use case for this data pertained to the steel manufacturer's accounts payable department. The data was used to track the ferrous scrap delivered to the mill per supplier so that the steel manufacturer knew how much each supplier was owed. Thus, for the second use case, the data functioned as a receipt. Understanding how the steel manufacturer used this data was helpful when data analysis was conducted as it provided insight into how the data was formatted and structured.

3.1.2 Identification of Wasted and Downgraded Heats

Prior to identifying wasted and downgraded heats, the structure of the historical heat chemistry data had to be interpreted. A sample of the dataset containing the historical heat chemistry is displayed in Table 3-1, which can be located in the supplementary files attachment. This table contains the following fields:

- *analysis_date* and *analysis_time* – were the date and time recorded when the chemistry sample of the heat was taken
- *heat_no* – provided the heat number. Valuable information was contained within the heat number. For example, "41600500" translated to the following meaning: the heat was melted in furnace "4", the heat was produced in year [20]16, and it was the 5^{th} heat of the year. The last digit (i.e. 0) in the heat number had no significance, hence it was ignored.
- *c_pct* – provided the percentage of carbon contained in the liquid steel per heat
- *mn_pct* – provided the percentage of manganese contained in the liquid steel per heat
- *p_pct* – provided the percentage of phosphorus contained in the liquid steel per heat
- *s_pct* – provided the percentage of sulfur contained in the liquid steel per heat
- *si_pct* – provided the percentage of silicon contained in the liquid steel per heat

- *cu_pct* – provided the percentage of copper contained in the liquid steel per heat
- *cr_pct* – provided the percentage of chromium contained in the liquid steel per heat
- *ni_pct* – provided the percentage of nickel contained in the liquid steel per heat
- *mo_pct* – provided the percentage of molybdenum contained in the liquid steel per heat
- *v_pct* – provided the percentage of vanadium contained in the liquid steel per heat
- *sn_pct* – provided the percentage of tin contained in the liquid steel per heat
- *pb_pct* – provided the percentage of lead contained in the liquid steel per heat
- *nb_pct* – provided the percentage of niobium contained in the liquid steel per heat
- *Total SW (Scrap Weight)* – provided the total weight of the scrap entered into the furnace. The unit of measurement was pound.
- *Total SW (ton)* – provided the total weight of the scrap entered into the furnace. The unit of measurement was US ton.

In Phase I of the research, data analysis was conducted to identify all of the wasted and downgraded heats. The threshold weight percentages per residual element allowed within heat and still have the heat satisfy its chemistry requirements were obtained from the steel manufacturer. Carbon (C) and Manganese (Mn) were two residual elements that did not have a threshold weight percentage because both of these elements are beneficial to the quality of steel relative to its tensile strength. The threshold weight percentages for the residual elements considered in this research are displayed in Table 3-2.

Table 3-2: Threshold Weight Percentages of Residual Elements

Element	Max wt %
C	N/A
Mn	N/A
P	0.015
S	0.0065
Si	0.09
Cu	0.114
Cr	0.100
Ni	0.100
Mo	0.030
V	0.003
Sn	0.0094
Pb	0.006
Nb	0.003

A wasted or downgraded heat was experienced if the weight percentage of one of the residual elements defined in Table 3-2 was elevated pass its respective threshold. The residual elements were sorted one at a time by year in a descending order from their highest weight percentage to lowest per heat. As the data analysis proceeded, the research was narrowed to the top 5 residual elements most detrimental

to the quality of steel as these elements were the culprits behind all of the wasted and downgraded heats. As defined in section 2.3.2, the 5 residual elements most deleterious to the quality of steel are: copper, chromium, tin, nickel, and molybdenum. A heat was marked if the weight percentage of a residual element was above its threshold for a respective heat (e.g. for copper, any heat that contained a weight percentage above 0.114 was marked). Once all of the heats containing weight percentages above the thresholds of the residual elements were marked, the process of determining whether a marked heat was wasted or downgraded was then conducted.

As noted previously, any heat containing a weight percentage above the threshold of a residual element was considered a wasted or downgraded heat and subsequently marked. The rule set to distinguish whether a marked heat was wasted or downgraded depended on how much the weight percentage of a residual element was above its threshold. The steel manufacturer, who furnished the dataset, confirmed that if the weight percentage of a residual element was more than 2.5 times pass its respective threshold, as defined in Table 3-2, then the heat was considered wasted. There were multiple kinds of downgraded heats, however a factor that remained constant across all of them was the elevated weight percentages of the residual elements were less than 2.5 times their respective threshold.

3.1.2.1 Verification of Residual Elements

The methodology used to verify the contributions each residual element had on wasted and downgraded heats and the portion each residual element was present

across all wasted and downgraded heats was Predictor Screening. The Predictor Screening method screened multiple predictors for their ability to predict an outcome. This method was also able to identify predictors (i.e. residual elements) potentially weak on their own but strong when combined with other predictors. Although, it only took the weight percentage of one residual element to be above its threshold for a heat to be considered wasted or downgraded. Thus, this method was applied to verify the residual elements which caused the wasted and downgraded heats by predicting whether a heat was considered wasted or downgraded based on the weight percentages of the residual elements present.

A Predictor Screening model was executed using a statistical software package called JMP 14 from SAS (2018). The historical chemistry data containing all of the wasted and downgraded heats was entered into the Predictor Screening model. This model calculated the contributions, which were sorted by ranking, relative to the residual elements most significant in predicting a wasted or downgraded heat. The portion each residual element was present across all of the wasted or downgraded heats was also calculated, which provided insight into the residual elements most frequently contained within the ferrous scrap the steel manufacturer purchased.

The Predictor Screening model was executed twice, once for the wasted heats and once for the downgraded heats. For this model to function appropriately, the heats were labeled in binary fashion. The wasted and downgraded heats were identified by a “1”, while a “0” represented heats within specification (i.e. satisfied chemistry requirements). The predictor screening model tested the residual elements on their ability (i.e. contributions) to predict whether a heat was wasted or

downgraded, and the frequency in which they were present across wasted and downgraded heats. Thus, this verification method supported the data analysis previously completed in section 3.1.2.

3.1.3 Identification of Problematic Suppliers

Once the wasted and downgraded heats were located, the next task in the data analysis was to correlate these heats to the suppliers who contributed ferrous scrap to them. Understanding the workflow and operations of the scrap bay was a critical step in realizing this correlation. Figure 3-1 depicts the scrap bay layout at the steel mill of the steel manufacturer who provided the dataset.

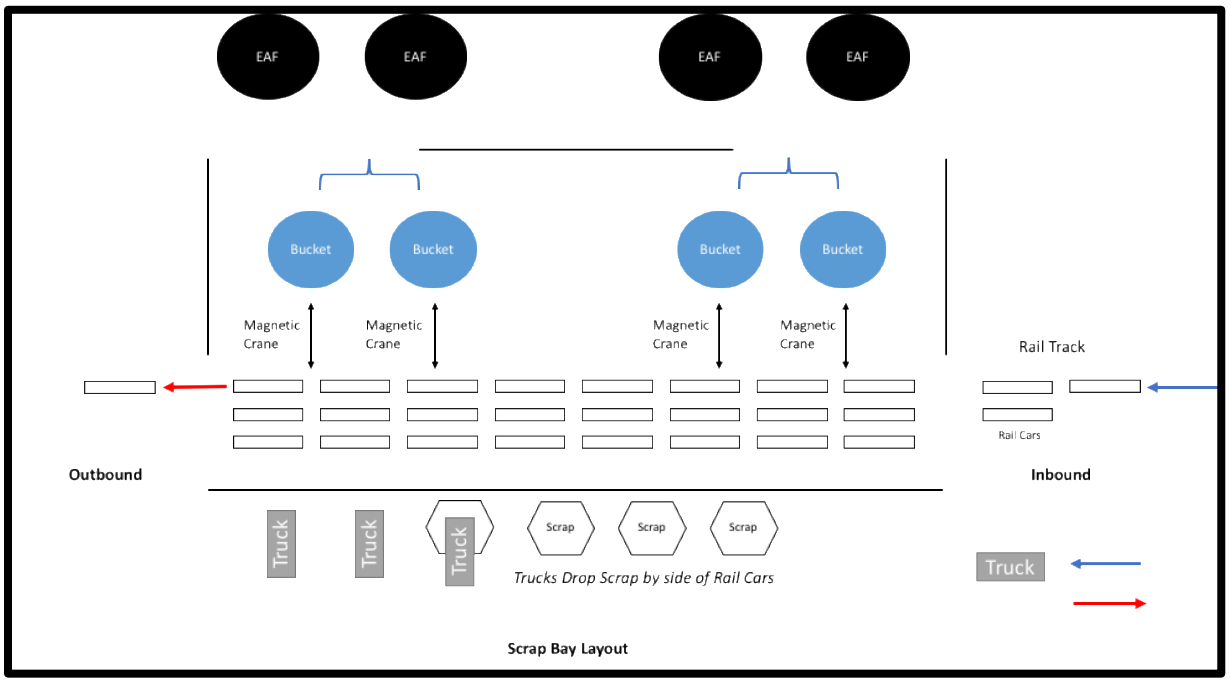


Figure 3-1: Scrap Bay Layout of Steel Manufacturer

The steel manufacturer has a twin-shelf furnace operation, thus at any time four furnaces are in use barring any maintenance issues. The workflow of this configuration consists of two furnaces melting ferrous scrap while the other two are being tapped. The term 'tapped' refers to the process of pouring the liquid steel out of the furnace and into a ladle (i.e. emptying the furnace of one heat so that a new one can be created). The small amount of hot metal (i.e. 5 tons, where an average heat weight was 175 tons) left in the EAF after it was tapped was ignored in the research conducted for this praxis because the amount was not enough to negatively impact the outcome of a heat. The time it took to load a furnace with ferrous scrap, melt the ferrous scrap, and then pour the liquid steel out of the furnace was approximately 50 minutes. This time was referred to as the tap-to-tap time. The tap-to-tap time was important in determining which suppliers' ferrous scrap was used for a heat.

The 4 steps used to realize the correlation of wasted and downgraded heats to the suppliers who contributed ferrous scrap to these heats was the following:

1.) Locate the date and time of the wasted or downgraded by using the *analysis_date* and *analysis_time* fields in Table 3-1.

2.) Identify the time of when the ferrous scrap was used in a respective heat by accounting for the tap-to-tap time and when it was delivered to the mill using the *TareDate* and *TareTime* fields in Table 3-3, which is located in the supplementary files attachment.

    a. For a rail car, the *TareDate* and *TareTime* could have been either before or after the *analysis_date* and *analysis_time* because on

average it took 8 hours to empty the 24 rails cars of their ferrous scrap, which needed to be completed so that the next 24 rails cars could enter the scrap bay. Each rail lane consists of only one grade of ferrous scrap from car to car; therefore, across all 24 rail cars there were only 3 grades of ferrous scrap present.

b. For a truck, the *TareDate* and *TareTime* had to be at least 50 minutes prior to the *analysis_date* and *analysis_time* because the amount of ferrous scrap provided by one truck was normally used in a single heat. Furthermore, the ferrous scrap delivered by trucks had a shelf-life of 4 hours after being delivered.

3.) Reconstruct the scrap bucket based on the scrap recipe, in Table 3-4, used by the steel manufacturer to create the heat. The *Total SW (ton)* field in Table 3-1 provided the total weight of ferrous scrap used per heat, thus the *Net Wt (ton)* field in Table 3-3 was used to determine the amount of ferrous scrap each supplier provided per heat based on the scrap recipe.

4.) The supplier who contributed the ferrous scrap to the wasted or downgraded heat per rail car or truck was identified in the *SupplierAlpha* field located in Table 3-3, which is located in the supplementary files attachment.

3.1.3.1 Scrap Recipe Contribution to Identifying Problematic Suppliers

As described in section 2.3.3, the scrap recipe was a critical piece of information in the steel manufacturing process. The recipe defined the amount of ferrous scrap by grade to be included in a bucket, which was the input used to create a heat. Additionally, as noted in Chapter 1, the ferrous scrap entered into an EAF has a direct impact into whether a heat was wasted, downgraded, or within specification (i.e. the chemistry requirements of the liquid steel are met). Thus, the scrap recipe used had the potential to increase or decrease the amount of wasted or downgraded heats encountered.

The ferrous scrap recipe identified, below, in Table 3-4 was used to reconstruct the contents of each scrap bucket prior to it being emptied into the furnace. The *MaterialDesc* field, as shown in Table 3-3, provided crucial information for this reconstruction effort, which was the grade of ferrous scrap delivered. The descriptions of the ferrous scrap grades found within the *MaterialDesc* field in Table 3-3 are located in Appendix A. The percentage of ferrous scrap grades used from heat to heat varied slightly from the percentages defined in Table 3-4, however one percentage of the scrap recipe that remained constant throughout all heats was the percentage of pig iron. This grade of ferrous scrap was essentially pure carbon, which is beneficial to the quality of steel and used to dilute the other ferrous scrap grades containing residual elements as described in section 1.1.3. Additionally, an important aspect considered when reconstructing the contents of each scrap bucket was the ferrous scrap grades with higher densities. Special consideration was given

to these ferrous scrap grades as they had the potential to break the electrodes used to melt the scrap if they were not located towards the bottom of the bucket.

Ferrous Scrap Grade	Percentage Per Bucket
#1 Busheling	40%
5' Plate & Structural	5%
#1 Dealer Bundles	25%
Cold Mill Crops & Skulls, Cast Crops	8%
Pig Iron	10%
#2 Shredded	12%

Table 3-4: Scrap Recipe used by Steel Manufacturer

The reconstruction effort conducted relative to the scrap buckets used to create the heats was vital to realize the correlation of the suppliers who contributed ferrous scrap to the wasted and downgraded heats. Once the scrap buckets used to create the heats were rebuilt based on the scrap recipe in Table 3-4, it was possible to identify which suppliers contributed ferrous scrap to the wasted and downgraded heats via the *SupplierAlpha* field located in Table 3-3. The suppliers who the steel manufacturer procured ferrous scrap from were contained in the *SupplierAlpha* field. The steel manufacturer procured approximately 70% of their ferrous scrap from one supplier who had multiple locations, but was listed as one name. For this supplier, internal procurement data was used to identify the location where the ferrous scrap was delivered from. Linking the other suppliers (i.e. approximately 30% of the total suppliers) to wasted and downgraded heats was trivial because their names and corresponding locations were listed as such. Thus, the scrap recipe was a critical component in realizing the correlation between suppliers to wasted and downgraded

heats as it provided the basis for the reconstruction effort which allowed the for the suppliers to be identified via the *SupplierAlpha* field in Table 3-3.

3.2 Phase II: Value-in-Use Price for Ferrous Scrap

The literature review identified promising methodologies that were used to predict the value-in-use price of ferrous scrap per supplier. These methodologies used the information generated in Phase I and each predicted the value-in-use ferrous scrap price in a unique manner. The methodology identified in section 2.5.3 lead to a model, which incorporated a machine learning algorithm, that discovered patterns in the historical data relative to the residual element weight percentages per heat and the market price to predict the value-in-use ferrous scrap price per supplier. Section 2.5.5 identified a methodology used to develop a model, which focused on raw material factors to predict the value-in-use price of ferrous scrap per supplier. Lastly, the methodology identified in section 2.6 lead to a model that predicted the value-in-use ferrous scrap price through an assessment of the suppliers' contributions to wasted and downgraded heats.

The methodologies used in this research were compared against each other via a quantitative metric, which was the actual ferrous scrap price paid by the steel manufacturer, to determine which model was the best at predicting the value-in-use ferrous scrap price. Additionally, the quantitative metric was not used in the development of any of the models.

3.2.1 Decision Support Analysis Model

The decision support analysis methodology, which was described in section 2.6, provided an assessment of the suppliers' performance relative to how often frequently they contributed to wasted and downgraded heats as well as the residual elements most detrimental to the quality of steel that were present in these heats. Thus, the decision support analysis model used all of the information available from Phase I of the research to predict the value-in-use price of ferrous scrap per supplier.

The nomenclature used to describe the elements of the decision support analysis model is as follows (Pandolfini, 2018):

- Atom – a 'Yes/No' question that captures the response of a supplier's performance
- Factor – an associated collection of logical atoms that describe an attribute of a supplier's performance
- Factor level – a subgroup of all the logical sentences within a factor that have equal value
- Logical sentence – a combination of all the logical atoms in a factor
- State Table – the arrangement of factor level subgroups within a factor into an increasing order of desirability
- Normalized Weighted Raw Score – a metric formed by combining the values of a supplier's weightings within each state, which is divided by the difference in maximum and minimum values.

As stated in section 2.6, the first step in the process to create a decision support analysis model was to define the evaluation factors. The model developed through the decision support analysis methodology consisted of 6 evaluation factors, which were all weighted evenly. The 6 evaluation factors used in the decision support analysis model all pertained to wasted and downgraded heats, and are as follows:

a) Percentage of Contribution to Wasted Heats
b) Percentage of Contribution to Downgraded Heats
c) Scrap Contributions in 2016
d) Scrap Contributions in 2017
e) Scrap Contributions in 2018
f) Problematic Chemical Composition

Once these 6 factors were identified, the essential considerations related to the factor were enumerated to construct atomic statements. For each factor, a state table was generated. The state tables for 4 of the factors are located below in Tables: 3-5, 3-6, 3-7, and 3-8. The state tables were constructed by creating a series of sentences built from the atoms (e.g. the atom for Factor (a) was, "Did the Supplier contribute to 0% wasted heats?"). The compound sentences generated fell into two general areas: those which were logically permitted in the state space and those which were outside of this space and not permitted. If the responses received for the atoms within a factor were not logical relative to a supplier's performance, (e.g. a "yes" was entered in 2 atoms for Factor (a)) then a normalized weighted raw score was not calculated.

Thus, these compound sentences provided a means to validate if the responses entered for the atoms within a factor were logically permitted.

3.2.1.1 State Tables

Factor (a): Percentage of Contribution to Wasted Heats was calculated by the amount of ferrous scrap contributed by a supplier to wasted heats for a given year (e.g. 2016). This percentage was then totaled across the years (i.e., 2016, 2017, and 2018) in the dataset and depending on the sum a response of "yes" was entered into one of four possible atoms for this factor. The response of a supplier who contributed 7% to wasted heats across approximately 2.5 years is shown in Table 3-5.

Table 3-5: State Table for Factor (a)

		ANSWER THESE QUESTIONS
	Factor (a): Percentage of Contribution to Wasted Heats	
Atoms	Description	**Enter Y or N**
a1	**Question 1 (Best Case): Did the Supplier contribute to 0% wasted heats?**	**n**
a2	**Question 2: Did the Supplier contribute to wasted heats between 0.0001% - 4.9999% of the time?**	**n**
a3	**Question 3: Did the Supplier contribute to wasted heats between 5% - 10% of the time?**	**y**
a4	**Question 4: Did the Supplier contribute to wasted heats more than 10% of the time?**	**n**

Likewise, Factor (b): Percentage of Contribution to Downgraded Heats was calculated in the same manner as Factor (a). The response of a supplier who contributed 4% to downgraded heats across the dataset, which spanned approximately 2.5 years, is displayed in Table 3-6.

Table 3-6: State Table for Factor (b)

		ANSWER THESE QUESTIONS
	Factor (b): Percentage of Contribution to Downgraded Heats	
Atoms	Description	**Enter Y or N**
b1	**Question 1 (Best Case): Did the Supplier contribute to 0% downgraded heats?**	**n**
b2	**Question 2: Did the Supplier contribute to downgraded heats between 0.0001% - 4.9999% of the time?**	**y**
b3	**Question 3: Did the Supplier contribute to downgraded heats between 5% - 10% of the time?**	**n**
b4	**Question 4: Did the Supplier contribute to downgraded heats more than 10% of the time?**	**n**

Factor (c): Scrap Contribution in 2016 was calculated by determining whether the supplier contributed to a wasted or downgraded heat in 2016. If the supplier did contribute to both types of heats in 2016, then the response for that supplier would have been "yes" for both atoms. Likewise, Factor (d): Scrap Contributions in 2017 and Factor (e): Scrap Contributions in 2018 were calculated in the same manner. The responses for a supplier who contributed to downgraded heats but not to any wasted heats in 2016 are shown in Table 3-7.

Table 3-7: State Table for Factor (c)

		ANSWER THESE QUESTIONS
	Factor (c): Scrap Contributions in 2016	
Atoms	**Description**	**Enter Y or N**
c1	**Contributed to 2016 downgraded heats**	**y**
c2	**Contributed to 2016 wasted heats**	**n**

Factor (f): Problematic Chemical Composition was calculated by determining whether a supplier's ferrous scrap was frequently present in heats that contained residual elements most detrimental to the quality of steel. This factor focused on three of these residual elements, specifically: copper, chromium, and tin, as they accounted for all of the wasted heats and over 90% of the downgraded heats. If a supplier's ferrous scrap was contained within heats which repeatedly had one of these residual elements present, then a response of "yes" was provided for the respective atom. The response of a supplier whose ferrous scrap was associated with numerous downgraded heats due to elevated levels of copper but not because of chromium or tin is shown in Table 3-8.

Table 3-8: State Table for Factor (f)

		ANSWER THESE QUESTIONS
	Factor (f): Problematic Chemical Contribution	
Atoms	**Description**	**Enter Y or N**
f1	**High quantity of COPPER?**	**y**
f2	**High quantity of CHROMIUM?**	**n**
f3	**High quantity of TIN?**	**n**

3.2.1.2 Supplier Distribution

Figure 3-2, below, provided a graph where suppliers' contributions to wasted and downgraded heats, which are embodied in 17 yes/no questions across 6 factors, were plotted. The red curve was developed using a formalized approach that used state tables and appropriate non-biased weighting to calculate a total score (i.e.

normalized Weighted Raw Score, nWRS) (Pandolfini, 2018). The nWRS is the sum of the supplier's scores respective to the 6 factors divided by the maximum difference in the sum. Additionally, a baseline of the factors (i.e. the weightings were adjusted so that they all added to the same value) was executed to ensure each factor had an equal influence on the nWRS.

The nWRS and corresponding percentile were calculated based on the supplier's contributions to wasted and downgraded heats relative to the 6 evaluation factors described in section 3.2.1. The nWRS and percentile were plotted in a 2-deminisional graph with the nWRS as the x-axis and percentile as the y-axis. The y-axis, percentile, was partitioned in the following 5 levels from lowest or highest:

- 0 – 19 (Level 1)
- 20 – 39 (Level 2)
- 40 – 59 (Level 3)
- 60 – 79 (Level 4)
- 80 – 100 (Level 5)

These 5 levels corresponded to a percentage in which the ferrous scrap market price was reduced per supplier. The rational for why 5 levels were used instead of 2, 3, or 4 was to enable a meaning distribution of the suppliers based on their contributions to wasted and downgraded heats. The 5 levels allowed for the percentage used to reduce the ferrous scrap market price, for suppliers who had similar contributions to wasted and downgraded heats, to be applied in an unbiased manner. Additionally, the 5 levels provided granularity of the percentages used to reduce the ferrous scrap market price. It

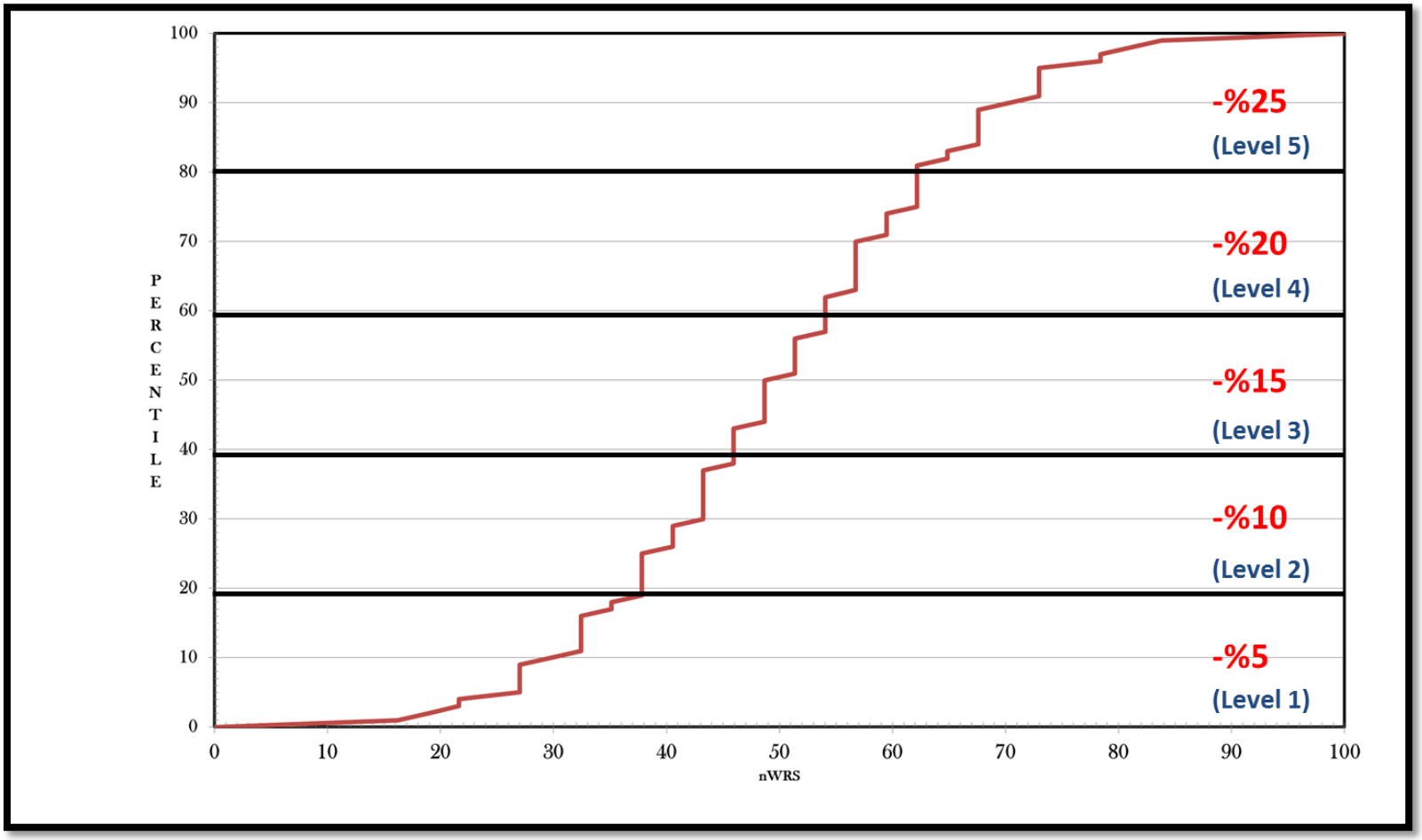
would have been unfair to reduce the ferrous scrap price of a supplier who had contributed to 3 wasted heats in the same manner as one who had contributed to 15 wasted heats.

The financial data furnished by the steel manufacturer was used to determine the percentage reduced from the ferrous scrap market price for each of the 5 levels. The financial data provided the following information: the loss of profits due to input costs (i.e. raw materials) and the missed opportunity cost (i.e. potential profit gained if the heat was not wasted or downgraded). Upon review of the financial data, it was noticed that the prices paid to a small portion of the suppliers were greatly reduced as compared to others. The steel manufacturer confirmed these suppliers' ferrous scrap prices were reduced based on their egregious contributions to wasted and downgraded heats. While the steel manufacturer had reduced the prices paid for some suppliers' ferrous scrap, which were known to contain elevated weight percentages of residual elements, the percentages reduced by the steel manufacturer were applied in a random and inconsistent manner. Therefore, the levels used within the decision support analysis model ensured the percentage reduced from the ferrous scrap market price per supplier was applied in a quantitative and unbiased manner.

As stated previously, the 5 levels corresponded to a percentage in which the ferrous scrap market price was reduced per supplier. The largest percentage, which was calculated from the financial data, used by the steel manufacturer to reduce a supplier's ferrous scrap price was approximately 25%. Since this was the largest percentage applied by the steel manufacturer to reduce a supplier's ferrous scrap price, it was the percentage used for level 5. The percentages used for the subsequent 4 levels were decremented by

5% between levels because these percentages ensured the steel manufacturer remained profitable on downgraded heats and minimized losses when wasted heats were experienced. The percentage reduced from the ferrous scrap market price for each level is displayed below in Figure 3-2.

Figure 3-2: Graph used in the Decision Support Analysis Model



3.2.2 Ferrous Scrap Price Model

The concept of the should-cost model was related to the research conducted for this praxis as aggregate historical chemistry and financial data was used to predict the value-in-use price of ferrous scrap per supplier. The ferrous scrap price model was created to determine the value-in-use price for ferrous scrap per supplier from a raw material perspective. As described in section 2.5.5, the ferrous scrap price model was adapted from the should-cost model. The purpose of the ferrous scrap price equation was to represent a relationship between the historical heat chemistry and suppliers' contributions to wasted and downgraded heats. Leveraging this relationship, the value-in-use price per supplier was calculated and compared against the ferrous scrap prices previously paid by the steel manufacturer to validate its effectiveness.

The procurement process used by the steel manufacturer was made explicit prior to developing the Ferrous Scrap Price model, which was necessary for adapting the should-cost model to the Ferrous Scrap Price model. As stated in section 2.5.5, the should-cost model used aggregate historical financial information and an understanding of the overall procurement process to predict the price of specialized components used within the oil and gas industry. The steel manufacturer confirmed the following factors were considered when negotiating the ferrous scrap price with a supplier: reputation, expected delivery amount, transportation costs, and business operations (e.g. stamping plants receive a premium on their scrap). Understanding this process allowed for critical factors to be considered, which were related to whether heats are wasted or downgraded, when calculating the value-in-use ferrous

scrap price per supplier. The Ferrous Scrap Price model placed a heavy emphasize on the raw material cost, which was logical as ferrous scrap is steel. The part of the should-cost model as defined by Mealer & Park (2013) applicable to the research conducted for this praxis was the equation for the cost of Raw Material (RM), which is:

- **RM Cost** = (Standard Material Weight) * (Standard Material Unit Price) * (1+ Material Production Defect Rate)

The RM Cost equation was developed for the oil and gas industry and used to predict what a specialized component might cost, which was Mealer's and Park's (2013) intent. However, as stated above, this equation was adapted for the ferrous scrap market. The reason for this adaption was because 2 factors deemed to have an impact on the outcome of heats needed to be incorporated. These factors were: density and the weight percentage of residual elements. The requirement to account for these factors altered the RM Cost equation above to the following Ferrous Scrap Price equation:

- **Ferrous Scrap Price** = (Standard Material Weight) * (Standard Material Unit Price) * (1 + Material Production Defect Rate) * [1 + (1 / Density) * Σ(Weight Percentage of Residual Elements)]

The values used for the variables in the ferrous scrap price equation are defined as:

- **Standard Material Weight** – weight of the ferrous scrap delivered
- **Standard Material Unit Price** – the monthly ferrous scrap market price provided by the American Metal Market was used as this price
- **Material Production Defect Rate** – the total weight a supplier contributed to wasted and downgraded heats over a given year was totaled and then divided by the gross weight across all wasted and downgraded heats for the respective year, thus producing the Material Production Defect Rate
- **Density** – the density of the ferrous scrap, which was used to account for the yield of the ferrous scrap when converted to liquid steel
- **Weight of Residual Elements** – this value was calculated by summing the 5 residual elements most detrimental to the quality of steel. The residual elements summed were: copper, chromium, tin, nickel, and molybdenum.

The profits lost due to wasted and downgraded heats also needed to be considered in the Ferrous Scrap Price model. This model considered a supplier's contributions to wasted and downgraded heats on a per heat basis. Since the model operated in this manner, it was not possible to identify suppliers who had a history of providing ferrous scrap with elevated weight percentages. Thus, the percentage reduced from the value-in-use ferrous scrap price predicted by this model was applied in a uniform fashion because the model did not account for suppliers' cumulative performance.

The percentage used to reduce the value-in-use ferrous scrap price predicted by the Ferrous Scrap Price model was 5%. The justification for this conservative

percentage used was due to a previous evaluation of the suppliers' contributions to wasted and downgraded heats, which showed that any percentage higher than 5% would have impacted 52% of the suppliers who did not exhibit a history of negative performance. Although a conservative percentage was applied to the value-in-use ferrous scrap prices predicted by the Ferrous Scrap Price model, the steel manufacturer was still able to increase their profits when this percentage applied.

3.2.3 Predictive Modeling

Unlike the Predictor Screening model described in section 3.1.2.1, the predictive model used in this part of the research was used to predict the value-in-use ferrous scrap price. This predictive model (i.e. KNN model) applied statistics to predict a response variable (i.e. value-in-use ferrous scrap price) based on a set of predictors. The predictive model was applied to the dataset described in section 3.1 as this data provided the set of predictors. The predictors used for this model were market price, historical heat chemistry, and supplier names that were converted to numerical values. The market price data was provided by the American Metal Market. The historical heat chemistry and supplier data was furnished by the steel manufacturer. The response used in this model was the value-in-use ferrous scrap price calculated in section 3.2.1. As stated in sections 2.5.1, 2.5.2, and 2.5.3, models that employ a machine learning algorithm have shown promise to be more effective than traditional models when using historical data to predict price. To this end, a machine learning model that was described in section 2.5.3 (i.e. K-Nearest Neighbors) and applicable to the research being conducted for this praxis was used to

determine if a model which contained a learning capability was more effective at predicting the value-in-use price of ferrous scrap per supplier.

The performance of the machine learning model was measured differently from the methods suggested by statistical techniques. While in classical statistics a model is defined in order to better explain a phenomenon, but in predictive modeling a strong emphasize is placed on how well a predication can be performed on unseen data (Spedicato et al., 2018). The significance of assessing the predictive performance on a test set rather than a validation set, which is used to calibrate the model cannot be emphasized enough. Kuhn and Johnson (2013) list the following steps to use when building a predictive model:

1.) *Model selection*: an assessment of which model among the ones tested performs best on a test set, making the results generalizable to unused data.
2.) *Data pre-processing*: this task consisted of cleaning the data, transforming predictors (feature engineering) and selecting those that will be used in the modeling stage (feature selection).
3.) *Data splitting*: the dataset was divided into a training, a validation, and a test set, thereby reducing the "overfitting" that occurs when a model appears to be extremely performant on the same data used for finding the underlying structure (e.g. training set), whilst showing significantly less performance on unseen data.
4.) *Fitting the selected models on the training set*: the model used tuning parameters which were set in advance to uniquely define a model. These

parameters cannot be derived analytically and their class is also known as "hyper-parameters".

3.2.3.1 Model Selection

In the literature review, models that incorporated machine learning algorithms were identified. These models were of interest as they were applied to historical data to predict a price based on this data. The diversity of these models, all of which used machine learning algorithms, were reviewed relative to optimal pricing strategies, and it was determined that not all of them were applicable to the research conducted for this praxis.

The research covered in section 2.5.1 used the following machine learning algorithms: Neural Networks and Random Forest to predict the optimized insurance premiums based on historical data. The models that incorporated either of these machine learning algorithms were not applied in the research conducted for this praxis because of the difficulty relative to interpreting their results. Interpreting the results produced by the Neural Networks model was arduous because it was not clear how the network was solving the problem (i.e. the model operated as a black box). Additionally, the model that used Neural Networks was not intuitive to train because the results were nondeterministic and depended heavily on the choice of initial parameters, which made it difficult to determine which ones should be used. Similar to the Neural Network model, it was an onerous task to interpret the results produced from the Random Forest model as this model also operated as a black box. While it was possible to understand how the decision trees were generated, comprehending how the model decided on which trees to use when the variables were averaged across the trees to produce the final result was perplexing.

As stated in section 2.5.3, a model that employed a machine learning algorithm (i.e. k-nearest neighbors) and was applicable to the research being conducted for this praxis was called the K-Nearest Neighbors (KNN). This model used a clustering technique to predict the value-in-use ferrous scrap price per supplier. Additionally, the KNN model was selected due to its ability to accept numerical values to output a continuous numerical value.

3.2.3.1.1 K-Nearest Neighbors

The K-Nearest Neighbors (KNN) was a model used to predict the value-in-use price for ferrous scrap based on the following 7 inputs: market price, historical heat chemistry (i.e. 5 residual elements most detrimental to the quality of steel as defined in section 3.2.2), and supplier name. The trade journal, American Metal Market, provided the market price. The steel manufacturer furnished the historical heat chemistry and supplier name.

The KNN model was chosen because it was intuitive and the runtime needed to generate results was reasonable. This model provided predictions for a new observation by searching through the entire training set looking for the most similar instances (i.e. neighbors) and summarized the output variable (i.e. value-in-use ferrous scrap price) based in these instances. Thus, this model provided a robust method for predicting the value-in-use price of ferrous scrap that was not exercised in the previous 2 models used in this research.

An issue with machine learning algorithms is overfitting. This deficiency was overcome by keeping the test set separate from the training and validation set.

Additionally, numerous input variables can negatively affect the performance of the KNN model. This concern was addressed by using only 7 input variables for this model, which were: market price, historical heat chemistry (i.e. 5 residual elements as defined in section 3.2.2), and supplier name.

3.2.3.2 Data Pre-Processing

Data pre-processing methods were applied to transform the data in various manners, e.g. addition and deletion. The grades of ferrous scrap data and names of suppliers were recoded from categorical to nominal values so that they were handled appropriately. The complete success or failure of the entire analysis is dependent on this part of the process because the machine learning technique used, K-Nearest Neighbors, was sensitive to the format and scale of the predictors (Spedicato et al., 2018). Furthermore, the dataset was standardized to ensure of the weight data was in the same measurement units and the chemistry of the heats used the same scale.

3.2.3.3 Data Splitting

The dataset was split between a training set and a validation set where the model was fit and tuned, respectively, and a test set where the data was used to estimate the model's performance. The evaluation of the model's effectiveness in predicting the value-in-use price for ferrous scrap was completed using the test set, which was composed of samples withheld from the training and validation sets so that an unbiased estimate is obtained. Russell & Norvig (2009) confirmed this approach in their book *Artificial Intelligence: A Modern Approach* as they stated, "…the model should be

evaluated on samples that were not used to build or fine-tune the model, so that they provide an unbiased sense of model effectiveness".

In this praxis, the portion of data identified for the "validation set" and "test set" are used for different and distinct purposes. The method in which the training, validation, and test set were used aligned with the definitions discovered in research [(Russell & Norvig, 2009); (Ripley, 1996); (Brownlee, 2017)]:

- *Training set*: the sample of data used to fit the model
- *Validation set*: the sample of data used to provide an unbiased evaluation of a model fit on the training set while tuning model hyperparameters. The evaluation becomes more biased as performance gained from the validation dataset is incorporated into the model configuration.
- *Test set*: the sample of data used to provide an unbiased evaluation of a final model fit on the training dataset.

3.2.3.4 Fitting the Model

The K-Nearest Neighbors model used a single tuning parameter, k, which was set in advance to uniquely define the model. A lower value of k was more biased, which was undesirable, while a larger value of k was less biased but suffered from large variability. Therefore, the method used to determine the right value of the tuning parameter (i.e. k) was the k-fold cross-validation technique.

3.2.4 Comparison

The methodology of comparison was applied to determine which model was the

best for addressing the research questions. The results generated from the Decision Support Analysis model, Ferrous Scrap Price model, and the K-Nearest Neighbors model were compared against each other. Thus, this methodology was used to determine which model was the best at predicting the value-in-use price for ferrous scrap per supplier and the one in which the steel manufacturer implemented.

3.2.4.1 Paired T-Test

The paired t-test was used to determine whether the mean of a dependent variable (i.e. quantitative metric – the actual ferrous scrap price paid by the steel manufacturer) was the same for the pricing models (i.e. Decision Support Analysis model, Ferrous Scrap Price model, and KNN model). The intent of applying this statistical test was to understand whether there was a difference in the price between the actual prices paid by the steel manufacturer for suppliers' ferrous scrap and if the pricing models were able to predict the value-in-use ferrous scrap (i.e. the price that the steel manufacturer should have paid). The paired t-test was used to determine whether the mean difference of the quantitative metric and the prices predicted by the respective pricing models were statistically significantly different to zero. Findings from these statistical tests also provide insight into which model provided the most significant difference from the actual price paid, thus resulting in the biggest increase of profits amongst the models.

When the paired t-test was conducted, 4 assumptions were made, which were:

- The dependent variable must be continuous (interval / ratio)
- The observations are independent of one another

- The dependent variable should be approximately normally distributed
- The dependent variable should not contain any outliers

The dependent variable (i.e. quantitative metric) was continuous. Since the observations were on a per supplier basis, it was understood that they were independent of one another. The dependent variable was approximately normally distributed, and did not contain any outliers. Therefore, all 4 of these assumptions were satisfied which verified the applicability of using this statistical test for the pricing data.

3.3 Conclusion

For this praxis, the research process was conducted in two phases. Phase I consisted of obtaining the dataset, conducting data analysis, and realizing the correlation of wasted and downgraded heats to suppliers who contributed ferrous scrap to these heats. Predictor Screening was the statistical method used to verify the residual elements most detrimental to the quality of steel and their contributions to wasted and downgraded heats.

Phase II commenced with the development of a Decision Support Analysis model to predict the value-in-use ferrous scrap price per supplier. A Ferrous Scrap Price model was created to predict the value-in-use price of ferrous scrap per supplier, which used an equation that placed heavy emphasis on raw material factors. The KNN model incorporated a machine learning algorithm, which searched the dataset for similar instances to predict the value-in-use ferrous scrap price. A comparison of the prices generated from these models against a quantitative metric was conducted to determine which one was the best at predicting the value-in-use ferrous scrap price per supplier.

Finally, Phase II concluded with paired t-tests to determine which model increased the profits of the steel manufacturer the most.

Chapter 4 – Results

This chapter contains the results of the analysis conducted during Phase I and II of the research for this praxis. The literature review coupled with the threshold weights of the residual elements provided the knowledge needed to complete the first step in Phase I of the research. Statistical analysis was used to verify the results produced in this step. The correlation of wasted and downgraded heats to suppliers who contributed ferrous scrap to these heats was realized through data analysis. The solutions for Phase II of the research were attained by using the following models: Decision Support Analysis, Ferrous Scrap Price, and K-Nearest Neighbors. The results from Phase II of the research are displayed in tables, graphs, and charts. Samples of the dataset are presented in this chapter; however, major portions are located in the appendices.

4.1 Phase I Results

The profits of the steel manufacturer are impacted on an annual basis due to wasted and downgraded heats. Prior to conducting data analysis, the dataset was interpreted. Once the structure of the dataset was understood, the next step was to identify the wasted and downgraded heats. A heat was wasted or downgraded if the levels of residual elements (i.e. copper chromium, tin, nickel, molybdenum) were elevated as these elements are detrimental to the quality of steel. The predictive screening model tested the residual elements on their ability (i.e. contributions) to predict whether a heat was wasted or downgraded, and the frequency in which they were present across wasted and downgraded heats. Finally, data analysis was used to

correlate the wasted and downgraded heats to suppliers who contributed ferrous scrap to them.

4.1.1 Interpreting the Dataset

The steel manufacturer who provided the dataset annually procured and produced over 2 million tons of ferrous scrap and steel, respectively. This dataset spanned approximately 2.5 years and contained over 39,000 heats. Ferrous scrap procurement information was also shared, which was used to determine the effectiveness of the models at predicting the value-in-use ferrous scrap price. The dataset was provided in a Microsoft Excel file and composed of 5 sheets. One sheet contained all of the historical heat chemistry for approximately 2.5 years and was labeled “Chemistry”. A sample of the historical heat chemistry data was displayed in Table 3-1, which is located in the supplementary files attachment.

Three of the sheets contained the ferrous scrap procurement information for the following years: 2016, 2017, and 2018. These sheets were labeled, “2016”, “2017, and “2018”. A sample of this data from the year 2016 was shown in Table 3-3.

The last sheet was labeled “Orders”. The steel manufacturer, who provided this dataset, procured approximately 70% of the ferrous scrap they used during this time period from one company. This sheet contained the ferrous scrap procurement information of this supplier and was used to identify the exact location where the ferrous scrap was delivered from as this supplier was geographically disbursed.

4.1.2 Identification of Wasted and Downgraded Heats

Once the structure and format of the data was comprehended, the data analysis proceeded to the next step. The wasted and downgraded heats were identified in this step. The threshold weight percentages of residual elements allowed within liquid steel for a heat to satisfy its chemistry requirements were displayed in Table 3-2. As stated in section 3.1.2, a weight percentage of a residual element that is more than 2.5 times the threshold resulted in the heat being considered as wasted. All of the other heats that contained elevated weight percentages of residual elements, but were less than 2.5 times the thresholds were considered as downgraded. Additionally, each residual element was sorted one at a time by year in a descending order from its highest weight percentage per heat to lowest. This step helped to confirm the residual element responsible for the wasted or downgraded heat.

Table 4-1, below, provides a summary of all the wasted and downgraded heats identified in the dataset, which are sorted by the residual element that caused the heat to be considered wasted or downgraded. Samples of wasted and downgraded heats are shown in Tables 4-2 and 4-3, respectively, which are located in the supplementary files attachment. The residual element responsible for the downgraded or wasted heat was bolded. In Table 4-2, copper, chromium, and tin were responsible for 5, 9, and 8 wasted heats, respectively. The residual elements responsible for wasted heats in Table 4-2 were the same perpetrators that caused all of the downgraded heats in Table 4-3. A full list of the wasted heats is located in Appendix C, which is also located in the supplementary files attachment.

Element	Wasted Heats	Downgraded Heats
Copper (Cu)	17	2945
Chromium (Cr)	16	446
Nickel (Ni)	0	12
Molybdenum (Mo)	0	287
Tin (Sn)	12	396
Total:	**45**	**4086**

Table 4-1: Summary of Wasted and Downgraded Heats per Residual Element

4.1.2.1 Verification of Residual Elements

As described in section 3.1.2.1, the Predictor Screening model provided a method of screening multiple predictors (i.e. residual elements) for their ability to predict an outcome. In the context of this research, the outcome was whether a heat would be considered wasted or downgraded. This model also calculated the portion each residual element was present across all wasted and downgraded heats.

The results generated from the Predictor Screening model regarding the residual elements' ability to predict whether a heat was considered wasted or downgraded are shown below in Figures 4-1 and 4-2, respectively. The residual elements with the highest values in the *Contribution* column are more likely to determine whether a heat was wasted or downgraded. The *Portion* column represented the total percentage each residual element was present across all the wasted and downgraded heats. Not surprisingly, the residual elements most deleterious to the quality of steel, specifically: copper (Cu), chromium (Cr), and tin (Sn), had the highest values in the *Contribution* column. These results corroborated the data analysis conducted previously as these same residual elements were responsible for the wasted and downgraded heats listed in Tables 4-2 and 4-3, respectively.

An interesting finding generated from the Predictor Screening model relative to wasted heats, displayed in Figure 4-1, was tin had a higher *Contribution* value than copper or chromium. As shown in Table 4-1, copper was responsible for 5 total more wasted heats than tin. Since copper and tin were responsible for a similar amount of wasted heats it was peculiar why tin had a *Contribution* value almost twice that of copper relative to wasted heats as displayed in Figure 4-1. An explanation for this

anomaly was due to the fact that the weight percentage of tin was near or over its threshold value, as defined in Table 3-2, for the majority of wasted heats caused by copper. However, the opposite is not true for copper as the weight percentage of copper was over its threshold for only 1 wasted heat caused by tin.

Additionally, the Predictive Screening model helped to confirm the reliability of the dataset. The top 5 residual elements (i.e. copper, chromium, tin, nickel, and molybdenum) in the *Contribution* column for both wasted and downgraded heats aligned with findings of Silver et al. (1970), which identified these same residual elements as the most detrimental to the quality of steel.

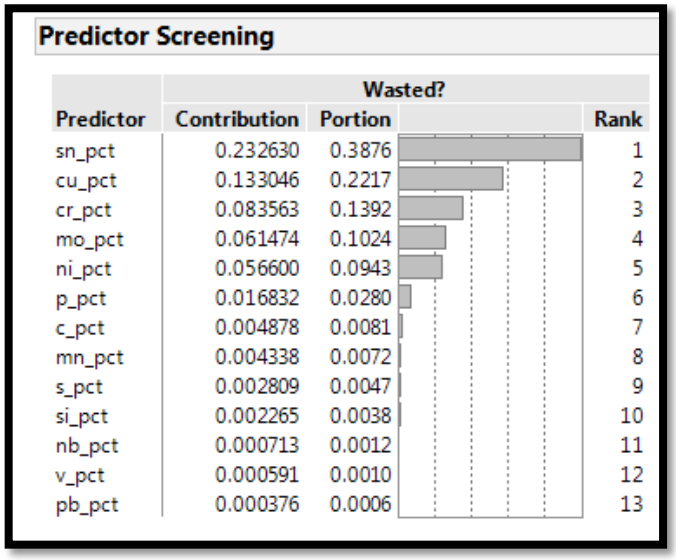


Figure 4-1: Detrimental Residual Elements to Wasted Heats

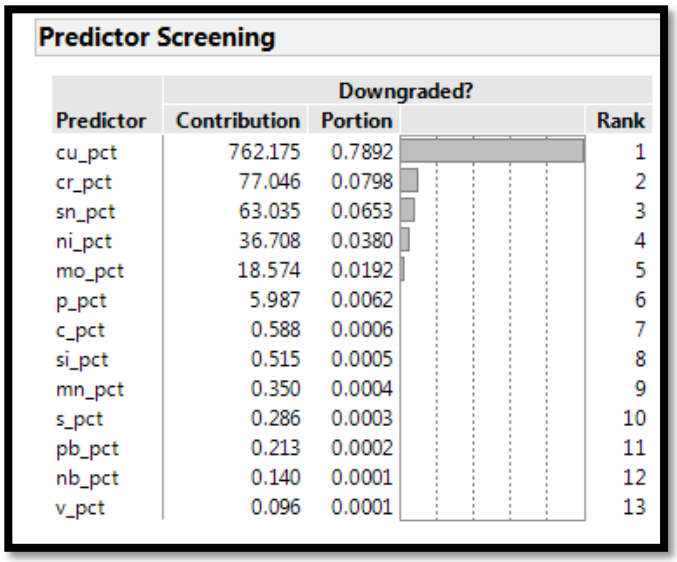


Figure 4-2: Detrimental Residual Elements to Downgraded Heats

4.1.3 Identification of Suppliers

The correlation of wasted and downgraded heats to the suppliers who contributed ferrous scrap to these heats was realized via the methods described in section 3.1.3. Tables 4-4 and 4-5, located below, display the correlation of wasted and downgraded heats to the suppliers who contributed ferrous scrap to these heats, respectively. The *heat_no* column corresponds to the *Supplier* column. Thus, in Table 4-4, the following suppliers: 30, 27, and 22 contributed to the wasted heat numbered: 21601811. The *Quantity* column was used for the reconstruction effort. The values in the *Quantity* column were calculated based on the scrap recipe, which was defined in section 3.1.3, as it determined the grade (i.e. *MaterialDesc*) and amount of ferrous scrap needed for each heat.

Figure 4-3, below, and Figure 4-4, which is located in the supplementary files attachment, displays the weight percentages of ferrous scrap each supplier contributed to wasted and downgraded heats in 2016, respectively. The weight

percentages of ferrous scrap each supplier contributed to wasted and downgraded heats in 2017 and 2018 are located in Appendix D and E, respectively, which are located in the supplementary files attachment.

Table 4-4: A Sample Set of the Correlation between Wasted Heats and Suppliers

analysis_date	analysis_time	heat_no	Quantity	Po Number	Supplier Alpha	MaterialDesc
1/14/16	7:28	21601811	71.20	BI11142	30	#1 BUSHELING
			17.80	BI11187	27	#2 SHREDDED
			44.50	BI11152	30	#1 DEALER BUNDLES
			10.70	BI11175	22	5' PLATE & STRUCTURAL
3/7/16	19:38	11608410	35.60	BI11238	30	#1 BUSHELING
			35.60	BI11331	30	#1 BUSHELING
			44.50	BI11254	30	#1 DEALER BUNDLES
			17.80	BI11303	30	#2 SHREDDED
3/8/16	23:09	11608580	23.90	BI11260	30	#1 DEALER BUNDLES
			16.00	BI11294	31	RAIL CROPS
			17.80	BI11155	30	#2 SHREDDED
			22.25	BI11365	35	#1 DEALER BUNDLES
			23.73	BI11322	30	#1 BUSHELING
			23.73	BI11319	30	#1 BUSHELING
			23.73	BI11318	30	#1 BUSHELING
3/14/16	20:46	31609350	24.02	BI11364	25	#1 BUSHELING
			23.77	BI11318	30	#1 BUSHELING
			23.77	BI11319	30	#1 BUSHELING
			10.70	BI11390	32	5' PLATE & STRUCTURAL
			17.80	BI11370	30	BLENDED BRIQUETTES
3/22/16	9:34	11610630	71.20	BI11337	30	#1 BUSHELING
			10.70	BI11108-03	29	RAIL CROPS
			12.43	BI11382	37	#2 SHREDDED
			44.50	BI11347	31	#1 DEALER BUNDLES

Table 4-5: A Sample Set of the Correlation between Downgraded Heats and Suppliers

analysis_date	analysis_time	heat_no	Quantity	Po Number	Supplier Alpha	MaterialDesc
1/4/16	17:52	21600520	23.7	BI11126	10	#1 BUSHELING
1/4/16			23.5	BI11142	14	#1 BUSHELING
1/4/16			23.8	BI11127	42	#1 BUSHELING
1/4/16			10.7	BI10971	30	BLENDED BRIQUETTES
1/4/16			22.3	BI11152	14	#1 DEALER BUNDLES
1/4/16			22.3	BI11007	33	#1 DEALER BUNDLES
1/5/16	15:25	21600660	17.8	BI11142	14	#1 BUSHELING
1/5/16	15:25		22.3	BI11127	42	#1 BUSHELING
1/5/16	15:25		10.7	BI11172	57	#1 DEALER BUNDLES
1/5/16	15:25		23.3	BI11147	18	#1 DEALER BUNDLES
1/5/16	15:25		23.7	BI10971	30	BLENDED BRIQUETTES
1/6/16	21:30	21600770	23.9	BI11000	13	#2 SHREDDED
1/6/16			22.3	BI11144	41	#1 DEALER BUNDLES
1/6/16			71.2	BI11100-01	47	5' PLATE & STRUCTURAL
1/6/16			22.3	BI10971	30	BLENDED BRIQUETTES
1/6/16			22.3	BI11142	14	#1 BUSHELING
1/6/16			10.7	BI10971	30	BLENDED BRIQUETTES
1/6/16			17.8	BI11007	33	#1 DEALER BUNDLES
1/8/16	14:18	31600850	71.2	BI11142	14	#1 BUSHELING
1/8/16			10.7	BI11144	41	#1 DEALER BUNDLES
1/8/16			17.8	BI11190	34	#1 DEALER BUNDLES
1/8/16			16.0	BI11180	36	5' PLATE & STRUCTURAL
1/8/16			44.5	BI11102-01	51	BLENDED BRIQUETTES
1/12/16	22:43	41601660	10.7	BI11142	14	#1 BUSHELING
1/12/16			44.5	BI11180	37	5' PLATE & STRUCTURAL
1/12/16			17.8	BI10971	30	#2 SHREDDED
1/12/16			71.2	BI11146	9	5' PLATE & STRUCTURAL

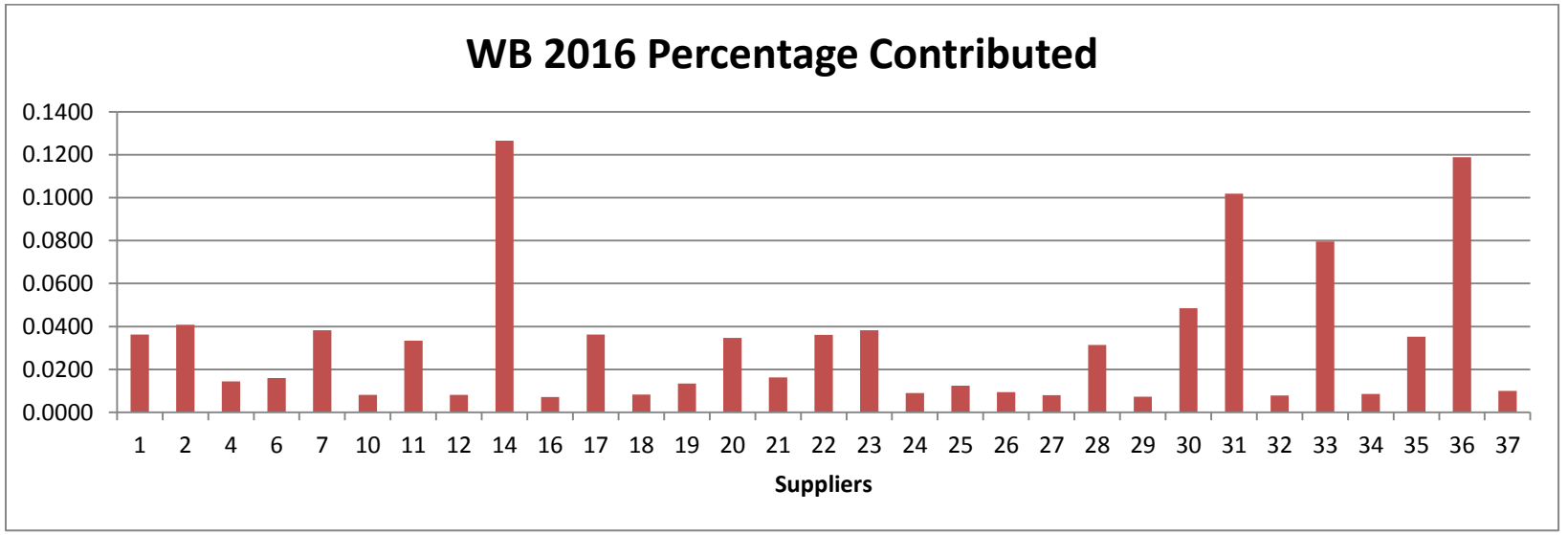


Figure 4-3: Weight Percentages of Ferrous Scrap Contributed by Suppliers to Wasted Heats in 2016

4.2 Phase II Results

The arbitrary purchasing structure employed by steel manufacturers when negotiating the price of ferrous scrap with suppliers relies on qualitative factors. In section 2.2, promising methodologies were identified to enable a quantitative purchasing structure for ferrous scrap. From these methodologies, models were developed as defined in section 3.2. All of the models developed for this praxis, used the information attained in section 3.1 to predict the value-in-use ferrous scrap price per supplier. Each model predicted the value-in-use ferrous scrap price in a unique manner; however, the intent of these models was to hold the suppliers accountable for the residual elements contained within their respective ferrous scrap. The quantitative metric, which was the actual ferrous scrap price paid by the steel manufacturer, was used to determine which model was the best at predicting the value-in-use or "true" price that should have been paid for a respective supplier's ferrous scrap.

4.2.1 Decision Support Analysis Model

The first method used to predict the value-in-use price of ferrous scrap per supplier was the Decision Support Analysis model. As defined in section 3.2.1, the decision support analysis model was composed of 6 evaluation factors that directly related to wasted and downgraded heats. The response to these 6 evaluation factors and corresponding graph for Supplier #1 are shown, below, in Table 4-6 and Figure 4-5, respectively.

Table 4-6: Completed State Tables for Supplier #1

Atoms	Factor (a): Percentage of Contribution to Wasted Heats Description	ANSWER THESE QUESTIONS Enter Y or N
a1	Question 1 (Best Case): Did the Supplier contribute to 0% wasted heats?	n
a2	Question 2: Did the Supplier contribute to wasted heats between 0.0001% - 4.9999% of the time?	y
a3	Question 3: Did the Supplier contribute to wasted heats between 5% - 10% of the time?	n
a4	Question 4: Did the Supplier contribute to wasted heats more than 10% of the time?	n

Atoms	Factor (b): Percentage of Contribution to Downgraded Heats Description	ANSWER THESE QUESTIONS Enter Y or N
b1	Question 1 (Best Case): Did the Supplier contribute to 0% downgraded heats?	n
b2	Question 2: Did the Supplier contribute to downgraded heats between 0.0001% - 4.9999% of the time?	y
b3	Question 3: Did the Supplier contribute to downgraded heats between 5% - 10% of the time?	n
b4	Question 4: Did the Supplier contribute to downgraded heats more than 10% of the time?	n

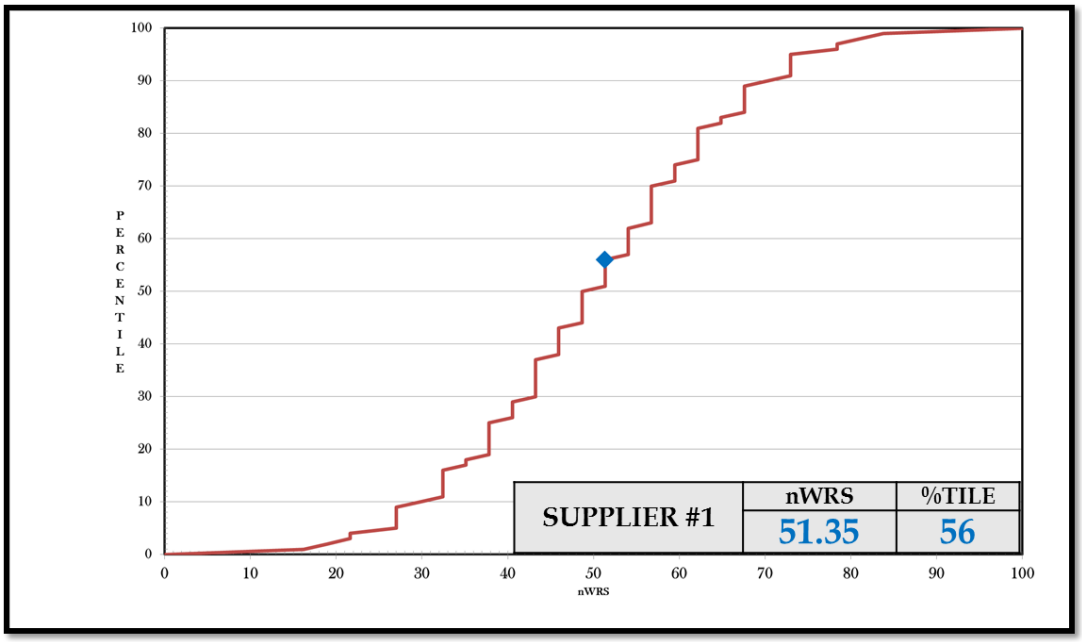
Atoms	Factor (c): Scrap Contributions in 2016 Description	ANSWER THESE QUESTIONS Enter Y or N
c1	Contributed to 2016 downgraded heats	y
c2	Contributed to 2016 wasted heats	y

Atoms	Factor (d): Scrap Contributions in 2017 Description	ANSWER THESE QUESTIONS Enter Y or N
d1	Contributed to 2017 downgraded heats	y
d2	Contributed to 2017 wasted heats	n

Atoms	Factor (e): Scrap Contributions in 2018 Description	ANSWER THESE QUESTIONS Enter Y or N
e1	Contributed to 2018 downgraded heats	y
e2	Contributed to 2018 wasted heats	n

Atoms	Factor (f): Problematic Chemical Contribution Description	ANSWER THESE QUESTIONS Enter Y or N
f1	High quantity of COPPER?	y
f2	High quantity of CHROMIUM?	n
f3	High quantity of TIN?	y

Figure 4-5: Completed Graph regarding nWRS and Percentile for Supplier #1



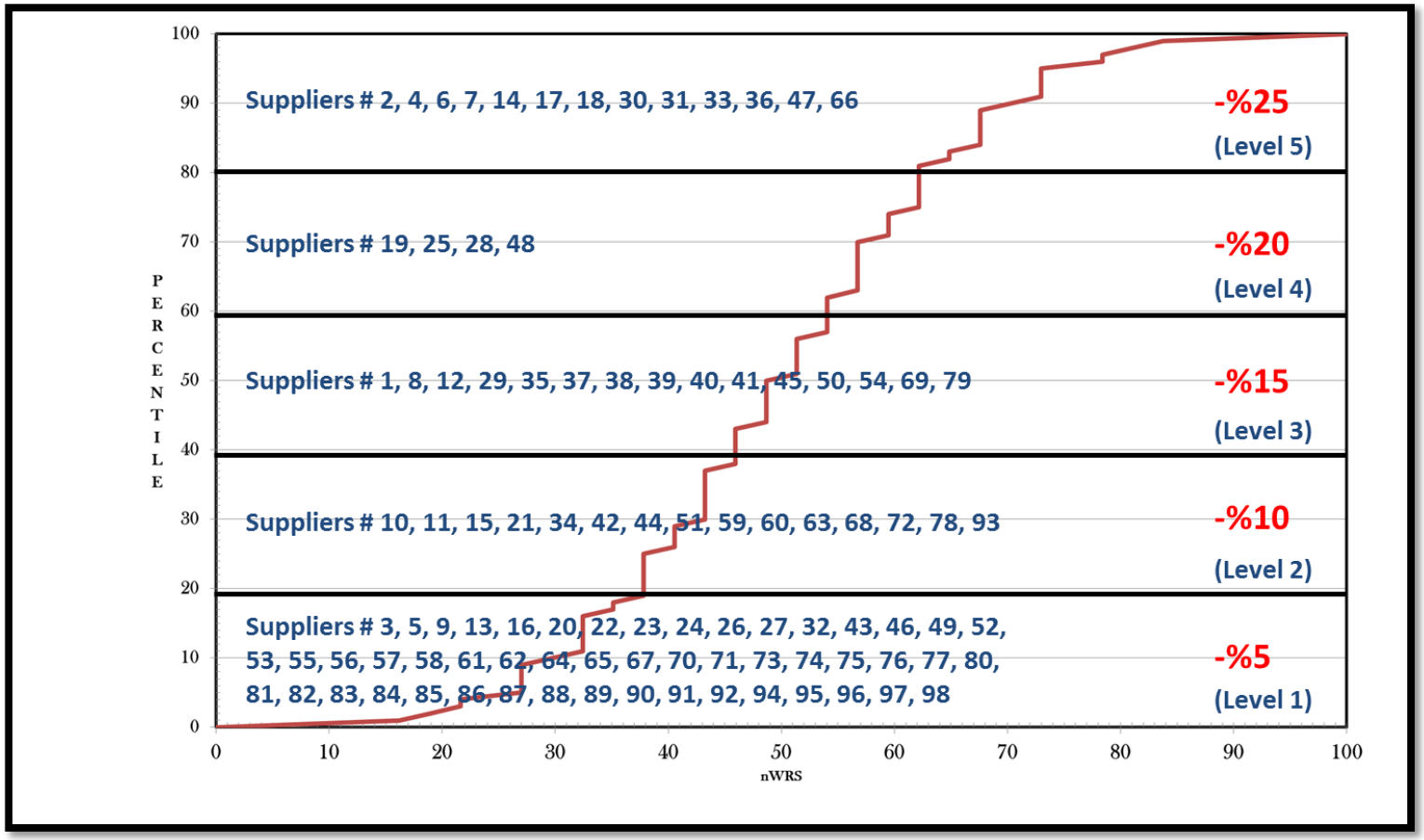
The model calculated a normalized Weighted Raw Score (nWRS), which corresponded to a percentile, when responses were provided for all of the factors. The nWRS and percentile were the x-axis and y-axis, respectively, in the graph used for the decision support analysis model. The nWRS and corresponding percentile were calculated and plotted for all suppliers who contributed to wasted and/or downgraded heats. The percentile, which is partitioned into categories, of where each supplier's nWRS was located is displayed below in Figure 4-6.

The suppliers who contributed the most ferrous scrap to wasted and downgraded heats had the lowest value-in-use prices. This result was not groundbreaking since these suppliers had the highest percentage reduced from their price.

Intuitively, one would suspect most suppliers would be in the lowest percentile range (i.e. level 1) and the number of suppliers would decease as the percentile range increased (i.e. level 2, 3, 4, and 5). Therefore, an interesting finding was that there was 3 times the amount of suppliers in the highest percentile range (i.e. level 5) than in the second highest percentile range (i.e. level 4). This result should be noted because some of the suppliers listed in the highest percentile range (i.e. level 5) are subsidiaries of the steel manufacturer. Thus, it would be in the steel manufacturer's interest to provide support to these suppliers as they could influence their (i.e. the supplier) actions so that these suppliers reduce the amount of ferrous scrap they provide with elevated levels of residual elements, which would increase the steel

manufacturer's profits. If this model was used to calculate the value-in-use ferrous scrap price per supplier, then the steel manufacturer would have reduced the amount they overpaid for ferrous scrap by approximately 12%.

Figure 4-6: The Percentiles per Supplier



4.2.2 Ferrous Scrap Price Model

As noted in Chapter 1, the steel manufacturer incurs a raw material cost of $80,000 per each wasted heat. The Ferrous Scrap Price model was developed to predict the value-in-use ferrous scrap price per supplier, which was based on an equation that placed heavy emphasis on the raw material cost. As detailed in section 3.2.2, this model was adapted to account for the correlation of the wasted and downgraded heats to the suppliers who contributed ferrous scrap to these heats. Additionally, the value-in-use ferrous scrap price predicted by the Ferrous Scrap Price model was compared against a quantitative validation metric (i.e. the actual ferrous scrap price paid by the steel manufacturer) to determine the effectiveness of the model.

The Ferrous Scrap Price model predicted the value-in-use price of ferrous scrap using factors relative to raw material. The value-in-use ferrous scrap prices predicted by this model usually aligned closely with market prices. This trend was logical because ferrous scrap is raw material, thus prices predicted by a model that placed emphasis on raw material factors should be in family with the market price.

As described in section 3.2.2, the Ferrous Scrap Price model was adapted from the Raw Material (RM) cost equation. This equation provided a solid foundation for predicting the value-in-use ferrous scrap price, but needed to be adjusted to account for the correlation of the wasted and downgraded heats to suppliers. The importance of considering this correlation when predicting the value-in-use ferrous scrap price cannot be understated. As shown in Table 4-7, below, the ferrous scrap price

equation, which was adapted from the RM cost equation, consistently outperformed the ferrous scrap prices predicted by the RM cost equation. Therefore, predicting the value-in-use ferrous scrap price based on the factors (i.e. total weight of ferrous scrap delivered, market price, material production defect rate, density, and heat chemistry) used in the Ferrous Scrap Price model proved effective.

An interesting finding from the results generated by the Ferrous Scrap Price model was that the value-in-use ferrous scrap prices predicted by the Ferrous Scrap Price model compared favorably with the prices predicted by the Decision Support Analysis model for suppliers who had minimal contributions to wasted and downgraded heats. The reason why the value-in-use ferrous scrap prices predicted by these 2 models were comparable for suppliers with minimal contributions to wasted and downgraded heats was because the Decision Support Analysis model did not vastly reduce these suppliers' prices since they were not known to consistently provide ferrous scrap with elevated levels of residual elements. Hence, the value-in-use ferrous scrap price for these suppliers was similar to the ferrous scrap market price.

In summary, the results from the Ferrous Scrap Price model were encouraging as they would have reduced the amount the steel manufacturer overpaid for ferrous scrap by approximately 7%. A sample set of value-in-use ferrous scrap prices predicted by the Ferrous Scrap Price model are shown in Table 4-7.

Table 4-7: Ferrous Scrap Prices predicted by the Raw Material Cost and Ferrous Scrap Price Equations

Suppliers	Market Price (per ton)	Raw Material Cost (per ton)	Ferrous Scrap Price (per ton)
SUPPLIER #1	$223.21	$225.83	$215.49
SUPPLIER #2	$198.98	$208.51	$179.96
SUPPLIER #3	$238.49	$239.74	$215.55
SUPPLIER #4	$208.90	$216.13	$207.22
SUPPLIER #5	$335.15	$345.59	$303.92
SUPPLIER #6	$208.40	$211.21	$189.33
SUPPLIER #7	$210.01	$210.22	$190.92
SUPPLIER #8	$198.98	$200.03	$179.98
SUPPLIER #9	$198.98	$200.11	$181.96
SUPPLIER #10	$196.64	$196.82	$177.73
SUPPLIER #11	$264.87	$266.73	$239.34
SUPPLIER #12	$200.45	$201.62	$171.11

4.2.3 K-Nearest Neighbors Model

The K-Nearest Neighbors (KNN) model used a machine learning algorithm to calculate the value-in-use price for ferrous scrap per supplier. This price was calculated by using the following predictors: market price, historical heat chemistry (i.e. 5 residual elements as defined in section 3.2.2), and supplier name. The response used to train this model was the value-in-use price calculated by the decision support analysis model. The KNN model predicted the value-in-use price by searching through the entire training set for similar instances, i.e. neighbors, and predicted the value-in-use based on these similarities (i.e. market price and weight percentages of residual elements). Additionally, this model made it obvious which predictors were the most significant.

A subset of the original dataset, which contained all of the downgraded heats

identified (i.e. 507 heats), was divided into three sets: training, validation, and test. The training set, which was used to fit the model, comprised of 60% of this data subset. 10% of the data was used for the validation set to calculate the model parameter (i.e. k value), which used the k-hold cross validation method. As displayed in Figure 4-7, below, the value of 8 was determined to be the best k value relative to this dataset. This k value is also noted by the asterisk in the verification table displayed in Figure 4-10, below. Finally, the test set, which was used to provide an unbiased evaluation of a final model fit on the training dataset, comprised of 30% of the data subset.

The actual by predicted plots are shown below in Figure 4-8. A visual depiction of the model's accuracy is shown in the test graph in Figure 4-8. The accuracy of the model was determined by how close a point was to the linear line because the closer the point was to the linear line the better the predicted price matched the actual price. Thus, the KNN model appeared to perform well as the prices predicted in the test set were close to the linear line in the test graph in Figure 4-8.

The problem presented in this praxis presented a regression problem, which the KNN model attempted to solve. The residual plots of the KNN model were examined to assess the appropriateness of this model. The residual by predicted plots are shown below in Figure 4-9. The residual plots displayed a fairly random pattern with a tight bandwidth as approximately 50% of the points were positive and 50% were negative. The random pattern indicated the model provided a decent fit to the data and provided some assurance the data was dependable.

The summary of the results produced by the KNN model, which contain the Root Mean Square Error (RMSE) statistic, for the training, validation, and test set, are displayed in Figure 4-10. “RMSE is a good measure of how accurately the model predicts the response, and it is the most important criterion for fit if the main purpose of the model is prediction” (Grace-Martin, 2018). The RSME provided an absolute measure of fit the model. The results displayed in Figure 4-10 showed, the RMSE value for the validation set (i.e. when the value of k was 8) was low (i.e. 14.794) indicating that this model had a good fit. Thus, there was confidence in predictive performance of the KNN model.

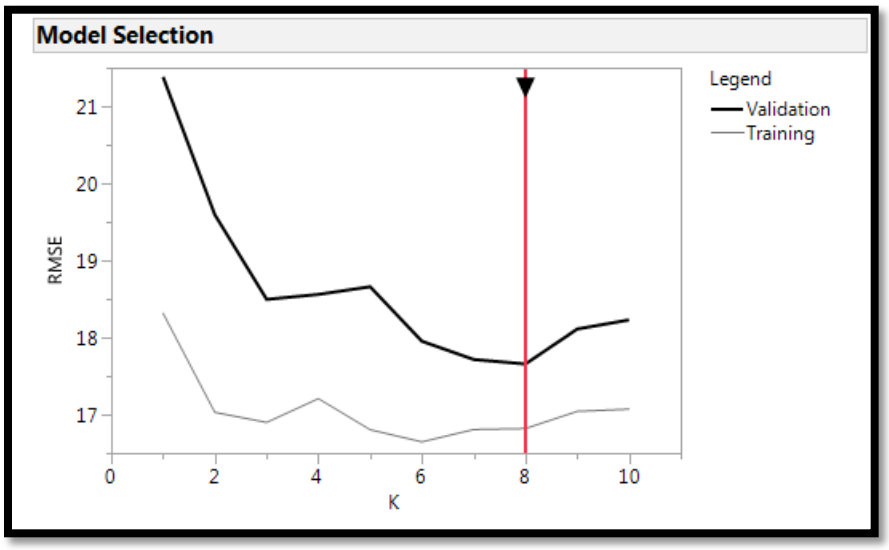


Figure 4-7: Selection of k value for the KNN Model

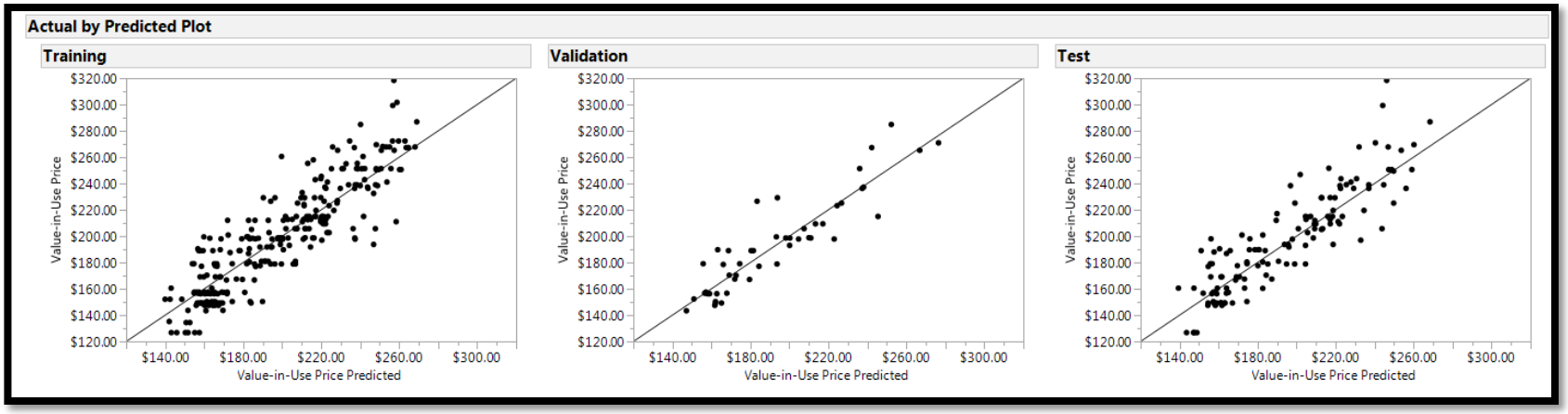


Figure 4-8: K-Nearest Neighbor Model Actual by Predict Plot

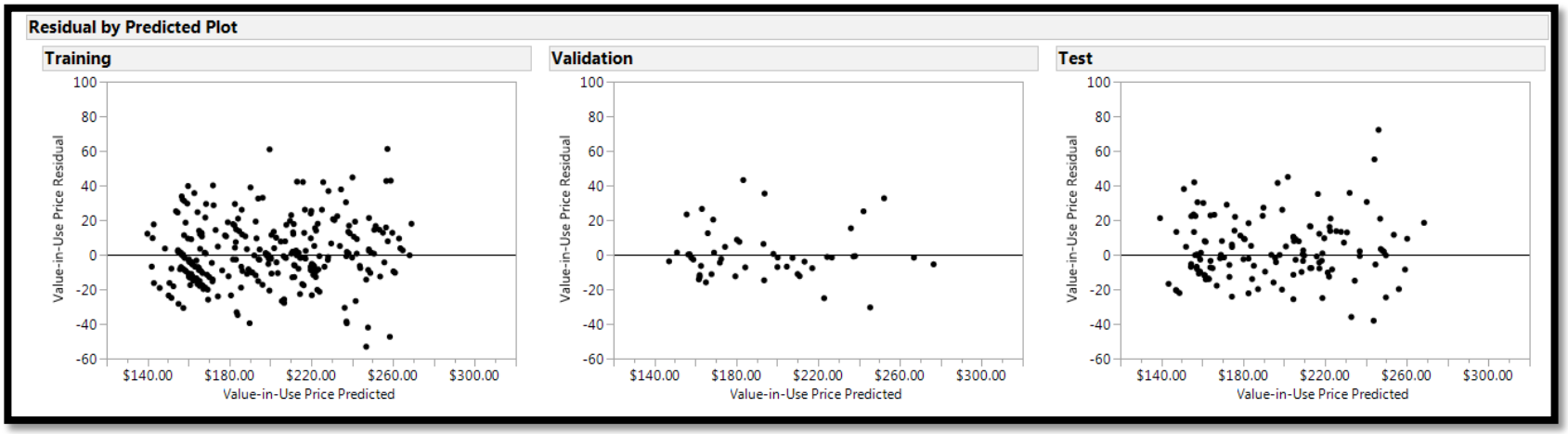
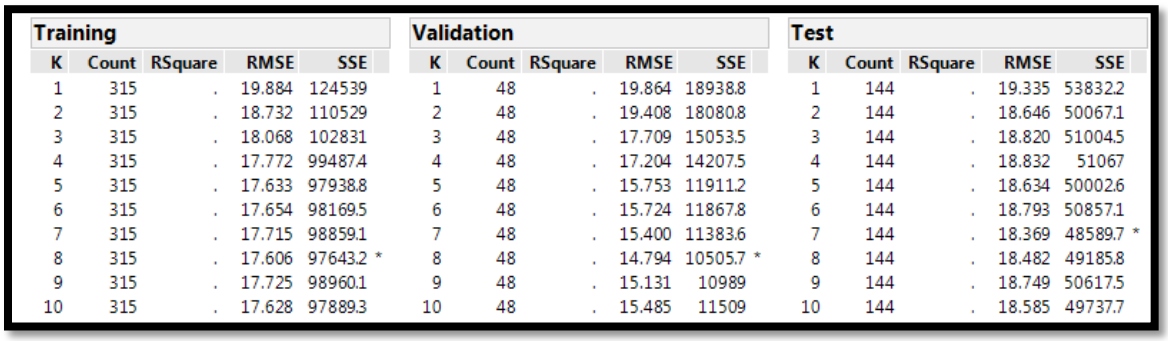


Figure 4-9: K-Nearest Neighbors Model Residual by Predict Plot



Training					Validation					Test				
K	Count	RSquare	RMSE	SSE	K	Count	RSquare	RMSE	SSE	K	Count	RSquare	RMSE	SSE
1	315	.	19.884	124539	1	48	.	19.864	18938.8	1	144	.	19.335	53832.2
2	315	.	18.732	110529	2	48	.	19.408	18080.8	2	144	.	18.646	50067.1
3	315	.	18.068	102831	3	48	.	17.709	15053.5	3	144	.	18.820	51004.5
4	315	.	17.772	99487.4	4	48	.	17.204	14207.5	4	144	.	18.832	51067
5	315	.	17.633	97938.8	5	48	.	15.753	11911.2	5	144	.	18.634	50002.6
6	315	.	17.654	98169.5	6	48	.	15.724	11867.8	6	144	.	18.793	50857.1
7	315	.	17.715	98859.1	7	48	.	15.400	11383.6	7	144	.	18.369	48589.7 *
8	315	.	17.606	97643.2 *	8	48	.	14.794	10505.7 *	8	144	.	18.482	49185.8
9	315	.	17.725	98960.1	9	48	.	15.131	10989	9	144	.	18.749	50617.5
10	315	.	17.628	97889.3	10	48	.	15.485	11509	10	144	.	18.585	49737.7

Figure 4-10: K-Nearest Neighbors Model Summary

4.2.4 Comparison

In this section, the 3 models developed to predict the value-in-use ferrous scrap price were compared against each other to determine which model was the best at predicting the value-in-use or "true" price that should have been paid for a respective supplier's ferrous scrap. All of the value-in-use ferrous scrap prices per supplier that were predicted by the Decision Support Analysis model, Ferrous Scrap Price model, and K-Nearest Neighbors model are displayed, below, in Table 4-8. A quantitative metric, which was the actual prices paid by the steel manufacturer for suppliers' ferrous scrap, was used to evaluate the effectiveness of these models in predicting the value-in-use ferrous scrap price. Therefore, the numbers bolded in Table 4-8 represent the best predicted value-in-use price per supplier amongst the 3 models.

The K-Nearest Neighbors model showed the potential of the clustering technique, which identified similarities amongst the data to determine the value-in-use ferrous scrap price. A possible reason for why the KNN model did not outperform the other 2 models could have been attributed to the lack of its ability to

learn when to reduce the ferrous scrap prices based on a supplier's contributions to wasted and downgraded heats. Additionally, a small portion of the prices predicted by the KNN model deviated significantly from the other 2 models. A probable explanation for the deviation in these predicted prices related to the number of observations used to train the model, thus if more observations were available to train the model it is possible that these anomalous prices would not have been predicted.

The Ferrous Scrap Price model proved effective at predicting the value-in-use ferrous scrap price, which was expected as this model placed emphasis on the raw material cost. Many of the value-in-use ferrous scrap prices predicted by this model closely aligned with those predicted by the Decision Support Analysis model. The value-in-use ferrous scrap prices predicted by these models were the closest for suppliers who had minimal contributions to wasted and downgraded heats. This trend was logical as these suppliers comprised the majority and their ferrous scrap price was not vastly reduced since they did not consistently contribute to wasted and downgraded heats.

The value-in-use ferrous scrap price for suppliers who repeatedly contributed to wasted and downgraded prices was best predicted by the Decision Support Analysis model. A reason for why this model provided the optimal pricing strategy for handling these suppliers was because of its ability to account for the overall historical contributions a supplier made to wasted and downgraded heats across the dataset. The Ferrous Scrap Price model was only able to consider a supplier's contributions

per heat, while the K-Nearest Neighbors model was unable to account for these historical contributions at all.

In conclusion, all of the models used to predict the value-in-use ferrous scrap price utilized the information obtained in Phase I of the research. All 3 models were able to predict a better ferrous scrap price as compared to the actual price paid by the steel manufacturer, which was confirmed via the quantitative metric. The K-Nearest Neighbors was the only model to predict over the market price, however this anomaly was attributed to its learning techniques as the majority of those prices were the first ones predicted. Moreover, the Ferrous Scrap Price model was effective when predicting the value-in-use ferrous scrap price for suppliers who had minimal contributions to wasted and downgraded heats. The Decision Support Analysis model was the best at predicting the value-in-use ferrous scrap price for the most egregious offenders relative to contributions to wasted and downgraded heats. Therefore, the ability to account for suppliers' contributions to wasted and downgraded heats across the entirety of the dataset appeared to distinguish the Decision Support Analysis model apart from the other 2 models as it predicted the best value-in-use ferrous scrap price for 68% of suppliers.

Table 4-8: Value-in-Use Price

Suppliers	Market Price (per ton)	DSA Model (per ton)	FSP Model (per ton)	KNN Model (per ton)
SUPPLIER #1	$223.21	$189.73	$215.49	**$173.03**
SUPPLIER #2	$198.98	**$149.24**	$179.96	$182.45
SUPPLIER #3	$238.49	$226.57	**$215.55**	$231.55
SUPPLIER #4	$208.90	**$156.68**	$207.22	$157.80
SUPPLIER #5	$335.15	$318.39	$303.92	**$247.34**
SUPPLIER #6	$208.40	**$156.30**	$189.33	$161.09
SUPPLIER #7	$210.01	**$157.51**	$190.92	$160.61
SUPPLIER #8	$198.98	**$169.13**	$179.98	$170.90
SUPPLIER #9	$198.98	$189.03	**$181.96**	$158.10
SUPPLIER #10	$196.64	**$176.98**	$177.73	$182.42
SUPPLIER #11	$264.87	**$238.38**	$239.34	$260.23
SUPPLIER #12	$200.45	**$170.38**	$171.11	$183.52
SUPPLIER #13	$198.98	$189.03	$170.87	**$160.65**
SUPPLIER #14	$223.21	**$167.41**	$202.98	$180.86
SUPPLIER #15	$283.67	$255.30	$256.32	**$215.20**
SUPPLIER #16	$169.00	$160.55	$154.36	**$148.61**
SUPPLIER #17	$283.67	**$212.75**	$256.32	$216.99
SUPPLIER #18	$198.98	**$149.24**	$180.84	$186.64
SUPPLIER #19	$196.64	**$157.31**	$177.73	$159.62
SUPPLIER #20	$208.90	**$198.46**	$203.58	$201.18
SUPPLIER #21	$223.21	**$200.89**	$201.78	$259.20
SUPPLIER #22	$241.27	**$229.21**	$231.48	$238.52
SUPPLIER #23	$208.90	**$198.46**	$199.31	$201.66

SUPPLIER #24	$238.49	$226.57	$229.33	**$211.14**
SUPPLIER #25	$241.27	**$193.02**	$230.12	$204.80
SUPPLIER #26	$169.00	$160.55	**$152.75**	$178.00
SUPPLIER #27	$223.21	**$212.05**	$214.05	$219.16
SUPPLIER #28	$318.75	$255.00	$304.11	**$243.28**
SUPPLIER #29	$264.87	$225.14	$254.16	**$206.19**
SUPPLIER #30	$265.15	**$198.86**	$254.43	$203.93
SUPPLIER #31	$198.98	**$149.24**	$190.71	$174.71
SUPPLIER #32	$169.00	**$160.55**	$162.77	$168.15
SUPPLIER #33	$315.05	**$236.29**	$300.43	$298.18
SUPPLIER #34	$198.98	$179.08	$180.51	**$156.77**
SUPPLIER #35	$258.33	**$219.58**	$246.40	$220.52
SUPPLIER #36	$335.15	**$251.36**	$320.96	$259.45
SUPPLIER #37	$210.01	**$178.51**	$201.65	$202.38
SUPPLIER #38	$279.18	**$237.30**	$238.25	$243.20
SUPPLIER #39	$169.00	**$143.65**	$162.28	$147.77
SUPPLIER #40	$281.38	**$239.17**	$268.54	$257.48
SUPPLIER #41	$198.98	$169.13	$191.90	**$167.13**
SUPPLIER #42	$198.98	$179.08	$194.31	**$158.15**
SUPPLIER #43	$208.40	$197.98	**$189.25**	$205.02
SUPPLIER #44	$279.18	$251.26	$267.36	**$234.94**
SUPPLIER #45	$283.67	**$241.12**	$271.53	$272.00
SUPPLIER #46	$223.21	$212.05	$214.05	**$197.32**
SUPPLIER #47	$255.72	**$191.79**	$245.42	$262.98
SUPPLIER #48	$283.67	**$226.94**	$270.56	$236.10

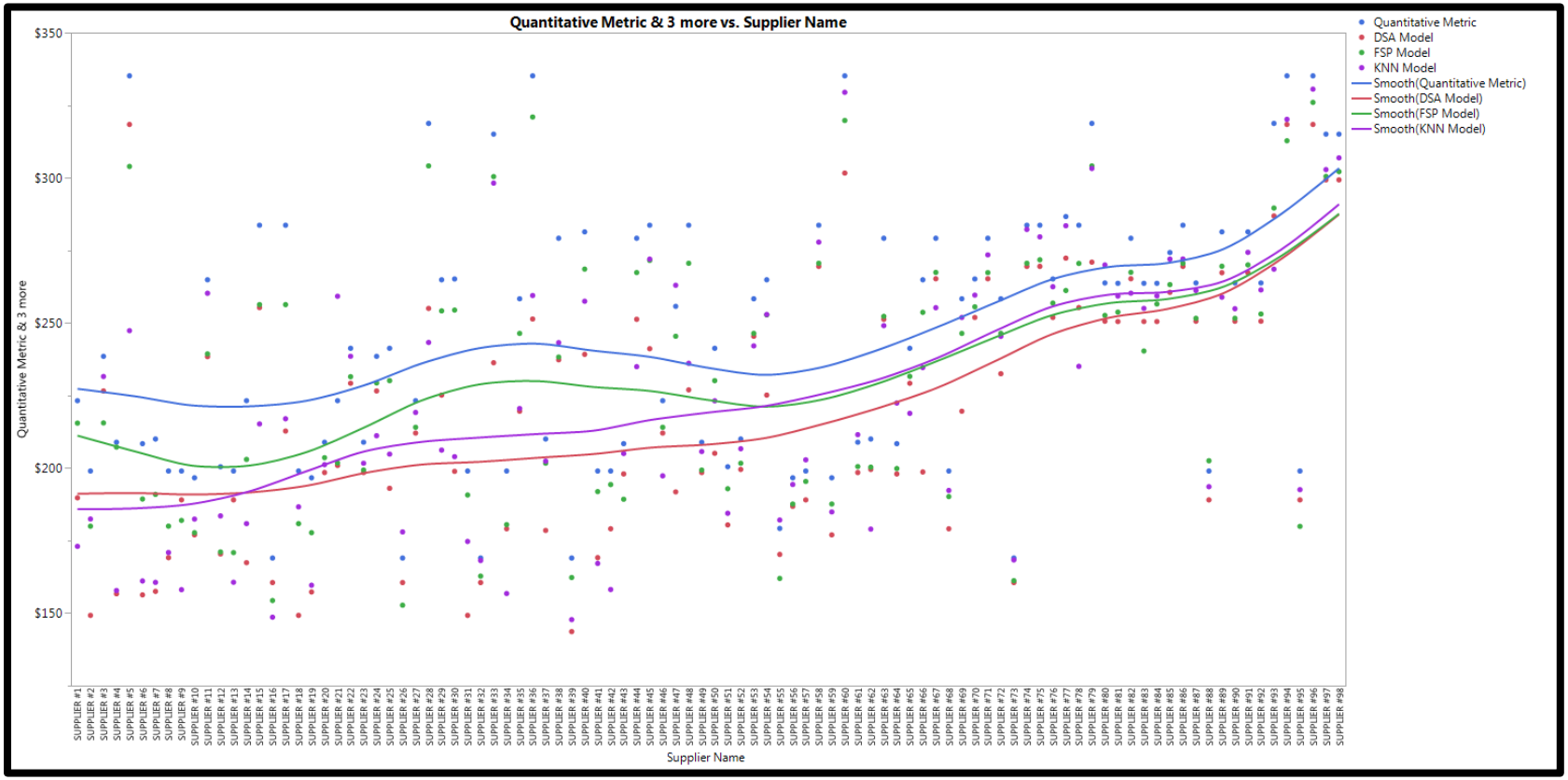
SUPPLIER #49	$208.90	**$198.46**	$199.31	$205.69
SUPPLIER #50	$241.27	**$205.08**	$230.12	$223.17
SUPPLIER #51	$200.45	**$180.41**	$192.88	$184.42
SUPPLIER #52	$210.01	**$199.51**	$201.65	$206.65
SUPPLIER #53	$258.33	$245.41	$246.40	**$242.09**
SUPPLIER #54	$264.87	**$225.14**	$252.77	$252.92
SUPPLIER #55	$179.20	$170.24	**$161.97**	$182.10
SUPPLIER #56	$196.64	**$186.81**	$187.61	$194.33
SUPPLIER #57	$198.98	**$189.03**	$195.39	$202.84
SUPPLIER #58	$283.67	**$269.49**	$270.56	$277.85
SUPPLIER #59	$196.64	**$176.98**	$187.61	$184.88
SUPPLIER #60	$335.15	**$301.64**	$319.76	$329.47
SUPPLIER #61	$208.90	**$198.46**	$200.52	$211.50
SUPPLIER #62	$210.01	$199.51	$200.31	**$178.97**
SUPPLIER #63	$279.18	$251.26	$252.27	**$249.06**
SUPPLIER #64	$208.40	**$197.98**	$199.83	$222.41
SUPPLIER #65	$241.27	$229.21	$231.59	**$218.85**
SUPPLIER #66	$264.87	**$198.65**	$253.66	$234.63
SUPPLIER #67	$279.18	$265.22	$267.41	**$255.25**
SUPPLIER #68	$198.98	**$179.08**	$190.17	$192.28
SUPPLIER #69	$258.33	**$219.58**	$246.40	$251.89
SUPPLIER #70	$265.15	**$251.89**	$255.57	$259.59
SUPPLIER #71	$279.18	**$265.22**	$267.34	$273.45
SUPPLIER #72	$258.33	**$232.50**	$246.40	$245.37
SUPPLIER #73	$169.00	**$160.55**	$161.20	$168.33

SUPPLIER #74	$283.67	**$269.49**	$270.56	$282.22
SUPPLIER #75	$283.67	**$269.49**	$271.76	$279.67
SUPPLIER #76	$265.15	**$251.89**	$256.83	$262.48
SUPPLIER #77	$286.66	$272.33	**$261.18**	$283.50
SUPPLIER #78	$283.67	$255.30	$270.50	**$235.05**
SUPPLIER #79	$318.75	**$270.94**	$304.11	$303.23
SUPPLIER #80	$263.78	**$250.59**	$252.60	$269.98
SUPPLIER #81	$263.66	**$250.48**	$253.74	$259.26
SUPPLIER #82	$279.18	$265.22	$267.44	**$260.26**
SUPPLIER #83	$263.66	$250.48	**$240.33**	$255.02
SUPPLIER #84	$263.66	**$250.48**	$256.53	$259.33
SUPPLIER #85	$274.26	**$260.55**	$263.21	$272.00
SUPPLIER #86	$283.67	**$269.49**	$270.56	$272.05
SUPPLIER #87	$263.78	**$250.59**	$251.59	$261.19
SUPPLIER #88	$198.98	**$189.03**	$202.52	$193.57
SUPPLIER #89	$281.38	$267.31	$269.53	**$258.88**
SUPPLIER #90	$263.78	**$250.59**	$251.59	$254.90
SUPPLIER #91	$281.38	**$267.31**	$270.00	$274.32
SUPPLIER #92	$263.78	**$250.59**	$253.08	$261.38
SUPPLIER #93	$318.75	$286.88	$289.60	**$268.52**
SUPPLIER #94	$335.15	$318.39	**$312.78**	$320.15
SUPPLIER #95	$198.98	$189.03	**$179.91**	$192.56
SUPPLIER #96	$335.15	**$318.39**	$326.00	$330.55
SUPPLIER #97	$315.05	**$299.30**	$300.49	$302.84
SUPPLIER #98	$315.05	**$299.30**	$302.14	$306.88

4.2.4.1 Paired T-Test

In Figure 4-11, a chart is displayed that contains the quantitative metric (i.e. actual prices paid by the steel manufacturer for suppliers' ferrous scrap) plotted against the value-in-use ferrous scrap prices predicted by the Decision Support Analysis model, Ferrous Scrap Price model, and the KNN model. All 3 models were able to predict a best value-in-use ferrous scrap price amongst the suppliers. The Decision Support Analysis model, Ferrous Scrap Price model, and the KNN model predicted the best value-in-use ferrous scrap price 68%, 10%, and 22% of the time, respectively. Since the value-in-use ferrous scrap price represented the "true" price that should have been paid to the suppliers, the steel manufacturer would have been able to increase their profits if these were the prices paid. Given these results, for the majority of the suppliers, it was evident that the Decision Support Analysis model was the best at predicting the value-in-use ferrous scrap price.

Figure 4-11: Quantitative Metric against Pricing Models



A paired sample t-test was conducted for each model against the quantitative metric, thus 3 t-tests were performed. This test compared the two means between the quantitative metric and the respective model (i.e. Decision Support Analysis model, Ferrous Scrap Price model, or KNN model). The purpose of the test was to determine whether there was statistical evidence that the mean between the value-in-use ferrous scrap prices predicted by the pricing models and quantitative metric were significantly different from zero. The results of each paired sample t-test performed with the quantitative metric against the Decision Support Analysis model, Ferrous Scrap Price model, or the KNN model are shown in Tables 4-9, 4-10, and 4-11, respectively.

Table 4-9: Paired T-Test for the DSA Model

	Quantitative Metric	*DSA Model*
Mean	292.4473571	219.6213
Variance	4800.521258	1934.84
Observations	98	98
Pearson Correlation	0.756931228	
Hypothesized Mean Difference	0	
df	97	
t Stat	15.65187039	
P(T<=t) one-tail	1.36915E-28	
t Critical one-tail	1.66071461	
P(T<=t) two-tail	2.73829E-28	
t Critical two-tail	1.984723186	

Table 4-10: Paired T-Test for the FSP Model

	Quantitative Metric	*FSP Model*
Mean	292.4473571	231.7468
Variance	4800.521258	1920.606
Observations	98	98
Pearson Correlation	0.775507422	
Hypothesized Mean Difference	0	
df	97	
t Stat	13.39792243	
P(T<=t) one-tail	4.30293E-24	
t Critical one-tail	1.66071461	
P(T<=t) two-tail	8.60586E-24	
t Critical two-tail	1.984723186	

Table 4-11: Paired T-Test for KNN Model

	Quantitative Metric	*KNN Model*
Mean	292.4473571	225.8643
Variance	4800.521258	2051.973
Observations	98	98
Pearson Correlation	0.738454664	
Hypothesized Mean Difference	0	
df	97	
t Stat	13.99849234	
P(T<=t) one-tail	2.57019E-25	
t Critical one-tail	1.66071461	
P(T<=t) two-tail	5.14038E-25	
t Critical two-tail	1.984723186	

The mean between the ferrous scrap prices predicted by the pricing models (i.e. value-in-use price – price that should have been paid) and the quantitative metric (i.e. actual price paid) should be different, which reflected the lower quality of the ferrous

scrap previously purchased. As displayed in Tables 4-9, 4-10, and 4-11, the *t* Stat was larger than the *t* Critical two-tail value for all of the models. The corresponding p-value calculated in the paired t-test for each model tested against the quantitative metric was less than the significance level of 0.05. The extremely small p-values along with the *t* Stat values being larger than the *t* Critical two-tail values for all of the paired t-tests performed provided evidence to support the claim that the null hypothesis should be rejected. Thus, these paired t-tests showed that there was a difference in the actual ferrous scrap price paid and the price that should have been paid.

The paired t-tests showed the value-in-use ferrous scrap price predicted by the pricing models was different than the actual price paid by the steel manufacturer. The predicted value-in-use ferrous scrap prices for all of the pricing models trended in the correct direction, as shown in Figure 4-11, which was downward to reflect the lower price due to the lower quality of the associated ferrous scrap (i.e. contained elevated residual elements detrimental to the quality of steel). All 3 of these models would have led to increased profits for the steel manufacturer since the price they should have paid (i.e. value-in-use price) was lower than the actual price paid. The Decision Support Analysis model resulted in the biggest difference in price, which was confirmed via the paired t-test, and predicted the best value-in-use ferrous scrap price for 68% of suppliers. Thus, the Decision Support Analysis model provided the optimal pricing strategy for the quantitative ferrous scrap pricing structure.

Chapter 5 – Conclusion

The purpose of the research conducted for this praxis was to address the quality of ferrous scrap via a quantitative purchasing structure, which leveraged historical heat chemistry data to determine the suppliers who contributed to wasted and downgraded heats. The steel manufacturer's profits are impacted annually due to wasted and downgraded heats. Wasted heats impact profits the most as the steel manufacturer incurs a cost of $80,000 per wasted heat, which does not include labor costs or profit loss due to the downtime of the furnace. Therefore, wasted and downgraded heats were identified in the dataset and then correlated to suppliers who contributed ferrous scrap to these heats. Statistical analysis verified the residual elements most detrimental to quality of the steel. Three pricing models were developed based on promising methodologies to predict the value-in-use ferrous scrap price per supplier. Finally, these models were compared against a quantitative validation metric to determine which one was the best at predicting the value-in-use ferrous scrap price.

5.1 Summary of the Results

The literature review confirmed the problem presented in the dataset, which was provided by a steel manufacturer. The problem was relative to how the chemical composition of ferrous scrap directly affected whether a heat was wasted, downgraded, or within specification (i.e. satisfied the levied chemistry requirements). Additionally, the steel manufacturer was uncertain on which suppliers were providing ferrous scrap with elevated levels of residual elements that are deleterious

to the quality of the final steel product. From the dataset, it was not possible to determine the chemical composition of the ferrous scrap prior to it entering the furnace. Although, it was possible to correlate which supplier contributed ferrous scrap to a wasted or downgraded heat.

To this end, all of the wasted and downgraded heats were identified in the dataset. Statistical analysis confirmed the residual elements responsible for the wasted and downgraded heats as well as which ones were the most prevalent amongst these heats. The correlation of these wasted and downgraded heats to the suppliers who contributed ferrous scrap to them was then realized. The analysis conducted in Phase I of the research turned data into information, which was used to develop the pricing models in Phase II.

In Phase II of the research, 3 models were developed to predict the value-in-use ferrous scrap price per supplier. Each model predicted this price in a unique manner, which allowed for the comparison of the alternative methodologies each used. All of these pricing models leveraged the historical heat chemistry to predict the value-in-use price of ferrous scrap. The quantitative validation metric, which was the actual ferrous scrap price paid by the steel manufacturer, was used to determine which model was the best at predicting the value-in-use ferrous scrap price. The results showed that the Decision Support Analysis model was the best at predicting the value-in-use ferrous scrap price.

5.2 Research Contributions

One contribution this research effort made was improving the situational awareness of the suppliers who are most likely to provide ferrous scrap with elevated levels of residual elements, specifically those that are the most detrimental to the quality of steel. Identifying these suppliers was critical for the steel manufacturer as this performance influenced the price paid for the respective supplier's ferrous scrap.

The largest contribution of this research effort was the development of the quantitative purchasing structure for ferrous scrap, which predicted the value-in-use ferrous scrap price per supplier based on historical performance. When comparing the value-in-use ferrous scrap price predicted by the Decision Support Analysis model against the quantitative metric, the pricing model displayed approximately a 12% improvement over the actual prices paid by the steel manufacturer. Furthermore, this pricing model was designed to be adaptable so that the steel manufacturer would be able to adjust it as the industry evolves.

5.3 Future Work Recommendations

The pricing models developed during this research provided a means for predicting the value-in-use ferrous scrap price per supplier. An aspect not investigated was the price that could be paid to suppliers who continually provided superior quality ferrous scrap and did not contribute to wasted or downgraded heats. The steel manufacturer always wants to pay the lowest price possible for ferrous scrap. However, it is a reasonable assumption that the steel manufacturer would pay

more for ferrous scrap if wasted and downgraded heats were guaranteed to not occur. Thus, determining the value of these suppliers' ferrous scrap is worth considering.

The information attained from the value-in-use ferrous scrap price could be used to influence the ferrous scrap recipe used at the steel mill. Some wasted and downgraded heats could be avoided if the crane operators knew when ferrous scrap of questionable chemical composition arrived at the steel mill, then they could be instructed to use the lower quality ferrous scrap sparingly across heats.

Furthermore, it might be possible to predict the residual elements suppliers are most likely to provide in their ferrous scrap by extrapolating this dataset to predict future chemistries. The steel manufacturer would need to be dedicated to this research as multiple heats would need to be analyzed prior to tuning this model.

5.4 Conclusion

The research conduct for this praxis successfully demonstrated a quantitative purchasing structure for ferrous scrap that can increase the profits for a steel manufacturer. This praxis addressed a real-world problem and provided value for the steel manufacturer by providing insight into the residual elements most prevalent in the ferrous scrap they purchase, and predicting the value-in-use ferrous scrap price for all of their suppliers. This research effort confirmed the knowledge on the subject and provided an opportunity to develop a solution based on engineering management practices and techniques.

Bibliography

Albertson, K., & Aylen, J. (1996). Modelling the great lakes freeze: Forecasting and seasonality in the market for ferrous scrap.*International Journal of Forecasting, 12*(3), 345-359. doi://doi.org/10.1016/0169-2070(96)00669-3

Aylen, J., & Albertson, K. (2006). Markets in ferrous scrap for steelmaking. *Ironmak Steelmak, 33*(3), 203-212.

Barnett, D. F., & Crandall, R. W. (1986). *Up from the ashes: The rise of the steel minimill in the United States*. Washington, D.C.: Brookings Institution.

Basson, E. (2017, May 29,). World steel in figures 2017. *World Steel Association* Retrieved: from https://search.proquest.com/docview/1903356245

Brownlee, J. (2017). Machine Learning Process. Retrieved: from https://machinelearningmastery.com/difference-test-validation-datasets/

Bureau of International Recycling. (2016). *World steel recycling in figures 2012 - 2016.* Retrieved from https://www.bdsv.org/fileadmin/service/markt_und_branchendaten/weltstatistik_2012_2016.pdf

Daigo, I., Fujimaki, D., Matsuno, Y., & Adachi, Y. (2005). Assessing environmental impact associated with cyclic use of steels. *Journal of the Iron and Steel Institute of Japan, 91*(1), 179-183.

Daigo, I., Matsuno, Y., & Adachi, Y. (2010). Substance flow analysis of chromium and nickel in the material flow of stainless steel in japan. *Resources Conservation and Recycling, 52*(2), 219-233.

EC (European Commission). (2014). The Circular Economy: Connecting, creating and conserving; *European Commission.*

Evans, M. (2006). A study of the relationship between regional ferrous scrap prices in the USA, 1958-2004. *Resources Policy, 31*(2), 65. Retrieved: from doi://dx.doi.org/10.1016/j.resourpol.2006.06.001

Fabian, T. (1958). A Linear Programming Model of Integrated Iron and Steel Production. *Management Science, 4*(4), 415-449.

Fenton, M. D. (2004). Flow Studies for Recycling Metal Commodities in the United States. 2004. *US Geological Survey,* G8. Retrieved from http://catalog.hathitrust.org/Record/004906510

Grace-Martin, K. (2018). Assessing the Fit of Regression Models. Retrieved from https://www.theanalysisfactor.com/assessing-the-fit-of-regression-models/

Gruver, G., & Giarratani, F. (2005). Modeling geographic ferrous scrap markets: Regional prices and interregional transactions in the United States. *Journal of Regional Science, 45*(2), 313-341. doi:10.1111/j.0022-4146.2005.00373.x

Hiraki, T., Takeda, O., Nakajima, K., Matsubae, K., Nakamura, S., & Nagasaka, T. (2011). Thermodynamic criteria for the removal of impurities from end-of-life magnesium alloys by evaporation and flux treatment. *Science and Technology of Advanced Materials, 12*(3)

Houck, G. W. (1994). *Iron and steel scrap 1994.* Washington, DC: U.S. Geological Survey.

Institute of Scrap Recycling Industries. (2018). *Scrap specifications circular 2018*. Washington, D.C.: Institute of Scrap Recycling Industries, Inc.

Janke, D., Savov, L., Weddige, H. & Schulz, E. (2000). *Scrap-based Steel Production and Recycling of Steel.*

Jaynes, E. T. (1978). (1978). “Where do we stand on maximum entropy?”. Paper presented at the *Maximum Entropy Formalism Conference.*

Jaynes, E. T. (2003). *Probability Theory, The Logic of Science.* Cambridge, MA: Cambridge University Press.

Jaynes, E. T., Smith, C. R., & Grandy, J., W.T. (1985). *“Where do we go from here?” Maximum-Entropy and Bayesian Methods in Diverse Problems* D. Reidel Publishing Company.

Johnson, J., Schewel, L., & Graedel, T. E. (2006). The contemporary anthropogenic chromium cycle. *Environmental Science & Technology, 40*(22), 7060-7069.

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*Springer.

Liu, X. B., Pan, R. L., Meng, Q. N., & Cui, F. J. (2005). Study on recipe cost optimization system based on ant colony algorithms. *International Seminar on Business and Information Management, 78*, 287-290.

Marcus, P., & Kirsis, K. M. (1994). Global metallics crisis. Paper presented at the Annual Conference. Colorado Springs: International Iron and Steel Institute.

Mazumdar, D., & Evans, J. W. (2010). *Modeling of steelmaking processes.* Boca Raton, FL: CRC.

Mealer, C. M., & Park, S. H. (2013). *A simplified and scalable should-cost tool in the oilfield services industry*.

Metal Bulletin Daily. (2008) *Steel Buyers See Fallout from Nucor, SDI Scrap Buys*, (97), 453. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=47482538&site=ehost-live&scope=site

Metal Bulletin Daily. (2015). US Midwest Ferrous Scrap Prices Take Hit, 1. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=101841210&site=ehost-live&scope=site

Metal Bulletin Holdings, L. (2018). PRICE NOTE: Shredded Scrap. Retrieved from http://www.amm.com/Article/3786825/PricingNotices/PRICE-NOTICE-Shredded-scrap.html

Mineral resources and the environment, supplementary report: Resource recovery from municipal solid wastes. (1975). Washington, DC.

Minter, A. (2013). *Junkyard Planet: Travels in the Billion-Dollar Trash Trade*. New York, NY: Bloomsbury Press.

Moon, I., Park, K. S., Hao, J., & Kim, D. (2017). Joint decisions on product line selection, purchasing, and pricing. *European Journal of Operational Research, 262*(1), 207. doi://dx.doi.org/10.1016/j.ejor.2017.03.062

Myers, M. B. (1997). The pricing of export products: Why aren't managers satisfied with the results? *Journal of World Business, 32*(3), 277-289. doi://www.sciencedirect.com/science/journal/10909516

Nakajima, K., Ohno, H., Kondo, K., Matsubae, K., Takeda, O., Miki, T., Nagasaka, T. (2013). Simultaneous material flow analysis of nickel, chromium, and molybdenum used in alloy steel by means of input-output analysis. *Environmental Science & Technology, 45*(11), 4929-4936.

Nakajima, K., Takeda, O., Miki, T., Matsubae, K., & Nagasaka, T. (2011). Thermodynamic analysis for the controllability of elements in the recycling process of metals. *Environmental Science & Technology, 45*(11), 4929-4936.

Nakajima, K., Yokoyama, K., Matsuno, Y., & Nagasaka, T. (2007). Substance flow analysis of molybdenum associated with iron
and Steel Flow in Japanese economy. *ISIJ International, 47*(3), 510-515.

Nakajima, K., Yokoyama, K., & Nagasaka, T. (2008). Substance flow analysis of manganese associated with iron and steel flow in japan. *ISIJ International, 48*(4), 549-553.

Nakamura, S., Kondo, Y., Matsubae, K., Nakajima, K., Tasaki, T., & Nagasaka, T. (2012). Quality and dilution losses in the recycling of ferrous materials from end-of-life passenger cars.*Environmental Science & Technology, 46*(17), 9266-9273.

Nitoiu, M. (2011). Using the Ferrous Scrap for the Steel Fabrication and their Price Interdependence. *Metalurgia International, 16*(7), 97-103. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-80052838366&partnerID=40&md5=b6c82d1f079783b9e9b77329d3c1e11a

Nuss, P., & Eckelman, M. J. (2014). Life Cycle Assessment of Metals: A scientific synthesis. *PLoS One, 9*(7), e101298.

Ohno, H., Matsubae, K., Nakajima, K., Nakamura, S., & Nagasaka, T. (2014). Unintentional Flow of Alloying Elements in Steel during Recycling of End-of-Life Vehicles. *Journal of Industrial Ecology, 18*(2), 242-253. doi:10.1111/jiec.12095

Pandolfini, P. (2018). *Decision Analysis of the Global Nuclear Smuggling Detection and Deterrence System*. Laurel, MD: Johns Hopkins University Applied Physics Laboratory.

Reck, B. K., Chambon, M., Hashimoto, S., & Graedel, T. E. (2010). Global stainless steel cycle exemplifies china's rise to metal dominance. *Environmental Science & Technology, 44*(10), 3940-3946.

Reck, B. K., & Graedel, T. E. (2012). Challenges in metal recycling.*Science, 337*(6095), 690-695.

Reck, B. K., Muller, D. B., Rostkowski, K., & Graedel, T. E. (2008). Anthropogenic nickel cycle: Insights into use, trade, and recycling. *Environmental Science & Technology, 42*(9), 3394-3400.

Reuter, M., & van Schaik, A. (2008). Thermodynamic metrics for measuring the "sustainability" of design for recycling. *Journal of Metals, 60*(8), 39-46.

Ripley, B. (1996). *Pattern Recognition and Neural Networks*. Oxford: Cambridge University Press.

Russell, S., & Norvig, P. (2009). *Artificial intelligence: A modern approach* (3rd ed.) Prentice Hall.

Sandoval, D. (2001). Quality Remains Key for Steel Mills. Retrieved from http://www.recyclingtoday.com/article/quality-remains-key-for-steel-mills/

Sara Hornby. (2015). Low-cost steel from low-cost scrap. *Steel Times International, 39*(8), 27. Retrieved from https://search.proquest.com/docview/1814328100

SAS. (2018). JMP Statistical Discovery. from SAS. Retrieved from https://www.jmp.com/support/help/14/

Sawyer, J. W. (2016). *Automotive scrap recycling*. London: Routledge Ltd. doi:10.4324/9781315659336 Retrieved from http://www.tandfebooks.com/isbn/9781315659336

Seabrook, J. (2008). American Scrap. Retrieved from https://www.newyorker.com/magazine/2008/01/14/american-scrap

Sevigne-Itoiz, E., Gasol, C. M., Rieradevall, J., & Gabarrell, X. (2014). Environmental consequences of recycling aluminum old scrap in a global market. *Resources, Conservation and Recycling*, (89), 94-103.

Silver, J., Koros, P. J., & Schoenberger, L. R. (1970). (1970). The effect of use of bundled auto scrap on sheet steel quality. Paper presented at the *ISIS 42nd Annual Convention,*

Singh, M. (1991). Knowledge support systems for 'smarter' pricing and resource allocation. *Control Systems, 11,* 3-7.

Soderholm, P., & Ejdemo, T. (2008). Steel Scrap Markets in Europe and the USA. *Minerals & Energy, 23*(2), 57-73. doi:10.1080/14041040802018497

Spedicato, G. A., Dutang, C., & Petrini, L. (2018). *Machine Learning Methods to Perform Pricing Optimization: A comparison with Standard GLMs.*

Statista. (2018). Steel production figures in the U.S. from 2006 to 2017. Retrieved from https://www.statista.com/statistics/209343/steel-production-in-the-us/

Steel Industry Profile: The United States. (2017). *Steel Industry Profile: United States.* 1-43. Retrieved: from http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=127463673&site=ehost-live&scope=site

Suh, S. (2009). Handbook of input-output economics in industrial ecology: Eco-efficiency in industry and science. *International Society for Industrial Ecology, 23*

Tailoka, F., Kumar, R. V., & Fray, D. J. (2003). Removal of tin from tin coated steel by chlorination in air. *Ironmaking & Steelmaking, 30*(5), 385. doi:10.1179/030192303225004024

Tilton, J. E. (1992). *Economics of the mineral industries* (2nd ed.). Littleton, CO: SME.

Tortora, P. G., & Johnson, I. (2014). *General quality specifications for scrap grades* (8th ed.) Bloomsbury Publishing Inc. doi:10.5040/9781501303579.6998 Retrieved:

from https://www.bloomsburyfashioncentral.com/products/fairchild-books/dictionary/the-fairchild-books-dictionary-of-textiles/grade

Toyota. (2018). Toyota Recycle. Retrieved: from https://www.toyota-europe.com/world-of-toyota/feel/environment/better-earth/recycle

Vandenbussche, H., & Zarnic, Z. (2008). US safeguards on steel and the markups of european producers. *Review of World Economics, 144*(3), 458. doi://dx.doi.org/10.1007/s10290-008-0156-x

von Gleich, A., Brahmer-Lohss, M., Gottschick, M., Jepsen, D., & Sander, K. (2004). *Sustainable metal management hamburg*. Hamburg, Germany.

World Steel Association. (2017). *Sustainable steel: Indicators 2017 and the future*. Retrieved from http://www.worldsteel.org

Appendix A – Descriptions of Ferrous Scrap Grades

Descriptions of the grades of ferrous scrap used in this research are defined below which are provided by the Institute of Scrap Recycling Industries (2018).

- **Pig Iron** – Cast Iron or Blast Furnace Iron, cast into Individual "Pigs", grouped "pigs" (broken into small pieces), or pyramids.

- **#1 Bundles** – New black steel sheet scrap, clippings or skeleton scrap, compressed or hand bundled, to charging box size, and weighing not less than 75 pounds per cubic foot. (Hand bundles are tightly secured for handling with a magnet.) May include Stanley balls or mandrel wound bundles or skeleton reels, tightly secured. May include chemically de-tinned material. May not include old auto body or fender stock. Free of metal coated, limed, vitreous enameled and electrical sheet containing over 0.5 percent silicon.

- **#1 Heavy Melting Scrap** – Wrought iron and/or steel scrap 1/4 inch and over in thickness. Individual pieces not over 60 x 24 inches (charging box size) prepared in a manner to insure compact charging.

- **#2 Bundles** – Old black and galvanized steel sheet scrap, hydraulically compressed to charging box size and weighing not less than 75 pounds per cubic foot. May not include tin or lead-coated material or vitreous enameled material.

- **#2 Heavy Melting Scrap** – Wrought iron and steel scrap, black and galvanized, 1/8 inch and over in thickness, charging box size to include material not suitable

as No. 1 heavy melting steel. Prepared in a manner to insure compact charging.

- **Plate and Structural Steel** – Cut structural and plate scrap, 5 feet and under. Clean open hearth steel plates, structural shapes, crop ends, shearings, or broken steel tires. Dimensions not less than 1/4-inch thickness, not over 5 feet in length and 18 inches in width. Phosphorus or sulphur not over 0.05 percent.

- **#2 Shredded Steel** – Homogeneous iron and steel scrap, magnetically separated, originating from automobiles, unprepared No. 1 and No. 2 steel, miscellaneous baling and sheet scrap.

- **#1 Busheling** – Clean steel scrap, maximum size 2 feet by 5 feet, including new factory busheling (for example, sheet clippings, stampings, etc.). May not include old auto body and fender stock. Free of metal coated, limed, vitreous enameled and electrical sheet containing over 0.5 percent silicon.

- **Cast Iron Borings** – Clean cast iron or malleable iron borings and drillings, free of steel turnings, scale, lumps or excessive oil.

- **Briquettes** – Clean steel turnings, wrought iron borings, or cast iron borings, free of excessive oil, nonferrous metals, and scale. Compressed into a high-density briquette shape.

- **Home Scrap** – Bars of blooms of local origin cut into size appropriate for re-melting. Tundish skulls and pit scrap broken down to usable dimensions. Material is color-coded to identify chemistry.

- **Gamma Shred** – Homogeneous shredded steel scrap magnetically separated then subsequently analyzed by gamma excitation analysis and certified below 0.20 Cu, originating from automobiles, unprepared # 1 Heavy Melting Steel and # 2 Heavy Melting Steel, and miscellaneous sheet steel.

Appendix B – Quality Specifications of Ferrous Scrap Grades

Table B-1, located below, contains the quality specifications that all ferrous scrap should adhere to when being sold to a steel mill for recycling. The table contains the density and maximum weight percentage per residual alloying element for the grades of ferrous scrap studied in this research. This information is applicable to all mini mills (Tortora & Johnson, 2014).

Grade	Typical Density (lbs / ft^3)	Cu (Max wt%)	Ni (Max wt%)	Cr (Max wt%)	Mo (Max wt%)	Sn (Max wt%)
Pig Iron	180 - 200	N/A	N/A	N/A	N/A	N/A
#1 Bundles	75 - 90	0.10	0.10	0.10	0.03	0.01
#1 Heavy Melting Scrap	45 - 60	0.35	0.25	0.25	0.06	0.025
#2 Bundles	60 - 70	Maximum Chemistries are difficult to determine as content varies				
#2 Heavy Melting Scrap	40 - 55	0.55	0.20	0.20	0.04	0.04
Plate and Structural Steel	60 - 70	0.30	0.15	0.15	0.03	0.015
#2 Shredded Steel	55 - 70	0.22	0.15	0.15	0.03	0.015
#1 Busheling	60 - 75	0.10	0.08	0.08	0.02	0.02
Cast Iron Borings	35 - 50	0.25	0.15	0.20	0.04	0.03
Briquettes	40 - 55	0.25	0.15	0.20	0.04	0.03
Home Scrap	80 - 100	N/A	N/A	N/A	N/A	0.04
Gamma Shred	55 - 70	0.20	0.15	0.15	0.03	0.015