Development of Analysis Tools for the Facilitation of Increased Structural Steel Reuse

By

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A thesis
presented to the University of Waterloo
in fulfillment of the thesis requirements
for the degree of
Doctor of Philosophy
in
Civil Engineering

Waterloo, Ontario, Canada, August 2016

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

I would like to acknowledge the contribution provided by Dr. Rebecca Saari towards the life cycle analysis and total life cycle cost analysis described in this thesis.

Abstract

Reuse of structural steel can be more attractive than recycling in many cases, if associated costs and risks are lowered, and if externalities are considered. The costs and risks typically associated with steel reuse arise through the unknown capacity of reused components and increased deconstruction activities that may be required to extract the components. Externalities include such aspects as environmental impact, which is commonly accepted as a benefit to reuse as an alternative to recycling.

Low-rise structures are particularly attractive for structural steel reuse, as these structures typically lack steel fireproofing, which can be difficult to remove. Low-rise structures also facilitate efficient deconstruction processes.

Geometric characterization is demonstrated in this research to have a key role to play in the decision process for each case of potential steel reuse, because it is used to identify unknown in-situ steel sections and assemblies, and it provides necessary input to structural design reliability analysis of reused steel. In this way, geometric characterization can contribute towards lower reuse costs and lower risk of component failure. Its key role is further validated through a series of 3D imaging experiments and associated reliability analyses. Semi-automated and line fitting techniques were utilized to understand the impact of the identification algorithm on the resulting phi factor results. It is concluded that semi-automated geometric characterization can support increased steel reuse through reduced identification costs and improved reliability. A new set of methods and an understanding of their utility in making reuse more attractive through reduced costs and improved reliability is thus contributed. It was identified that low occupancy structures present an opportunity for improving the phi factor comparison between reused and new steel components.

This research also contributes towards decision makers' and society's understanding of the life cycle impacts of reuse as an alternative to recycling by presenting a streamlined life cycle analysis methodology based primarily on process models. This methodology consists of a comparative life cycle analysis between recycling and reuse of structural steel components. The application of this methodology is demonstrated through its use in a case study. The results of this case study indicate that a significant reduction in some life cycle impact metric values, particularly greenhouse gases, can result from reusing structural steel rather than recycling it. The impact of the methodology developed and the results of this study on reuse decisions will also be influenced by prices placed on air pollutants, greenhouse gases, water, and other impact elements by society and local markets. Current price indexes support recycling as the lower market cost alternative, but relatively small changes to economic conditions could result in reuse being the less expensive alternative.

Acknowledgements

First, and foremost, I would like to express my most sincere gratitude to my advisors, Scott Walbridge and Carl Haas. I truly appreciate their patience and guidance throughout this process. Their support and the trust that they have shown in me has allowed me to reach my fullest potential. I would like to express my appreciation towards Prof. Rebecca Saari for her valuable input on the life cycle analysis and total life cycle cost aspects of this thesis. I would also like to thank Prof. Giovanni Cascante, Prof. Jeffery West, and Prof. Terri Meyer Boake for serving on my examination committee and their feedback and input during my comprehensive exam. Furthermore, I would like to thank Prof. Brenda McCabe for serving as the external examiner for my Ph.D. defense.

Industry input has been an essential part of work conducted in this thesis, and I have had the opportunity to work with a very talented group of industry members. I would like to express my thanks to Tim Verhey from Walters Group, David Pow from POW Technologies, Ted Dietrich from TMT Inc., Chris Adach from M & G Steel Ltd., and Christopher Hogan from EllisDon Corp. for their expert guidance and insight into industry issues.

I would not be in the position I am today without the love and support of my family. My parents have supported me for my entire life and have molded me into the man I am today, and for that I am indebted. Without their hard work and dedication, none of my accomplishments would have been possible. I also appreciate the support and motivation provided by my brother; this is the first time in my life where I have one-up’d him (at least academically).

My friends, whom I will not begin to try to name individually, have celebrated with me in the good times and pulled me through in the bad times, and for that I am grateful. There is no doubt in my mind that I would not have made it through this process without their support.

Finally, I would like to appreciatively acknowledge the financial support provided by the National Sciences and Engineering Research Council of Canada (NSERC).

For my family

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1 Introduction

This chapter provides an outline of the background of structural steel reuse as well as the motivation for performing the current study. Following this, the objectives and scope of the current study are stated. Finally, the structure of this thesis is described.

1.1 Motivation

The issue of climate change has been controversial for more than two decades. The "Hockey Stick Graph", originally presented by Mann and Bradley (1994) initiated much debate within the scientific community. The aforementioned graph showed a significant increase in the average temperature throughout the 20th century. Regardless of personal understandings and beliefs of the effects and severity of climate change, it is undeniably important to keep the environment in such a state as to provide future generations with the same opportunities that are available to the current population. Reusing steel, as an alternative to recycling, has been identified as one promising avenue for reducing the impact of steel construction on the environment. Reusing other building materials, such as timber or masonry, is fairly common due to historical significance and their relatively low value in a recycled or broken down state, so the question arises: *why is reuse of steel not as common as with other materials, and what can be done to improve that?*

Gorgolewski et al. (2006) presented their findings on facilitating greater reuse and recycling of structural steel in the construction and demolition process. This landmark report establishes an understanding of the current state of reuse and outlines some of the barriers that need to be overcome for structural steel reuse to become increasingly commonplace. Various groups involved in the steel industry were surveyed in order to understand the current state and their particular role in the steel reuse process. These groups included: steel service centres, demolition contractors, scrap steel dealers, steel fabricators, designers, the shoring industry, and material exchange websites. The general findings of the report are summarized as follows:

- The current high value of scrap steel (for the primary purpose of recycling) prevents reuse from being the economically superior alternative.
- The demolition process is on the critical path of most construction projects, so contractors are unwilling to take the care required to salvage steel members without damaging them.
- Pre-engineered buildings, for example, industrial buildings, have high reuse potential due to the ease with which they can be deconstructed.
- The shoring industry has demand for large beams of depth 250 mm or greater.
- It is logistically difficult to match a reused member to a new construction project. The designer needs to be aware of the member at the time of design and the member needs to be located close to the construction site to avoid prohibitive transportation costs.
- The structural characteristics and capacities of reused members are unknown. The various parties are therefore reluctant to assume liability for these members.
- Only around 10% of structural steel is currently being reused.

The current state of the art in structural steel reuse lacks a decision making framework to aid in the reuse process. This, along with a prohibitive economic environment, results in significantly lower rates of steel reuse than are possible, and perhaps optimal. Higher rates of reuse may be desirable from a life cycle cost and sustainability perspective. There are also significant barriers to reuse because the state of reused steel can be largely unknown, leaving the engineer with little confidence in the design of structures employing reused steel members.

Reusing structural steel is not a new or ground breaking concept but it is an underutilized process. Even small, rural salvage yards, such as the one depicted in Figure 1-1 from Breslau, Ontario, often maintain an inventory of structural steel. According to its owners, the structural steel at this salvage yard is typically purchased by private individuals for the purpose of trailers or storage sheds. There are also a number of one-of-a-kind projects that heavily utilize reused steel. For example, a Mountain Equipment Co-op building in Ottawa was able to reuse 75% of the materials from the pre-existing building on the site of a new retail outlet (MEC, 2016).

Figure 1-1: Structural steel being stored in a salvage yard in Breslau ON.

1.2 Research objectives

Against this motivation, the current study has the following objectives:

- develop a decision making framework focused on the reuse process,

- develop tools that enable the automated or semi-automated identification of structural steel components without a priori knowledge,
- quantitatively characterize the geometric properties of reused structural steel, and
- quantify the life cycle benefits of structural steel reuse as an alternative to current practices.

These issues are addressed through four related parts of this thesis. First, a decision making framework is incorporated into existing reuse process models (Chapter 2). Then automated object recognition methodologies are developed, and their implementation to determine important geometric properties of steel members and structures is described (Chapter 3). The statistical variation of these geometric properties is then assessed and incorporated into a structural reliability analysis to guarantee statistical confidence when designing with reused steel (Chapter 4). Extensive life cycle analysis using the process model approach is used to quantify the benefits of structural steel reuse and, finally, these life cycle analysis results are used to perform the total life cycle cost comparison between reuse and recycling (Chapter 5).

1.3 Scope

The decision making work presented in this thesis establishes a process model for structural steel reuse and then incorporates a decision making model into this process. This work is presented with a focus on the reuse process and decision making for structural steel, specifically, but the model has been developed in such a way as to allow for extension to other materials.

The 3D imaging tools portion of the research investigates the feasibility of semi-automated tools for the geometric identification of structural steel without a priori knowledge. These tools are developed with a level of automation and accuracy sufficient to demonstrate their potential, given the precision level that can be achieved with scanners currently on the market or expected to come on the market in the near future. This particular study focuses solely on the development of semi-automated identification of standard open structural steel cross-sections, as line-of-sight based 3D sensing is unable to fully identify the geometry of closed sections.

The statistical reliability analysis presented in this thesis incorporates the geometric uncertainty associated with reused steel. The geometric data is acquired using the two tripod-mounted 3D laser scanners available at the University of Waterloo. The variability of the measurements acquired by these devices is used as one of the inputs in the reliability analysis.

The life cycle analysis portion of this study compares current practices with the reuse process. In addition to labour and material processing costs, this analysis investigates the air pollutants, greenhouse gases, and water usage associated with the two processes. The entire life cycle of a steel structure is examined, but only differences between the two processes are quantitatively assessed. Finally, these impacts are unified in a total life cycle cost estimate.

1.4 Structure of the thesis

An outline of the thesis chapters is presented in Figure 1-2. Chapter 2 introduces a decision making framework for structural steel reuse, including the necessary information to make a knowledgeable decision. Chapter 3 presents a methodology for semi-automated identification of structural steel cross-sections using 3D point cloud data. Next, a structural reliability analysis, considering the geometric uncertainty associated with reuse steel, is performed in Chapter 4. In Chapter 5, a methodology for performing a comparative life cycle analysis of reuse vs. recycling is presented, and this life cycle analysis is used to enable a total life cycle cost comparison between these two end-of-life strategies. Finally, Chapter 5 presents a summary of the findings and conclusions, as well as areas that have been identified for future research.

The information presented in Chapter 2, Chapter 3, and Chapter 4 is adapted from the published journal paper (Yeung et al., 2015).

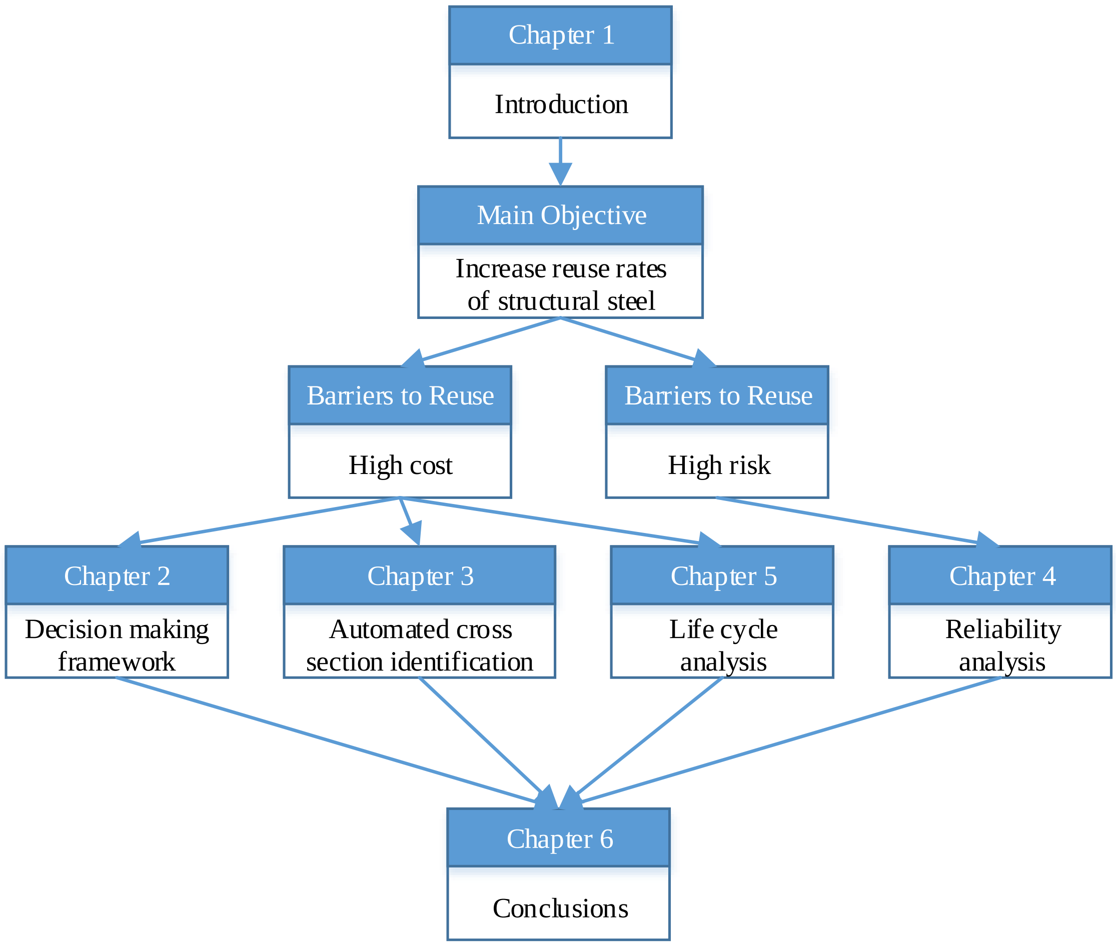


Figure 1-2: Thesis structure

2 Decision making framework for structural steel reuse

A study on the decision making process for implementing structural steel reuse as opposed to normal demolition/recycling practices is offered in this chapter. First, a comprehensive literature review of the topic is presented. Then, a reuse decision making framework is proposed, in detail. Important aspects of this framework include the demolition process and decisions, the deconstruction process and decisions, component analysis, and finally information requirements.

2.1 Introduction

Most structural steel from facilities that have reached the end of their service life is demolished and transported to recycling facilities where it is melted down and incorporated into the new steel production and fabrication supply chain. In spite of well-established recycling practices, iron ore and steel production is growing exponentially (Yellishetty, Ranjith & Tharumarajah, 2010). It is predicted that the steel industry will remain heavily dependent on new steel resources until at least the year 2050 (Oda, Akimoto & Tomoda, 2013). In the past there has been a focus on the recycling process (Ayres, 1997) but reusing steel avoids this process and eliminates the energy and water requirements of recycling steel.

2.2 Background

One important consideration for the life cycle impact of a structure is material choice, and the reuse and recycling potential of structural steel is noted as one of the material’s key advantages (Weisenberger, 2011). The process of incorporating these salvaged components into new designs, commonly referred to as “reuse”, is not an unknown process to the steel construction industry. These salvaged steel components come from the demolition or deconstruction processes. The differences between these processes are explored by Thomsen et al. (2011). The importance of reuse as a means to achieve sustainable steel construction has been explored providing a number of design considerations for reducing the cost and difficulty of steel reuse (Burgan & Sansom, 2006). These design considerations include using bolted connections and maximizing member length. The state of structural steel reuse in Canada was reported after extensive surveying of various groups in the steel industry (Gorgolewski, 2006). Based on this survey, it was estimated that the rate of steel reuse could be increased by up to 150% if economic conditions were less prohibitive or externalities were considered through a life cycle analysis. While conducting this survey, a process model was developed (Gorgolewski, 2006), linking the various steel industry stakeholders and showing their contribution to the reuse process. A summary of this model is provided in Figure 2-1.

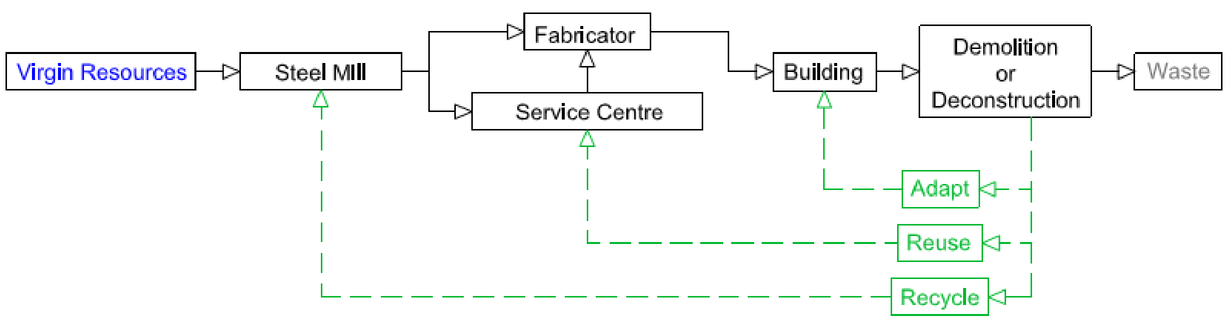


Figure 2-1: Process model for structural steel construction (adapted from Gorgolewski, 2006)

Significantly increasing the rate of structural steel reuse may require a change in practices before the building is even constructed. Designing steel structures in such a way as to maximize the ease of deconstruction is potentially one such change. Deconstruction is the process of carefully planning and executing the disassembly of a structure (Thomsen, Schultmann, & Kohler, 2013). In the case of steel structures, this can mean unbolting bolted connections or flame cutting welded connections before gently lowering members and assemblies to the ground where they are sorted and processed. The processes involved with, and the impacts of deconstruction have been studied in depth (Macozoma, 2002; Hurley, 2002; Chini and Balachandran, 2002; Guy &

Hinze, 2002). Generally speaking, deconstruction can be utilized to facilitate more effective reuse but it comes with the cost of increased end-of-life processes.

The feasibility and benefits of structural steel reuse were explored in a case study where it was found that reused steel could comprise up to 30% of the steel used in a rehabilitated train station in Italy (Pongiglione & Calderini, 2014). In the same study, it is suggested that new steel members may need to be over-sized to ensure the safety of the overall structure.

One method for reducing the uncertainty associated with the use of reused steel components in new building construction could come as a result of a paradigm shift in structural steel manufacturing. Ness et al. (2014) propose digital tracking and modelling of structural steel to help facilitate reuse. The proposed sensors and digital tags could hold information about a component's material properties, dimensions, and stress conditions during its service life. This information could be used to increase confidence in the resistance of the member and facilitate more efficient purchase and sale of reused components. Unfortunately, this paradigm shift does not aid in reusing structural steel that currently exists within buildings, because the proposed trackers and digital models have not been integrated into these buildings.

2.3 Structural steel reuse framework

Most reused steel ends up as bulk shoring materials. Existing connections are cut off and only simple sections remain. More complicated assemblies and sections are typically recycled. Use of a more thorough decision framework will increase the extent of steel that is considered reusable. Making the proper considerations for the possibility of reuse will reduce the cost and increase the effectiveness of any reuse that occurs. Figure 2-2 provides an overview of a proposed reuse process that incorporates decision making. The objective of the decision making framework is to inform owners and contractors when reuse alternatives should be investigated.

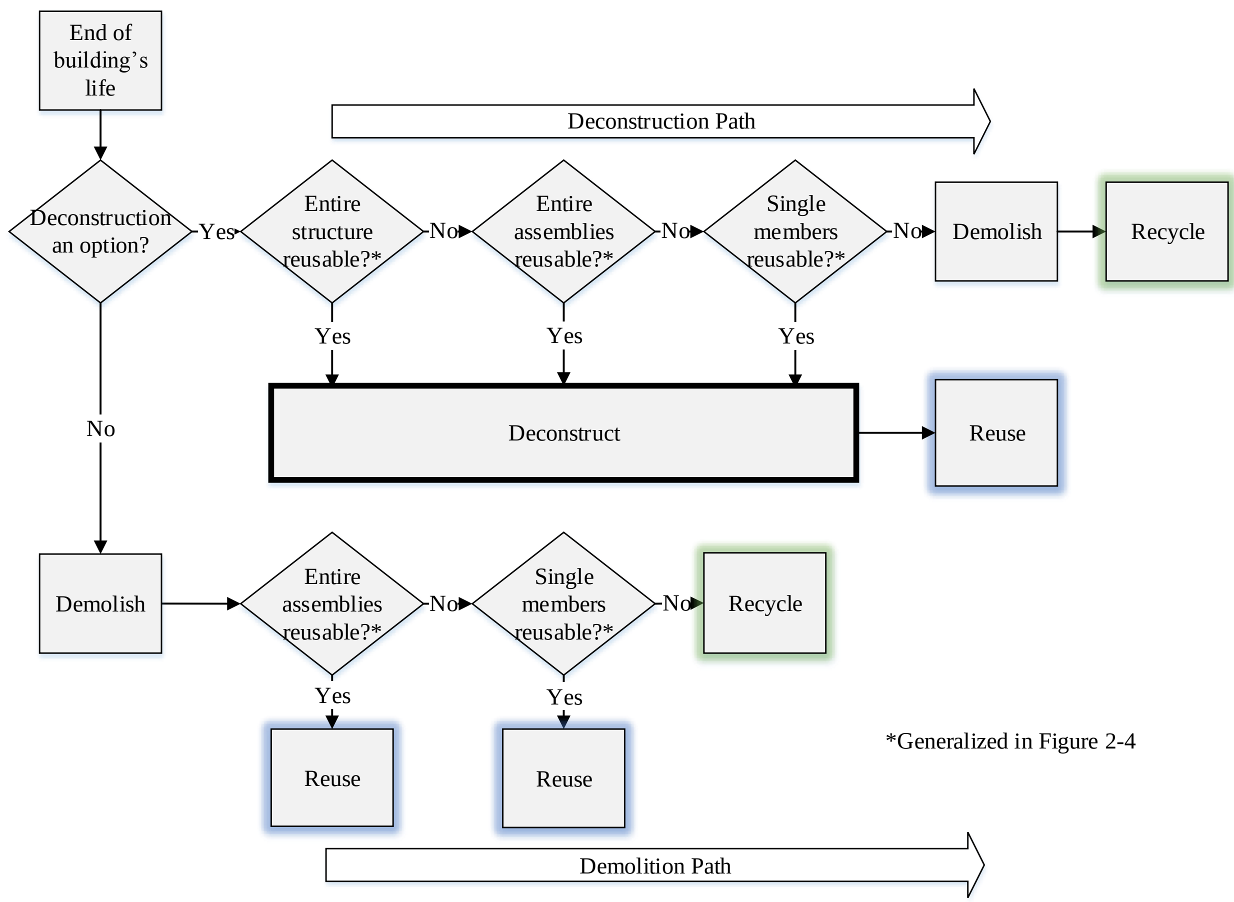


Figure 2-2: Decision making integrated into the steel reuse process model

This decision making framework is positioned within the overall steel reuse process model (Figure 2-1) such that it begins at the end of a building's service life and concludes with reuse or recycling. The first decision, and the most important one to make early in the process, is whether or not deconstruction (i.e., careful disassembly in a way that avoids damage) is an option. This question does not just apply to the possibility of deconstructing the entire structure, but also to individual members or larger assemblies of members if they can be carefully removed from the structure without causing them significant damage. A typical example of the type of damage that results from demolition practices can be seen in Figure 2-3. Factors that influence this decision include: 1) whether a stakeholder anticipates a net benefit based on the additional costs associated with careful deconstruction and the price of the deconstructed steel based on a speculative market or an actual buyer, 2) schedule constraints that may not allow for the additional time associated with deconstruction; and 3) the expertise and experience of those responsible for demolition and deconstruction, and their ability to safely execute the deconstruction option.


Figure 2-3: Typical damage to steel members sustained during demolition

The framework was validated through input and feedback from a number of industry experts. The areas of expertise included during this validation process were structural steel demolition, material salvage, steel fabrication, and structural design. Expertise in these areas were provided by construction super-intendents who oversee construction and demolition processes, salvage experts who perform material extraction from demolition and deconstruction projects, steel fabricators who are responsible for fabricating new steel construction, and design engineers who would are responsible for designing structures.

2.3.1 Demolition

The second, and less complicated path, applies when deconstruction is not an option (the Demolition Path in Figure 2-2). Unlike the previous path, this one begins by directly entering into a standard demolition procedure. Only after the demolition has concluded are the decision processes for potential reuse initiated. These processes are delayed until after demolition because the demolition process typically causes significant damage to the structural steel. One difference is that assessing the possibility of repurposing the entire structure is not performed. After demolition, there is a negligible likelihood that the entire structure will be reusable. Reusing entire assemblies is also unlikely, but still possible, after demolition. The largest potential for reuse in this path comes from salvaging individual members, e.g., for the shoring industry. Any assemblies or members identified for reuse will enter the reuse process whereas all remaining steel will enter the recycling process.

2.3.2 Deconstruction

Depending on whether or not deconstruction is an option, one of two recommended paths is available. The first, and more complicated path, applies when deconstruction is an option (the Deconstruction Path in Figure 2-2). This path consists of a three stage decision making framework where the possibility of repurposing the entire structure in a new location is first assessed, followed by the possibility of reusing structural assemblies, and then finally reusing individual members. A detailed description of the decision making framework for each one of these possibilities is presented in the following paragraphs. Each one of these decisions leads to deconstruction of the structure to remove components that have been identified for reuse. After deconstruction, the removed assemblies and/or components enter into the reuse process. Alternatively, if no components have been identified for reuse, standard demolition is executed, and the structural steel can then be separated and subsequently recycled.

2.3.3 Structure, structural system, and component assessment

Another important aspect of the decision making framework is what, precisely, is involved in determining if a structure, assembly, or member is suitable for reuse. Figure 2-4 presents an overview of a generalized decision making procedure (to be applied within the process illustrated in Figure 2-2) for considering the reuse of structural steel. The purpose of this decision making procedure is to outline the steps required to make an informed decision and to maximize the benefit of any potential reuse.

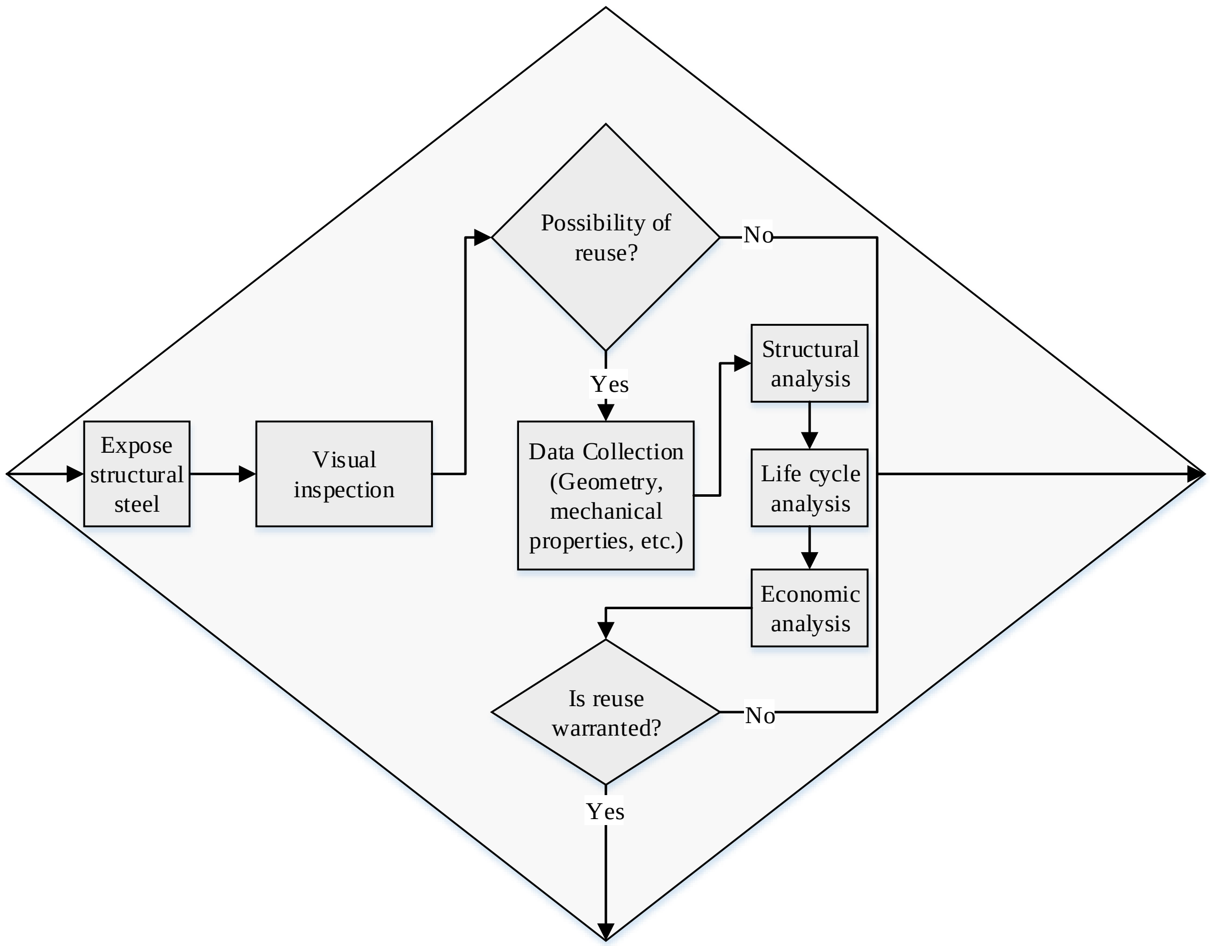


Figure 2-4: Generalized decision making procedure for steel reuse

For discussion purposes, the decision making procedure can be divided into three separate components: (1) preliminary analysis, (2) detailed analysis, and (3) final decision making. Before the preliminary analysis can occur, the structural steel needs to be exposed. This could potentially require the removal of cladding, fireproofing (for example spray gypsum) and finishings, such as drywall, stud walls, and drop ceilings. Fireproofing, in particular, could add significant costs to deconstruction processes. For this reason, it is recommended that low-rise structures be targeted for structural steel reuse because these structures often lack this type of fireproofing. The preliminary analysis is an optional visual inspection (Figure 2-4) of components or systems with the potential for reuse by a person with a deep understanding of structural steel design and the field experience required to make rough approximations of the remaining capacity of structural steel. Detailed analysis, in itself, contains four separate steps (Figure 2-4): (1) geometry and mechanical property acquisition, (2) structural analysis, (3) life cycle analysis, and (4) economic analysis. Each of these steps builds off the information gained in the previous step.

First, accurate geometric data and mechanical properties need to be obtained wherever possible. For obtaining the geometric data, a number of different systems can be implemented including 3D laser scanning, photogrammetry, ultrasonic thickness measurements, or manual measurements. If original structural drawings are available, then the goal of this step may simply be to confirm dimensions or assess deterioration (i.e., impact damage, corrosion, changes in geometry due to renovation, etc.). If no information is available, then the goal of this step will be to acquire section sizes, member dimensions, and connection geometry. The method of data collection is not critical, but the accuracy and precision of the results is. Wherever possible, mechanical properties should also be determined. The alternative for structural assessment is to make very conservative assumptions concerning these properties. With respect to steel, important properties include yield strength and ultimate strength. Non-destructive methods of determining the mechanical properties of steel include: hardness tests (Hashemi, 2011), and measurement of ultrasonic velocities for elastic properties (Chassignole et al., 2010).

The geometry and mechanical properties are then incorporated into a structural analysis. This takes into account the strength and size of all components, as well as the accuracy and precision associated with these measurements. Incorporating these variables into a structural assessment requires the consideration of reliability implications (i.e., assessment of uncertainties and failure probability) (Melchers, 1999).

Based on the structural assessment, a life cycle analysis can then be performed. The life cycle analysis is dependent on the results of the structural assessment, because the life cycle analysis compares reuse and new steel for components or assemblies that fulfill an equivalent role within the structure. The structural assessment determines the strength requirements of the new steel alternative to the reused component. The new steel component is assessed based on the materials and processes required to create it, whereas the reused component is assessed based on extraction, transportation, and storage processes. The outputs from each assessment are in terms of quantities of various life cycle metrics, such as carbon dioxide production, methane production, energy usage, and water usage.

The economic analysis is separated from the life cycle analysis, because it can be directly influenced by the results of the life cycle analysis. In many areas there are economic incentives to reduce environmental impact and these incentives should be taken into consideration when comparing alternatives. In the future, environmental impacts such as water and carbon could have direct costs associated with them. There are also additional costs associated with reusing materials. These costs include the additional transportation and storage costs associated with reuse processes. The cost of the additional analysis required to assess the potential for reuse is an important factor to consider when asking the larger question of, "What is the cost to industry of considering increased structural steel reuse?" However, on a given project where the decision to consider the possibility of reuse has already been made, the implications of this cost on the decision process will be minimal, since the analysis cost is largely incurred regardless of whether a given member, assembly, or structure is ultimately selected for reuse.

In many cases, the final decision will depend on who is making the decision. This is because capabilities and market positions vary, and because there are aspects of the decision making that cannot be objectively quantified, such as the image of a company that can demonstrate high rates of steel reuse. The goal of this decision framework is to provide the decision maker with the full spectrum of information so that an informed decision can be made.

2.3.4 Information requirements

To aid in the implementation of the framework, a description of the required information is presented in the following discussion and summarized in Table 2-1. Some of these have previously been outlined by (Gorgolewski, 2008). The information required for the structural analysis includes the geometry and material properties. The geometric information required includes cross-section dimensions, length, camber, twist, locations and severity of damage, and end-connection geometry if the connections are to be used “as is”. The damage can be expanded further into impact damage, corrosion, and post-production modifications such as web holes for duct work. Important material properties for steel are the yield strength, ultimate strength, and ductility. Additionally, the statistical uncertainties in these parameters need to be known to perform a reliability analysis. Geometric characterization pays a key role in this analysis as well as in the life cycle analysis and economic analysis.

Table 2-1: Summary of the required information for effective reuse

Structural Analysis	- Geometry - Material Properties - Uncertainties in Structural Parameters
Life Cycle Analysis	- Remaining Capacity of a Salvaged Component - Reuse Processes - New Steel Production Processes - Materials in New Steel - New Steel Material Mining Processes - Life Cycle Impacts of Processes and Materials
Economic Analysis	- Member Capacity - Market Value of Scrap Steel - Market Value of Reused Steel - Market Value of New Steel - Cost of Transportation - Cost of Storing Reused Steel - Storage Duration Before Being Sold - Economic Incentives for Reuse

2.4 Summary

The work presented in this study proposes a complete decision making framework that is integrated into an existing structural steel reuse process model. This decision making framework has been developed to assist decision makers at the early stages of a building decommissioning to maximize the likelihood and rate of structural steel reuse. The description of this framework includes an overview of the analysis required to achieve high levels of structural steel reuse, and the information required to perform this analysis. Of this information, two key areas for development are in understanding the structural capacity of reused members, and understanding the full economic and environmental implications of reusing steel compared to recycling it.

3 Semi-automated cross-section identification

The study presented in this chapter outlines a methodology for performing semi-automated cross-section identification of structural steel sections. First a comprehensive literature review is presented of current 3D imaging and automated identification techniques. Second, a semi-automated cross-section identification algorithm is proposed, which utilizes 3D imaging. Using this cross-section information, the results described in this chapter include parameters required for performing reliability analysis of reused structural steel.

3.1 Introduction

The ability to assess the capacity of structural steel elements in a manner that provides the designer with the confidence to incorporate these elements into new designs is essential for the execution of the decision making framework presented herein. The automation of this process, to the greatest extent possible, is critical for its cost effective execution. The general problem of generating models from 3D point clouds has been studied in depth (Tang et al., 2010). Here, the focus is on aspects of identifying structural sections for the sake of understanding the impact of 3D data acquisition and the modelling process on the reliability of the results.

3.2 Background

One possible approach for reducing the cost of analysis of existing structures for reuse is automating parts of the process. This might begin with acquiring the accurate 3D geometry of the structure. This may include the identification of connection geometry and deviations from the design dimensions, as well as basic information such as the nominal member sizes, in cases where original structural drawings are not available. Methods for capturing 3D point cloud data for this purpose can be separated into two categories: (1) image based systems, and (2) time-of-flight based systems. An example of point cloud data for a low-rise structural steel building can be seen in Figure 3-1. Image based systems typically have a higher speed data collection rate but lower accuracy (Dai et al., 2013). This makes image based systems ideally suited for real-time analysis (Han & Lee, 2013) and sufficiently accurate for activities such as infrastructure reconstruction (Brilakis et al., 2011). Image based systems also offer the flexibility of capturing data from unmanned aerial vehicles (UAVs) (Remondino et al., 2011). While time-of-flight based systems, such as laser scanners, lack the data collection speed of image based technologies, they are able to acquire very dense and highly accurate point clouds allowing them to be used (for example) for assessing initial imperfections of pipelines when constructing accurate models (Kainat et al., 2012) or tracking the progress of a construction project (Turkan et al., 2011).

Figure 3-1: Photograph (a) and 3D point cloud (b) of a low-rise structural steel building

In the field of civil engineering, automated object recognition has mainly focused on maintaining and updating building information models (BIMs). A method has been presented for calculating and monitoring the progress of a construction site by comparing 3D point clouds to 3D BIMs (Bosché & Haas, 2008; Bosché, 2009; Turkan et al, 2011). Point cloud data has also been used for dimensional compliance checks of concrete (Tang et al., 2011) and marble façades (Al-

Neshawy et al., 2010). However, both of these studies were developed with the assumption that the subject of the 3D scan is expected to be perfectly flat, as is the case for a wall or floor element (Bosché & Guenet, 2014).

All of the aforementioned automated object recognition methods require a priori knowledge in order to identify components. This limitation has been identified and is currently an area of high interest within the research community. The issue of automatically associating semantic content with simple, flat surfaces has been addressed recently (Xiong et al., 2013). Other automated methods for converting a 3D point cloud into a BIM also exist (Tang et al., 2010).

Developments in this field have led to various commercial products that are capable of locating structural steel sections (ClearEdge 3D, 2014) or identifying internal frame connections (Cabaleiro et al., 2014) within a 3D point cloud. Unfortunately, these methods do not provide the structural engineer with a confidence level in the results (i.e., a probability that the component has been correctly identified), which is essential before they can be used as input for new designs.

The geometric reliability of the automated results can be characterized using a bias factor, (δ). The bias factor is characterized by a statistical distribution, often the lognormal distribution, and the mean (μ) and coefficient of variation, (CoV), of the ratio between detected and actual dimensions. The geometric bias factor adjusts the resistance of the modelled component based on variability in the geometric characterization of that component. These parameters can then be compared to similar parameters for new steel members or used in a structural reliability analysis. Such an analysis can be performed to calibrate modified resistance factors for use in the limit states design process for the structural assessment of reused steel members, assemblies, or entire structures. The objective of the work presented herein is to demonstrate a methodology whereby these parameters can be acquired to facilitate structural steel reuse.

The resistance factors that result from the aforementioned reliability analysis are dependent on the accuracy of the geometry identification and will therefore change (i.e., increase) as remote sensing technologies and the algorithms used to analyze the generated scan data improve. Figure 3-2 shows a visual representation of the difference between the point clouds from a tripod-mounted 3D laser scan from a distance (Figure 3-2a) and a more accurate, handheld scanner (Figure 3-2b). As the accuracy and precision of remote sensing technologies improve, it is reasonable to expect that the bias factor will tend towards unity and the coefficient of variation will decrease. Despite this changing environment, the methodology for acquiring these statistical parameters is still applicable. Resistance factors aid designers in calculating the structural resistance associated with a target probability of failure. It is acknowledged that designers may initially be reluctant to use such an approach in applications involving reused steel. However, these factors should still be immediately useful for preliminary assessment of remaining structural resistance.

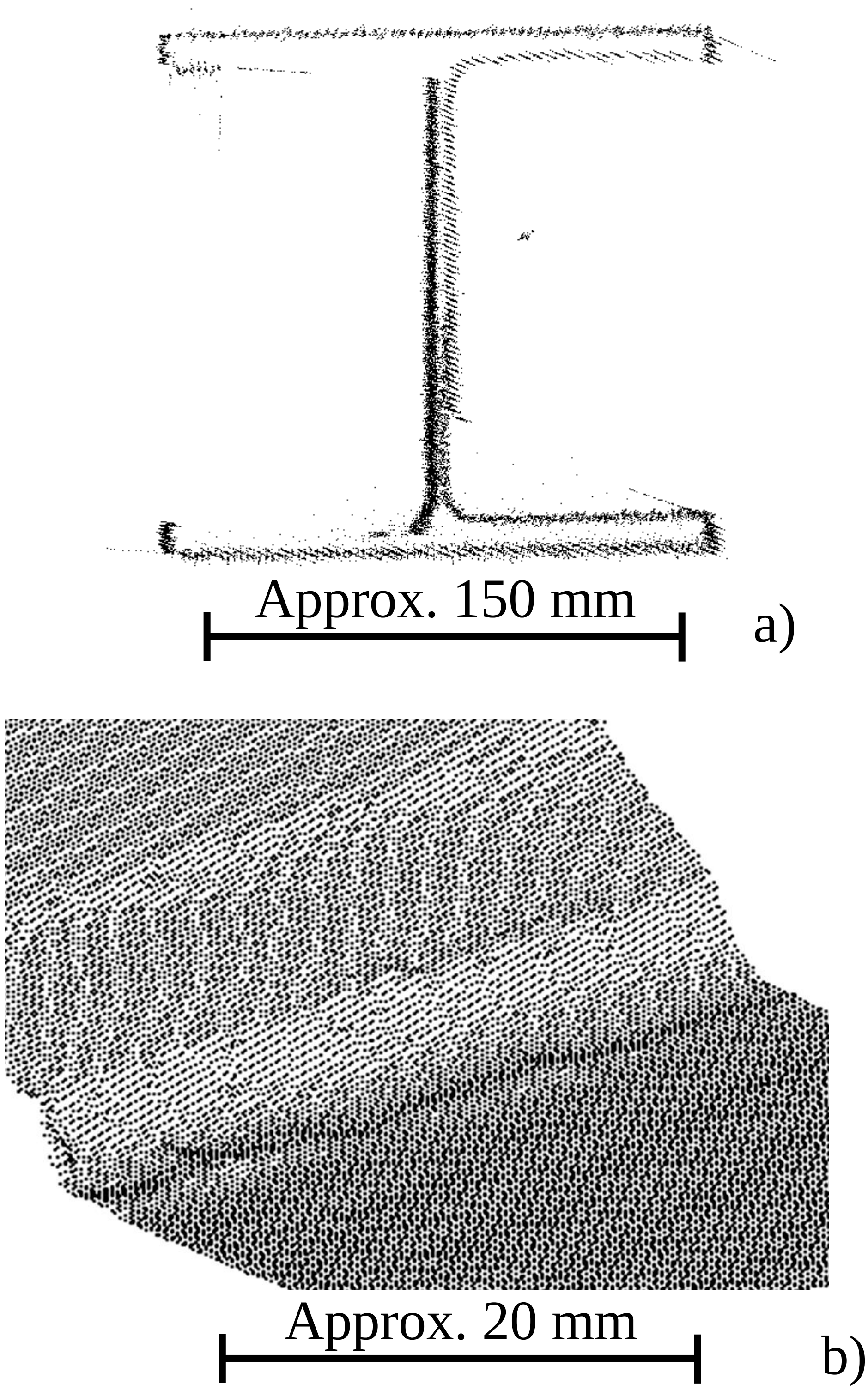


Figure 3-2: Visualization of the difference in scan accuracy for a tripod-mounted scan from a medium range of a W-section (a) and a handheld scan from close range of an impact-treated weld toe (b)

3.3 Methodology

Complete algorithms for the semi-automated cross section identification can be found in Appendix A. Images of the point clouds used for analysis can be found in Appendix B and all point cloud data has been made publicly available through Scholar's Portal.

Knowledge of the cross-section geometry of a structural steel member is critical for determining its capacity. As such, a five step methodology for semi-automating the process of section identification is presented. This methodology is particularly applicable in cases where as-built drawings or a BIMs aren't available and manual measurement would be prohibitively costly and/or time consuming. These five steps are as follows: (1) data collection, (2) data pre-processing, (3) filter creation, (4) binary image creation, and (5) filter convolution.

Geometric data was collected using a tripod-mounted 3D laser scanner from four different structures, resulting in point clouds for 17 members. The technical specifications of the laser scanner can be seen in Table 3-1 and a description of each member can be found in Table 3-1.

Table 3-1: Technical specifications for the 3D laser scanner (FARO, 2007)

Range	0.6 m – 40 m
Measurement Speed	120 000 points/sec.
Distance Error	±3 mm at 25 m
Laser Class	3R
Laser Wavelength	785 nm

Table 3-2: Member description and section designation

Member Label	Section Designation	Description of the Structure
A1	W460x158	structural steel teaching aid / sculpture
A2	W460x74	
A3	W250x33	
A4	W460x89	
A5	W460x89	
A6	W310x33	
A7	W530x82	
A8	W410x54	
A9	W310x33	
B1	W310x52	modular rack supporting a pipe spool
B2	W310x52	
B3	W310x52	
B4	W310x52	
C1	W610x241	column supporting a truss in an arena
C2	W610x241	
D1	W610x125	beam in a low-rise commercial building
D2	W610x113	

3.3.1 Data collection

The data collection phase of the semi-automated cross-section identification process is only limited by the information required as input in the remainder of the process. The following algorithms are based on the assumption that the data will be collected as a 3D point cloud. For the purposes of this study, a terrestrial (tripod mounted) 3D laser scanner was used to collect all data. This data collection method results in long lists of x, y, and z coordinates with each point representing an individually recorded point on the surface of the scanned object. The particular method of data collection is not important so long as the results are sufficiently accurate and in the proper x, y, and z listed format. For example, digital photogrammetry, videogrammetry, structured lighting, or 3D range cameras could have been used in this study to achieve similar results.

An example of one of the structures used for this study is a structural steel teaching aid found on the University of Waterloo campus, shown in Figure 3-3. Data was collected from three different perspectives around the structure. Care was taken to ensure that adequate data were collected from each surface of the structure but this was not necessarily possible for all members. For example, data could not be collected from the top surfaces of members that were above the maximum height of the tripod mounted scanner (approximately 1.5 m).

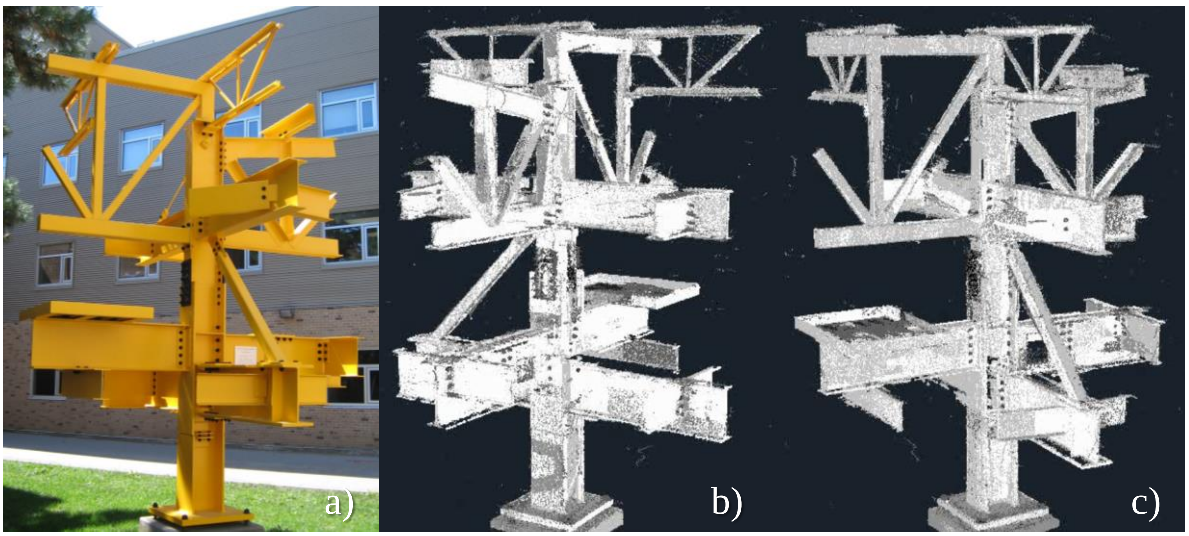


Figure 3-3: The example structure used for data collection (a) and two views of the sample data set (b) and (c)

3.3.2 Data pre-processing

The first pre-processing that must be completed is merging the individual scans into a single point cloud. 3D laser scanners are only capable of capturing geometry for what is visible from one point of view at a time. Several scans must be taken around a structure in order to capture the entire geometry. These separate scans must then be merged together after the field study has been completed. Merging the point clouds in this study was completed using commercial software provided by the manufacturer of the 3D laser scanner. It should be noted that many non-commercial methods exist for merging point clouds. Examples of these methods are plane-based registration and the iterative closest point algorithm (ICP). Plane-based registration is typically used as a course registration by aligning point clouds based on at least three planes of points that are common in each scan (Bosché 2012). The ICP algorithm is typically used for fine registration and merges point clouds by minimizing the distance between closest points (Besl and McKay 1992). The commercial software uses a combination of plane-based and point-based triangulation to merge point clouds. This type of software is most likely to be used in practice, and is therefore used in this study.

The next pre-processing step that must be completed is manually trimming the data to include only a single structural steel member, as in Figure 3-4b. The algorithms that have been developed to semi-automatically identify the cross-section of a member assume that the points in an encompassing volume of a single member will be used as input rather than that of an entire structural system. Removing data points that do not represent the surface of the member being analyzed was performed manually using standard commercial 3D computer aided design (CAD) software. This step could be automated using a point cloud segmentation algorithm, such as the one presented by Woo, Kang, Wang, and Lee (2002), but remains outside the scope of this investigation.

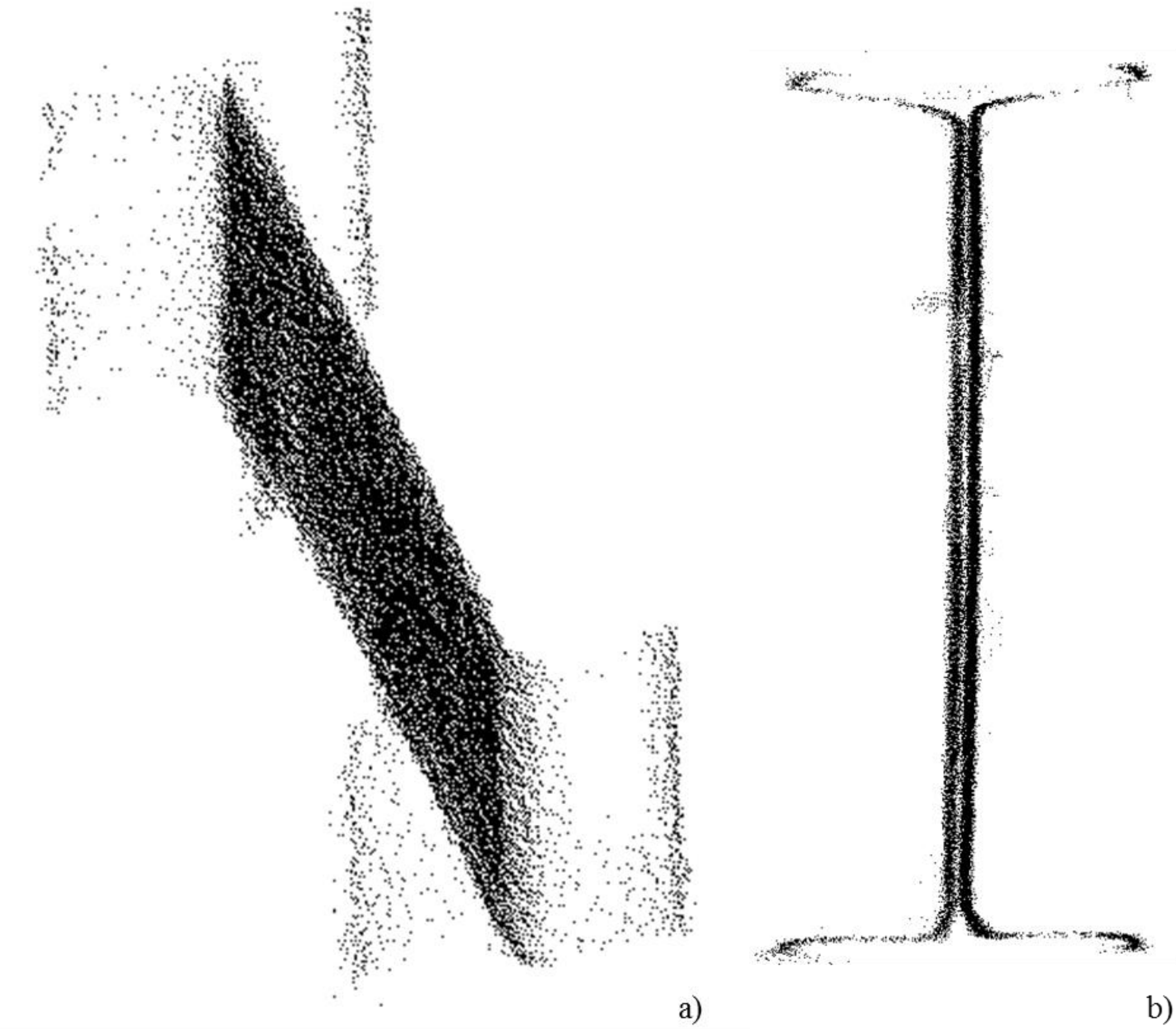


Figure 3-4: A point cloud of a structural steel member before (a) and after (b) alignment

In a similar manner to trimming the point cloud to result in a single member, the principle axis of the resulting point cloud needs to be aligned with the global z-axis and the strong axis of the member is parallel to the global x-axis, as can be seen in Figure 3-4b. The development of the cross-section identification algorithm dictated that this pre-processing needed to take place. This processing was, again, performed manually with commercial 3D CAD software. Based on the ease of this process, it was determined that this was not a necessary step to fully automate.

3.3.3 Filter creation

The method for identifying the cross-section uses a binary image of a known cross-section as a comparison. This binary image is referred to as a 'filter'. A filter, like the one in Figure 3-5a, is a graphical representation of the geometry of a known cross-section, thus a filter needs to be created for each possible cross-section. Fortunately, the geometries of standard steel sections are widely known and can be described with a small number of parameters, which results in easy creation of the filters. It is also convenient that the filters do not need to be created during each identification process once a database of filters for all standard cross-sections has been created.

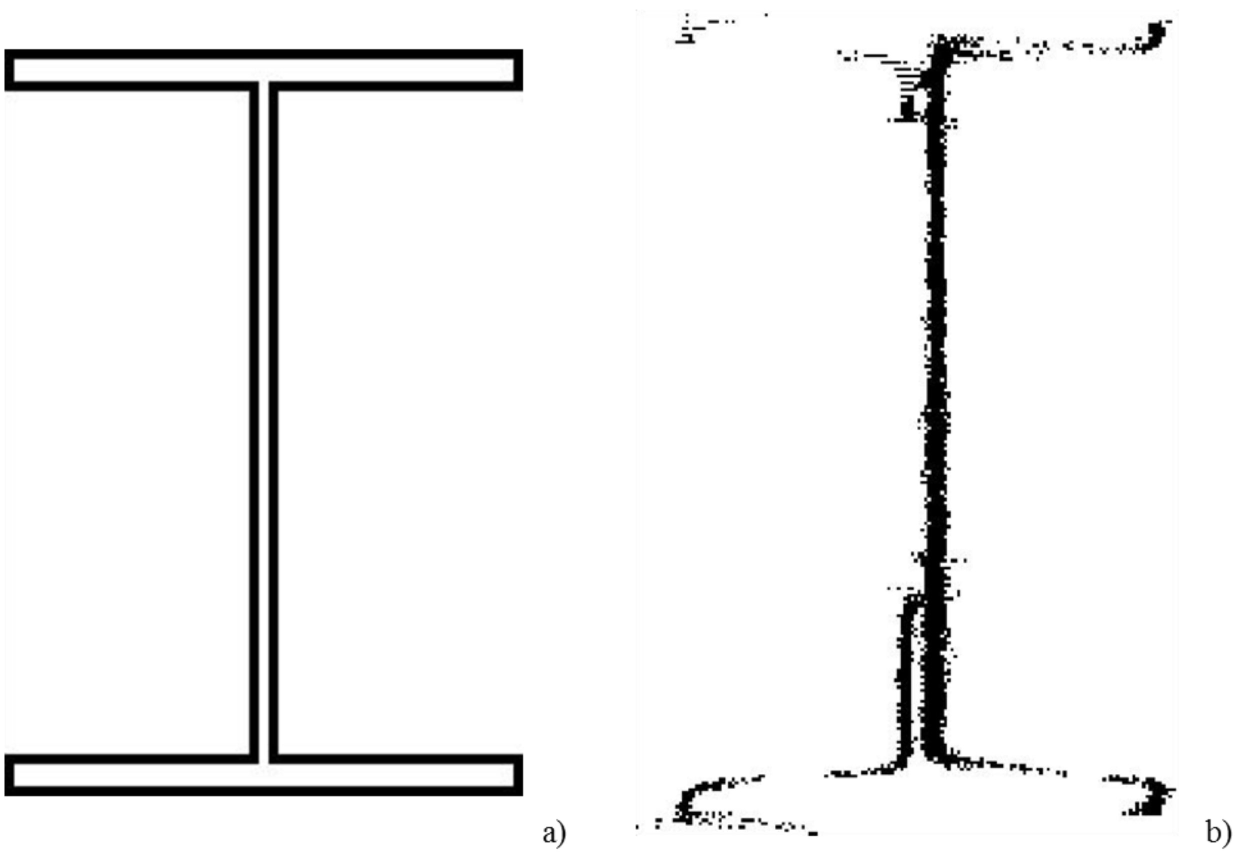


Figure 3-5: A typical filter for a wide flange beam (a) and a binary image of a data slice (b)

The filters used for this study were created using simplified versions of the geometries of standard wide flange sections. Actual wide flange cross-sections have a curvature where the flange meets the web. For the purposes of this study, it was assumed that the wide flange cross-sections were comprised of three rectangular components: two rectangular flanges with width and thickness equal to the nominal width and thickness, respectively; and one web with width equal to the nominal width and height equal to the beam depth minus the thickness of the flanges. A database of more precise filters could be created in the future if required.

3.3.4 Binary image creation

The next step in identifying the cross-section is to create binary images that represented the cross-section geometry that is recorded with the 3D laser scanner, as seen in Figure 3-5b. First, the aligned point cloud is split into a number of slices along its principle axis based on a user defined slice thickness. These slices of points are then individually projected onto a parallel plane and a binary image is created. The creation of the binary image is accomplished by pixelating the plane within the limits of the data points that have been projected onto it. Then, if a pixel contains a data point, the pixel is marked as 'black' or 'filled'. This results in a number of binary images that represent the measured cross-section at various points along the length of the member. The entire binary image creation process is depicted in Figure 3-6.

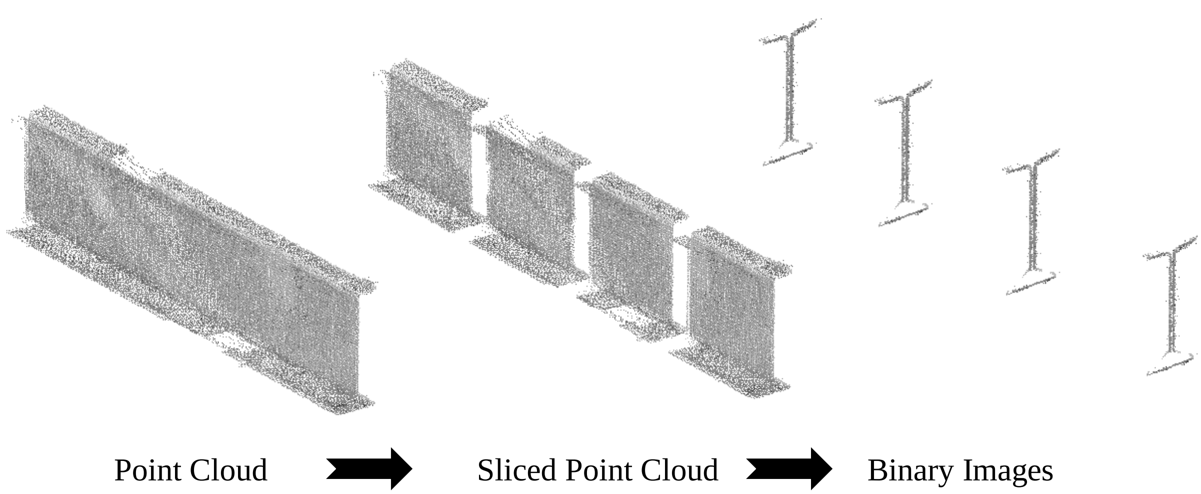


Figure 3-6: The binary image creation process

3.3.5 Filter convolution

The actual process of matching a cross-section with the measured, 3D geometry is performed during the filter convolution step. This step involves systematically convolving the binary image for each filter over the binary image for each cross-section. Figure 3-7 shows a summary of the convolution process. Convolving one image over another is a simple process that requires a large number of basic calculations.

```
For all cross sections
    For all filters
        Convolve filter over cross section
        Record maximum correspondences
    Next filter
Next cross section
```

Figure 3-7: Convolution process for all filters and all cross-sections

To understand the convolution process it is helpful to refer to the matrix form of a binary image. Binary images in matrix form represent pixels as corresponding cells of the matrix where white pixels contain a value of zero and black pixels contain a value of one. The correspondences are then summed for the filter matrix and a subset of the image matrix that matches the dimensions of the filter matrix. In other words, the number of matching filled pixels between the filter and the point cloud image are summed. The value of this sum represents how well the subset of the image matches the filter. The degree of matching between the image and the filter can only be concluded after all possible subsets of the image have been checked against the filter. This corresponds to the maximum value of the sum that has been calculated. This value is stored and the process is repeated for the remaining filters. This results in a cross section designation being matched with the binary image of the cross section. This process is repeated for each slice along the length of the member. When all filters have been convolved over all of the cross-section binary images, also known as slices, the best matching filter, and therefore the best matching cross-section, is indicated by the maximum value of the sum of correspondences.

3.3.6 Selection of pixel size and split thickness

In order to perform the semi-automated cross section identification, a pixel size and slice thickness must be selected by the user. A sensitivity analysis was performed to understand the impact that pixel size and slice thickness had on identification accuracy, and to identify the optimal pixel size and slice thickness for analysis.

Varying the pixel size changed the size of pixels used in the binary image creation. The impact of this can be seen in Figure 3-8. Varying the split thickness changed the distance between slices during the binary image creation, which resulted in more or less points being projected onto the plane of the binary image. The impact of this can be seen in Figure 3-9.

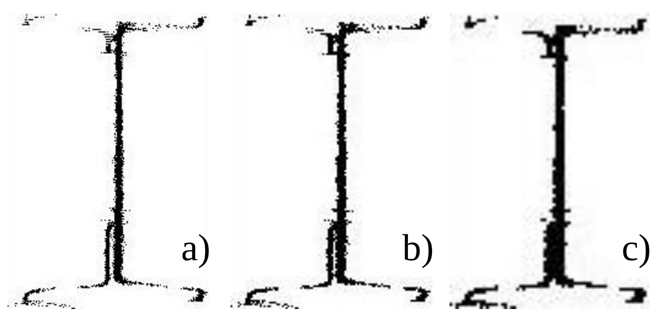


Figure 3-8: Cross section image with a pixel size of 2 mm (a), 3 mm (b), and 5 mm (c)

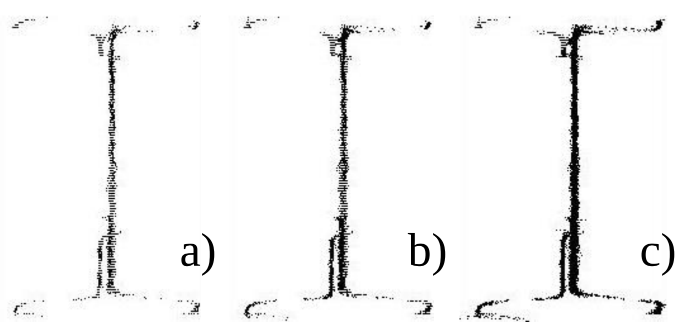


Figure 3-9: Cross section image with split thickness 50 mm (a), 100 mm (b), and 200 mm (c)

The sensitivity study was conducted using the cross section area as a metric. The results from this study can be seen in Figure 3-10 and Figure 3-11. For the study on pixel size, the slice thickness was held constant 200 mm. For the study on slice thickness, the pixel size was held constant at 2 mm. The results for the comparison of pixel size slightly favoured a pixel size of 2 mm. The average error for 2 mm, 3 mm, and 5 mm was 11%, 15%, and 16%, respectively. The results for the sensitivity study on slice thickness favoured 200 mm slices. The average error for 50 mm, 100 mm, and 200 mm slices was 20%, 15%, and 11%, respectively.

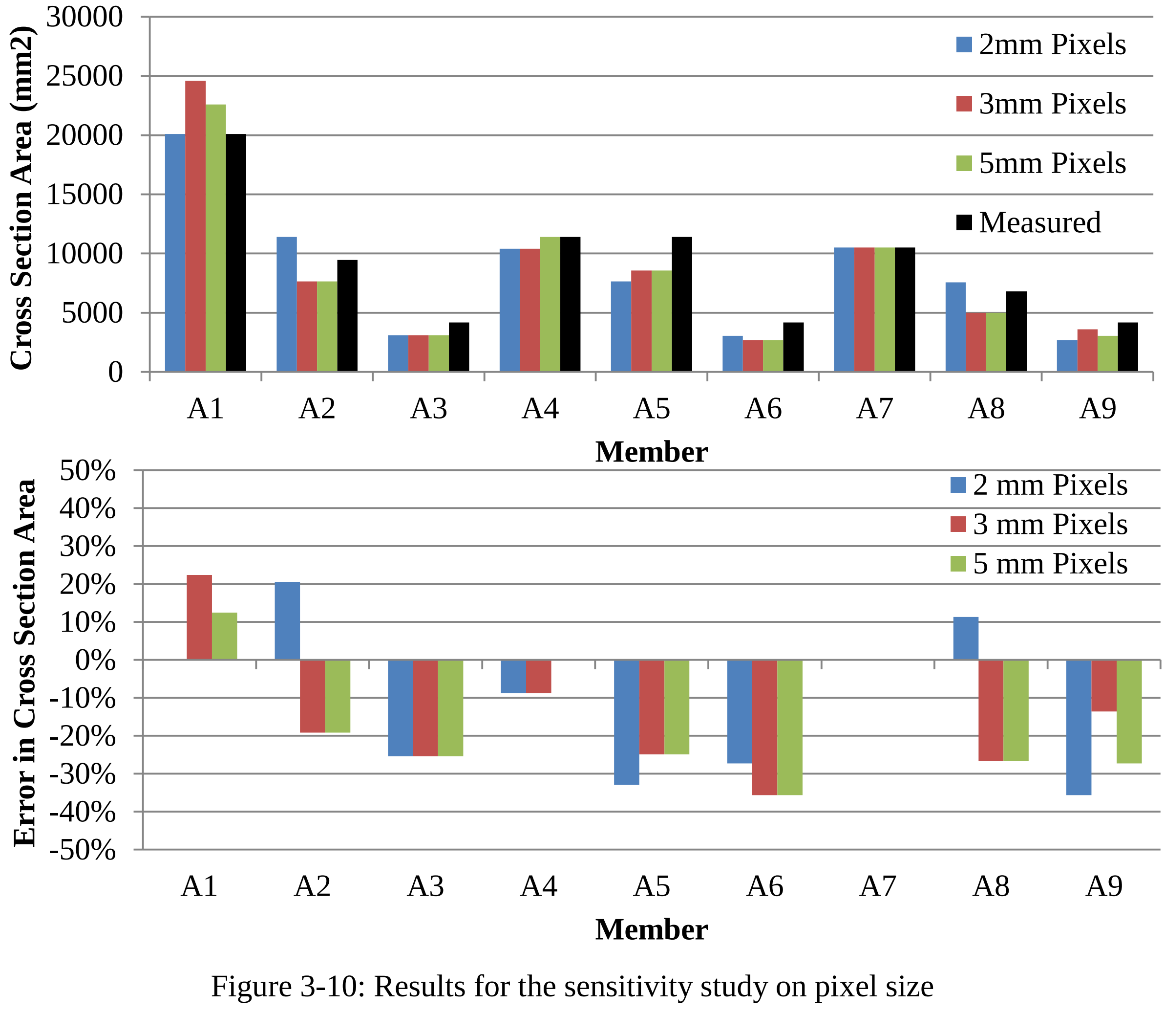


Figure 3-10: Results for the sensitivity study on pixel size

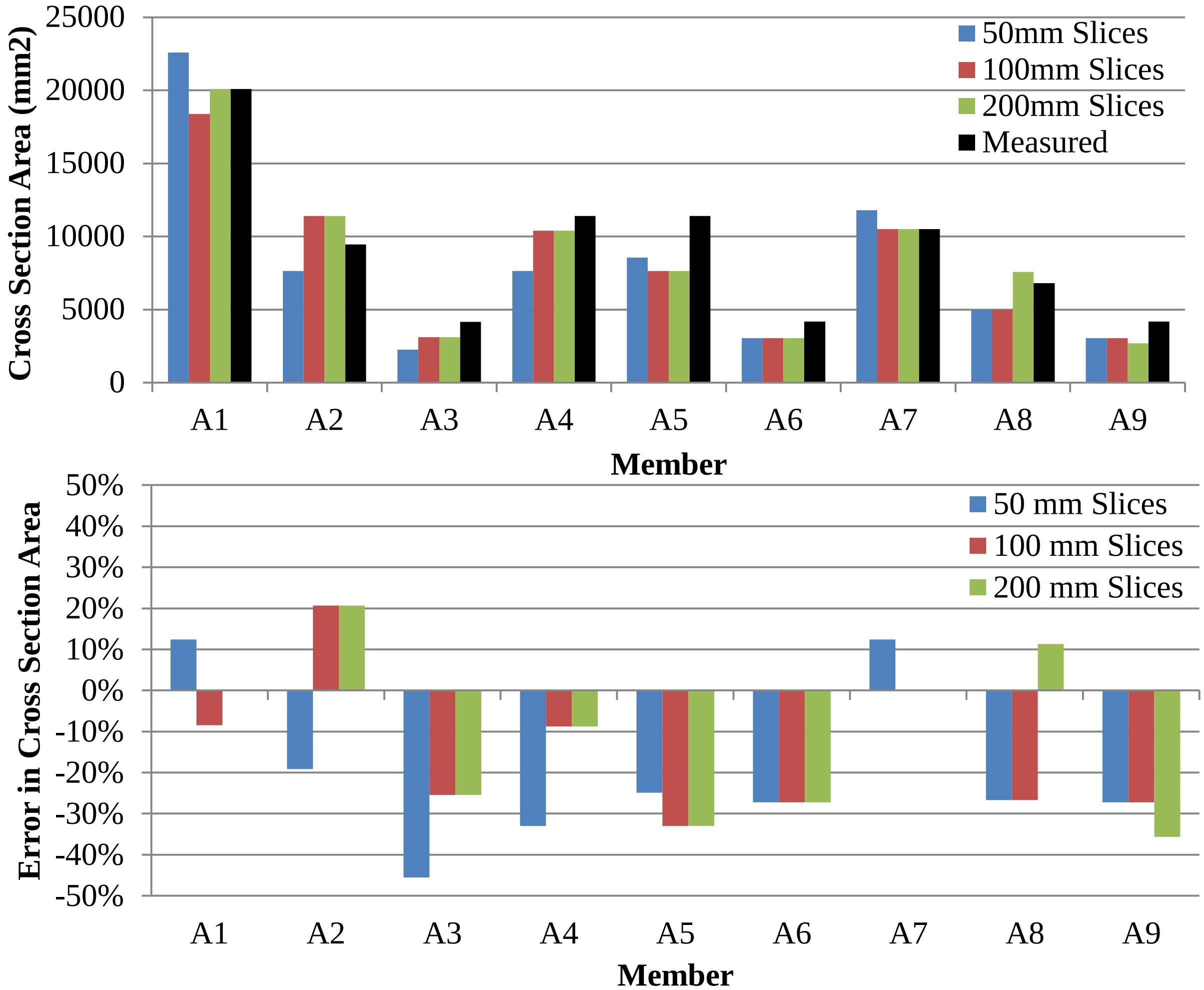


Figure 3-11: Results for the sensitivity study on slice thickness

3.4 Results

The identification algorithm yielded results in the form of a degree of matching for each section. This degree of matching is based on the maximum number of matching pixels between a binary image of point cloud data and a binary image of the idealized cross-section, therefore a higher degree of matching is better. The results for one of the members can be seen in Table 3-3.

Table 3-3: Sample section identification results

	A1	
Section Designation[a]	Degree of matching	Section Modulus 10^3 mm^3
W460x315	43	6850
W460x286	50	6230
W460x260	57	5650
W460x235	75	5080
W460x213	116	4620
W460x193	121	4190
W460x177	125	3780
W460x158[b]	**130**	3350
W460x144	128	3080
W460x128	118	2730
W460x113	106	2400

[a]E.g.: W460x158 has ~460 mm depth and weight of 158 kg/m
[b]Section designation based on hand measurements

The axial, shear, and bending capacities of a member are proportional to the cross-sectional area, web area, and elastic or plastic section modulus, respectively (CSA, 2009). Thus, Figure 3-12, Figure 3-13, and Figure 3-14 show the point cloud analysis vs. manually measured results for cross-sectional area, web area, and section modulus, respectively. Each analysis was performed with a pixel size of 2 mm and a slice thickness of 200 mm, based on the results of the sensitivity study presented in Section 3.3.6.

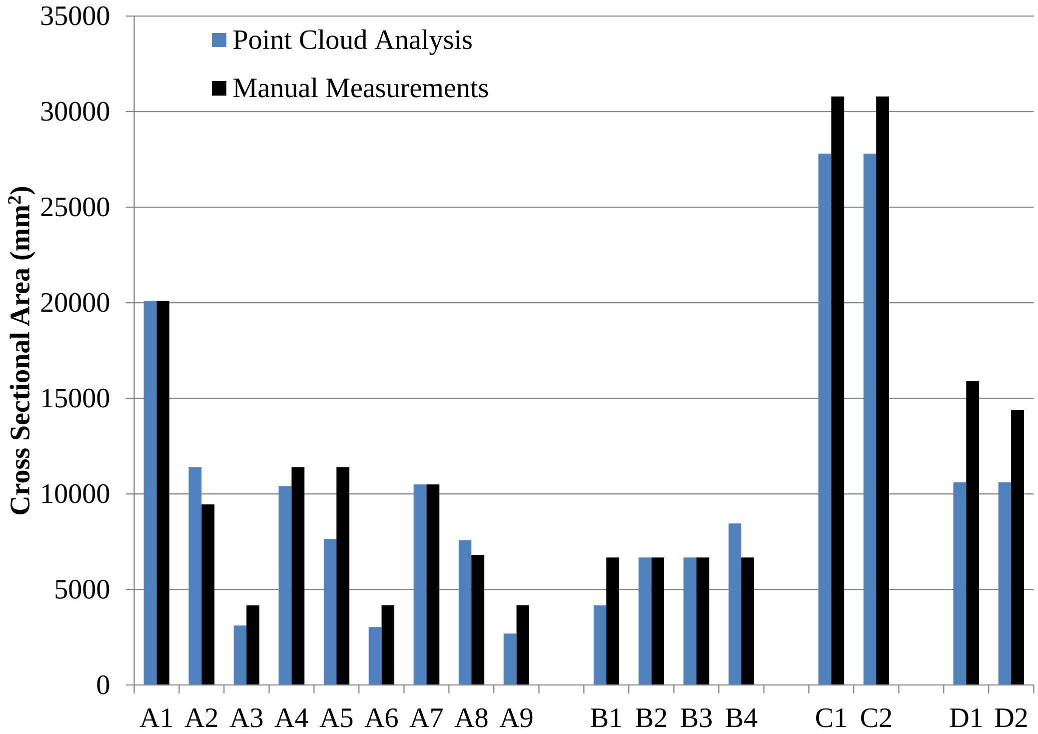


Figure 3-12: Predicted vs. actual (i.e., manually measured) cross-section areas

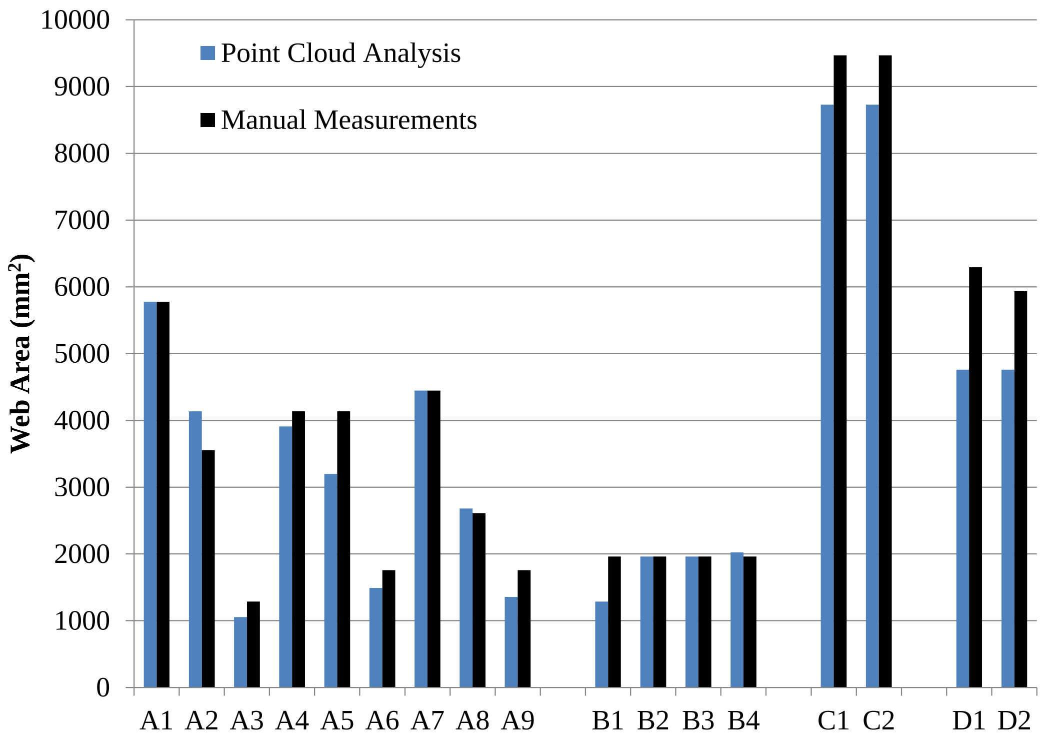


Figure 3-13: Predicted vs. actual (i.e., manually measured) web areas

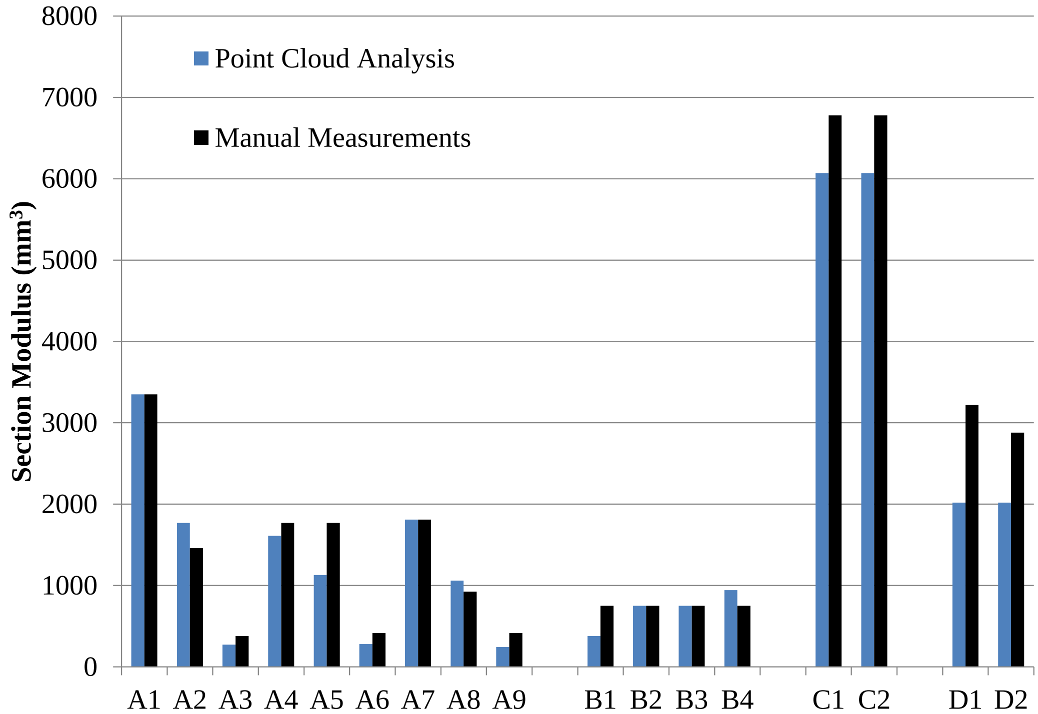


Figure 3-14: Predicted vs. actual (i.e., manually measured) section moduli

3.4.1 Reliability analysis parameters

The statistical variation in the identified cross-section properties can be quantified and compared to those associated with the fabrication tolerances for new steel members. Table 3-4 summarizes the results for cross-sectional area, web area, and section modulus. These results are presented in terms of number of samples, (n), their mean, ($\bar{\mu}$), and the coefficient of variation, (CoV), of the ratio between the detected and actual (i.e., manually measured) dimensions. Probability paper plot analysis was used to determine the shape of the statistical distribution. This analysis showed that the normal distribution was most representative of the data with an R^2 value ranging between 0.93 and 0.95 depending on the geometric characteristic (i.e., section modulus, web area, and cross-section area).

Table 3-4: Statistical parameters based on analysis results and accepted values for new steel

		Cross-section Area	Web Area	Section Modulus
Analysis Results	n	17	17	17
	μ	1.11	1.09	1.13
	CoV	0.225	0.145	0.262
New Steel Members	n	87	-	87
(Schmidt & Bartlett, 2002a)	δ	1.03	-	1.02
	CoV	0.031	-	0.035

3.5 Discussion

Using the described scanning technology and presented algorithms, structural steel W-sections can be detected remotely. The point cloud analysis results in a conservative estimate, on average, for the section properties and the variation that is an order of magnitude larger than for a member that has been produced in a steel mill. It is important to note that the previous results are strongly influenced by the ability to obtain thorough and accurate point cloud data. This means that the results will only improve as scanning technology and best practices advance.

3.6 Summary

The study presented herein presents a semi-automated methodology for the geometric characterization of structural steel. This methodology validates the key role that it plays in the decision making framework presented in Chapter 2. Specifically, the application of a semi-automated cross-section identification technique is demonstrated on 17 members in four different scanned structures. The application of this methodology resulted in a bias factor and coefficient of variation that can be used in a structural reliability analysis.

4 Reliability analysis of reused components

This chapter begins with a detailed literature review of the structural reliability analysis process. Next, a methodology for performing a structural reliability analysis for reused structural steel components is proposed. The results of this analysis are resistance factors that can be applied to reused structural steel members in a limit states design approach.

4.1 Introduction

In most of the world, steel structures are designed using a limit states design approach (e.g., CSA, 2009), which involves the application of load and resistance factors to the calculated load effects and nominal resistance of a structure to ensure that a particular level of safety is achieved. These factors consider the various sources of uncertainty and inherent variability associated with the parameters and models used to predict the structure's performance during its service life. A reliability analysis can be performed to incorporate the random nature of structural characteristics, whereby a target failure probability is assumed, and a set of load and resistance factors associated with this failure probability are calculated. The resistance factors for structural steel appropriate for the design of buildings in Canada (for example) have been reviewed as recently as 2002 in a study by Schmidt and Bartlett (2002a and 2002b). This review was performed based on the assumption that the mechanical and section properties of the steel are within the tolerances observed from steel mills. The impact on the design factors of additional uncertainties associated with: 1) deterioration due to environmental exposure or use, and 2) lack of knowledge concerning the actual section or material properties as it relates to the reuse of structural steel members in new construction has received little attention until now.

4.2 Background

Increased uncertainty in the geometry of a structural member can lead to reduced confidence in the safety of a structure. This can be mitigated by calculating an appropriate modified resistance factor that accounts for the increased uncertainty in a member's capacity to maintain an acceptably low probability of failure, p_f, which can be associated with a corresponding target reliability index, β, according to the following relationship (Melchers, 1999):

Equation 4-1: $p_f = \Phi(-\beta)$

where $\Phi(\,)$ is the cumulative density function for the standard normal distribution. The previously described cross-section identification algorithm provides the information on the uncertainty in the section geometry required to calculate an appropriate modified resistance factor, which can be used for structural design.

The use of load and resistance factors is a convenient simplification to make, but not a necessary one. A probabilistic design model has been established by the Joint Committee on Structural Safety (2000) wherein the same design requirements that are typically achieved through load and resistance factors are attained with probabilistic methods. Similar methods have been employed for the assessment of existing bridge structures as a means to increase the allowable loads without retrofitting the structure (Braml, Taffe, Feistkorn, & Wurzer 2013).

Once the individual random variables have been established, they are used to calculate the distribution for load and for resistance. The probability of failure is the probability that the load exceeds the resistance (Figure 4-1). This probability of failure can be described as:

Equation 4-2: $p_f = P(Load > Resistance) = P(z < 0)$

where p_f is the probability of failure and z = *Resistance* - *Load*. This probability can be calculated by determining the area under the probability density function *G(z)* for $z < 0$, where $G(z)$ is the limit state function and the probability of failure is the same as the probability that this limit state function is violated.

Equation 4-3: $p_f = \int_{-\infty}^{0} G(z)\, dz$

This representation of the calculation for probability of failure is valid for two-dimensional space but can similarly be expanded for n-dimensional space.

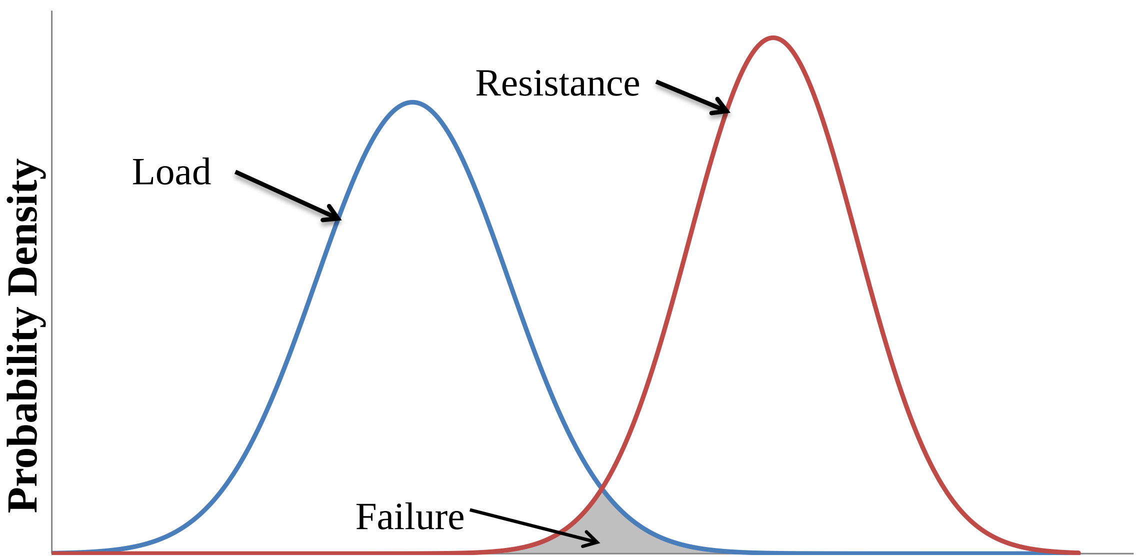


Figure 4-1: Typical probability density plots for load and resistance

One of the more straight forward and popular approaches for calculating the probability of failure is by crude Monte Carlo simulation (Kennedy 1984; Melchers 1999). Examples of non-crude methods of Monte Carlo simulation include: stratified sampling, importance sampling, and acceptance rejection sampling. Advanced techniques were not required or further explored because crude Monte Carlo simulation resulted in manageable run times. The theory behind a Monte Carlo simulation is that the distribution of a random variable can be determined by observing many samples of its behaviour (Mooney, 1997). Within the field of structural reliability, many samples of resistance and load will be calculated based on their own random variables. For example, a single sample of the resistance would be based on a number of random variables representing properties such as material strength, modulus of elasticity, and geometry. This sort of random sampling dictates that a large number of samples would be required to accurately represent the random variable being calculated. Unfortunately, there are no strict guidelines for determining the number of trials that are required. The number of trials should be selected based on the trade-off between computational effort and the statistical robustness of the calculated parameters. The nature of the results is also important when determining the ideal number of samples being used to calculate the distribution. For structural reliability, the tails of the curve are the most important because failure typically occurs at the lower tail of the resistance curve and the higher tail of the load curve, which results in a need for more samples than if the area of interest was at the peak of the distribution. More samples are required because samples will fall into the tails of the distribution much less frequently than near the peak and many samples are required to properly fit a distribution to the sample set.

4.3 Methodology

To investigate the impact of increased uncertainty in the cross-section of a structural steel member, a reliability model was developed based on data for new structural steel (Schmidt & Bartlett, 2002b). This model assumes the following form for the design equation:

Equation 4-4: $\phi \cdot R_n \geq \alpha_1 \cdot S_1 + \alpha_2 \cdot S_2 + \ldots$

where R_n is the nominal resistance, ϕ is the resistance factor (normally < 1), S_i are the nominal load effects from various sources, and α_i are the associated load factors (normally > 1).

For illustration purposes, the design equation for the moment resistance of a Class 1 section (i.e., a section that will reach plastic moment before local buckling), in accordance with the Canadian building and structural steel design codes, was chosen for the investigation (NBCC, 2010 and CSA, 2009):

Equation 4-5: $\phi \cdot Z \cdot F_y \geq \alpha_L \cdot M_L + \alpha_D \cdot M_D$

where Z is the plastic section modulus, F_y is the nominal yield strength, and M_L and M_D are the moments due to the live and dead loads respectively. A corresponding limit state function can be written by introducing the bias factors, δ_i, to account for the various sources of uncertainty associated with each of the model parameters:

Equation 4-6: $\phi \cdot Z \cdot F_y \cdot \delta_M \cdot \delta_G \cdot \delta_P \geq \alpha_L \cdot M_L \cdot \delta_L + \alpha_D \cdot M_D \cdot \delta_D$

where the description and statistical distribution for each bias factor can be found in Table 4-1. The professional factor, $\delta_{P,}$ accounts for the difference between the analyzed and measured capacity of a member (Kennedy & Gad Aly, 1979). For simplicity, the values of M_L and M_D were related by a factor representing the live to dead load ratio. It is recommended that $1 \leq M_L/M_D \leq 2$ (Schmidt & Bartlett, 2002b). In this analysis, the bias factor for uncertainty in the yield strength was not changed from the value applicable to new construction, modelling a case where the nominal properties are either known or have been conservatively estimated. The bias factors for live and dead load are calculated based on the uncertainty of a variety of parameters which collectively contribute to variation in the live and dead load.

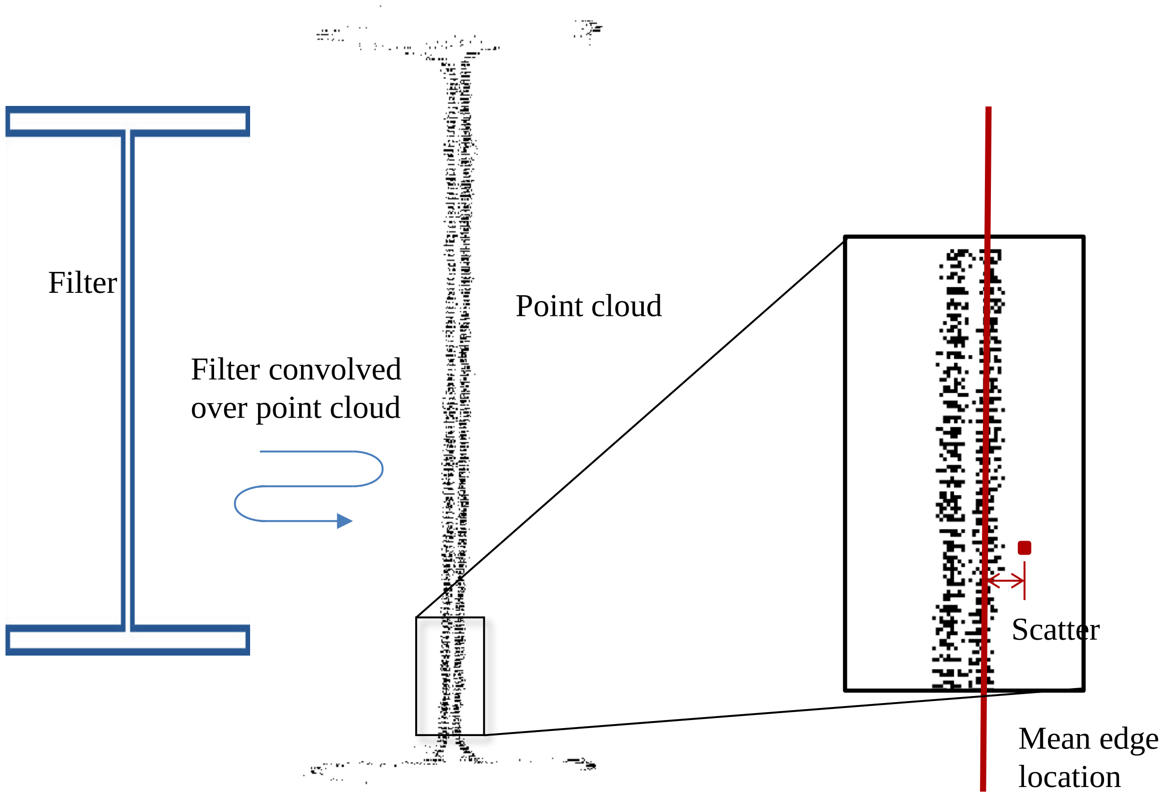
Table 4-1: Bias factors used in the reliability analysis (Schmidt and Bartlett, 2002a & Schmidt and Bartlett, 2002b)

Bias Factor	Description	Statistical Distribution	Mean (μ)	Coefficient of Variation
δ_M	Yield Strength	Lognormal	1.05	0.063
δ_G	Geometry	Lognormal	1.02	0.035
δ_P	Professional Factor	Lognormal	1.10	0.110
δ_L	Live Load	Lognormal	0.78	0.320
δ_D	Dead Load	Lognormal	1.05	0.100

Monte Carlo simulation was used to evaluate Equation 4-6 for an assumed resistance factor. This evaluation is performed by first setting the factored moment and moment resistance equal to 1.0. Next, the moment from dead load and the moment from live load are calculated based on the load factors, α_L and α_D, and the assumed live load to dead load ratio of 1.5. The calculation of the right side of the inequality in Equation 4-6 is completed by multiplying by the appropriate bias factors. These bias factors are calculated from the inverse function of their respective statistical distribution, mean, and CoV. The left side of the inequality in Equation 4-6 is calculated by determining the product of the moment resistance, yield strength bias factor, geometry bias factor, professional bias factor, and an assumed value for the resistance factor, ϕ. The algorithm used to perform the Monte Carlo simulation can be found in Appendix A. Each trial of the simulation was deemed a failure if the loads exceeded the resistances (i.e., the inequality in Equation 4-6 was violated). The number of failed trials divided by the total number of trials results in a probability of failure that is then converted into a reliability index, β, using Equation 4-1. If the calculated reliability index is less than the target index, the simulation is repeated using a reduced resistance factor until the target reliability index is met. In the current study, a target index of 3.0 was assumed, based on Schmidt & Bartlett (2002b).

Two methods were utilized to acquire statistical distributions for the δ_G parameter for a scanned structural steel member. First, the semi-automated cross-section identification results presented previously, as depicted in Figure 4-2a, were used, providing a mean and coefficient of variation of 1.13 and 0.262, respectively for the δ_G parameter. Second, a line fitting technique for geometric identification was utilized whereby the point cloud from the laser scan is simply used to locate each edge of the cross-section separately, as illustrated in Figure 4-2b. Given the statistical properties of the distance of each point in the point cloud from the assumed edge, a second statistical distribution for the section modulus can be obtained and used to establish a second estimate of the statistical distribution for the δ_G parameter, which includes the error associated with the inherent scatter in the point cloud data, but not the error due to the use of the semi-automated section identification algorithm. The scatter associated with individual points within the point cloud was found to be normally distributed with a standard deviation of 1.7 mm. It was assumed, as a simplification, that there is no systematic bias in the scan data (i.e., the mean of the scan data provides the exact edge location).

The impact of the line fitting technique on the mean and coefficient of variation for the geometric bias factor was determined using Monte Carlo simulation. Each face of the W section was modelled in a normally distributed random location with a mean of 0 mm and a standard deviation of 1.7 mm from its original location. The section properties of the W section were then calculated based on these randomized face locations. For the investigated W section, this translated into a mean and coefficient of variation for δ_G of 1.0 and 0.072.



a) Semi-automated section identification. b) Line fitting.

Figure 4-2: Semi-automated and line fitting geometry identification.

4.4 Results

The reliability analysis yielded results in terms of a resistance factor, ϕ, similar to those used for the design of new structures. The results can be seen in Table 4-2. The variation in resistance factor for each input methodology is due to varying the L/D ratio between 1.0 and 2.0.

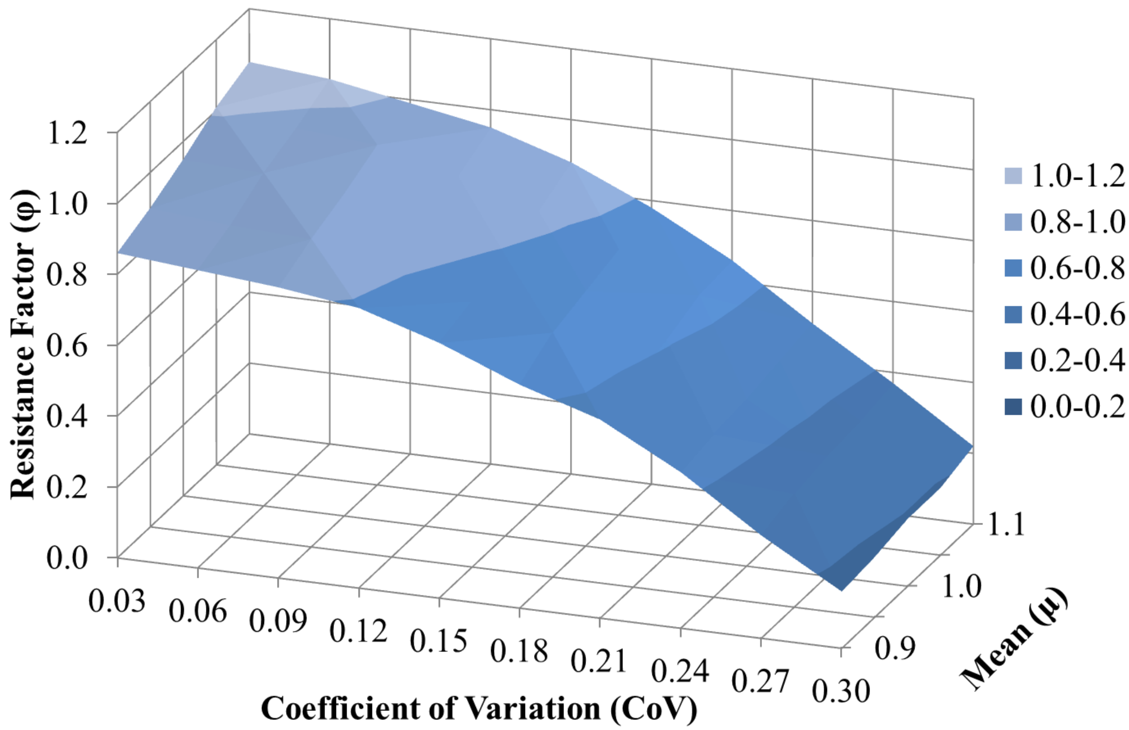
Table 4-2: Resistance factors for reused steel based on 3D laser scans

Input Methodology	Distribution	Mean (μ)	Coefficient of Variation	Resistance Factor
Semi-automated Cross-section Identification	Normal	1.13	0.262	0.42 - 0.43
Line Fitting	Normal	1.00	0.072	0.93
New Steel Members	Lognormal	1.020[a]	0.035[a]	0.95 – 0.98[a]

[a]Values reported by Schmidt and Bartlett (2002a and 2002b)

The reliability analysis resulted in a resistance factor for use with the semi-automated cross-section identification algorithm of ϕ = 0.42. This value is less than half that of the current resistance factor used for the design of new steel, which is 0.9, and less than half of the value of 0.95, suggested by Schmidt and Bartlett (2002b). While this resistance factor is significantly lower than that of new steel, it does serve to demonstrate the feasibility of achieving statistically reliable identification results using semi-automated methods. The line fitting technique resulted in a resistance factor of ϕ = 0.93. This value is similar to the current value for new steel, which mainly accounts for uncertainty in the section properties due to normal manufacturing tolerances.

The results of the reliability analysis are directly impacted by the accuracy and precision of the laser scanning technology used to capture the 3D point cloud, as well as the accuracy of the geometry identification algorithm employed. Assuming that scanner accuracy and automated geometry identification algorithms will continue to improve over time, 50 analyses were conducted with means for the δ_G parameter ranging from 0.9 to 1.1 and coefficients of variation ranging from 0.03 to 0.30. The modelled variations in the mean value account for systematic scanning biases, due to issues such as reflection or paint or corrosion product on the structure at the time of the scan. The modelled coefficients of variation account for future improvements in the scanner or automated geometry identification algorithm accuracy. Each analysis was performed using an L/D ratio of 1.5. The resulting resistance factors can be seen in Figure 4-3.



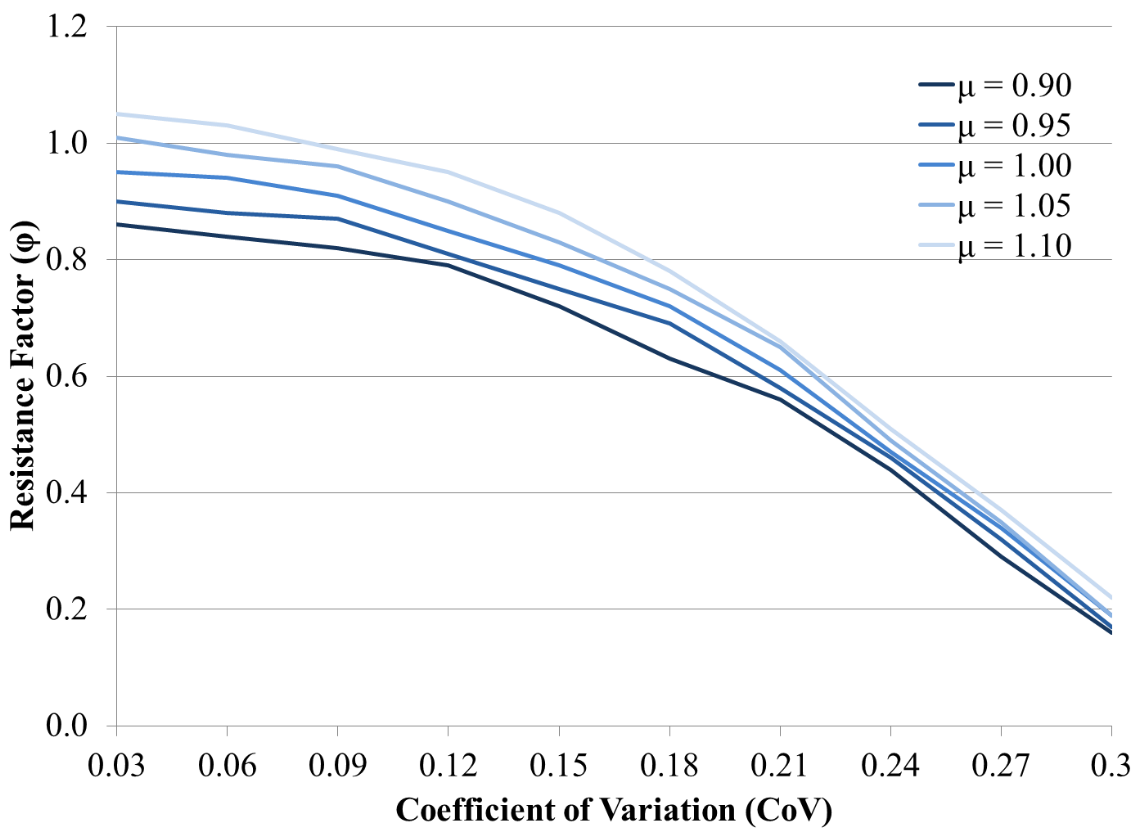


Figure 4-3: Reliability analysis results with various δ_G distributions assumed (L/D = 1.5)

4.5 Discussion

The reliability analysis presented provides a demonstration of how the scan data and semi-automated geometry algorithm can provide valuable input for a structural reliability analysis. In addition, the results of this analysis allow the benefit of efforts taken to reduce uncertainty in the geometry of the structure to be quantified in terms of their impact on the resistance factor, ϕ.

The similarity between the reliability analysis results associated with the line fitting technique and with new steel construction implies that the scanning technology, in its current state, is capable of reliably capturing geometric information for structural steel, sufficient for the purpose of structural assessment for reuse. The significant reduction in the resistance factor when a semi-automated geometry identification algorithm is utilized suggests that future efforts to improve the accuracy of this algorithm would have a considerable potential benefit. The analysis based on this algorithm and these experiments demonstrates the central role that geometric characterization plays in the decision to reuse steel from an existing structure.

The analysis presented in this study, and the resulting resistance factors, assumes a probability of failure equal to that of new structural steel structures. Higher resistance factor values would result for structures with a higher acceptable probability of failure, for example, low occupancy structures such as storage sheds. The implication of this is a more favourable phi factor comparison for reused components at lower target beta values.

It is important to note that the presented results do not account for uncertainty in the material properties of the steel. It is acknowledged that this uncertainty could have a significant impact on the resistance factor associated with reused steel, but this type of investigation was not performed as part of the current study.

4.6 Summary

Accuracy statistics are calculated using the methodology presented in Chapter 3 and then used in a structural reliability analysis to establish resistance factors for structural assessment. The semi-automated cross-section identification resulted in a resistance factor less than half that of new steel (0.42 vs. 0.95). A subsequent analysis wherein the scanned plate dimensions were obtained by a less automated interpretation of the laser scan data demonstrated that much of the uncertainty is associated with the section identification algorithm and not the accuracy and precision of the point cloud data.

5 Life cycle analysis comparison of reuse and recycling

This chapter presents a comparative life cycle analysis for reuse and recycling of structural steel. The chapter begins with a comprehensive literature review of life cycle analysis using the process model approach and the economic input-output method. This is followed by a review of previous life cycle analyses of steel production in general. Next, a comparative life cycle analysis is presented, which is based on the process model approach. A methodology for converting life cycle impact metrics into a unified total life cycle cost is also presented. Following this, the proposed methodology is applied to a case study structure to demonstrate its application, and the results of this analysis are presented. Finally, a discussion of the results, including a comparison to a similar comparative analysis using the economic input-output method, is presented and conclusions are drawn.

5.1 Introduction

As natural resources become less available, it will be increasingly important to minimize the life cycle impact of all aspects of modern living. In the field of construction, and particularly structural steel construction, reuse is poised to make significant contributions to reducing the life cycle impact of steel construction. Reusing steel provides the opportunity to eliminate much of the energy and water requirements of steel production – even more so than recycling processes (Ayres, 1997).

It is predicted that steel production will remain highly dependent on harvesting virgin resources through the year 2050 (Oda, Akimoto & Tomoda, 2013) due to the continually increasing world-wide demand for steel (Yellishetty, Ranjith & Tharumarajah, 2010). Material recycling and reuse provide an opportunity for reducing the demand on virgin resources. The high recycling and reuse potential of steel is currently one of its main advantages over other construction material alternatives such as reinforced concrete (Weisenberger, 2011).

Great strides have been made towards making steel reuse a less costly alternative at the end of a structure's service life. One such concept is "design for deconstruction" whereby a structure is designed in such a way as to facilitate efficient deconstruction of its component parts at the end of its service life (Guy, Shell, & Esherick, 2006). The differences between deconstruction, demolition and destruction have been explored by Thomsen, Schultmann, and Kohler (2011) where the reasons, objectives, forms, and contexts of each process are defined.

In spite of the broad research that has been conducted in the fields of structural steel reuse and life cycle analysis, a quantitative comparison of the life cycle impacts of reuse versus recycling does not exist. Such a study is presented here. The objective of this work is to contribute towards our general understanding of the life cycle impacts of reuse versus recycling processes. This is accomplished by outlining a methodology for the life cycle comparison of capital facilities' structural steel recycling and reuse. In addition, recommendations are made for the acquisition of life cycle inventory data. The proposed methodology begins by identifying sub-processes that are unique to the process of reuse and the process of recycling. Then, a life cycle inventory is conducted on these unique sub-processes to quantify the net benefit of using one process as an alternative to the other. The methodology is then applied to a steel structure as a case study to demonstrate its applicability and produce typical results for comparing reuse with recycling. Lastly, results obtained using the methodology are compared with similar results obtained using an alternative method commonly referred to as the economic input-output (EIO) method. Based on this comparison, advantages of the proposed methodology are discussed.

5.2 Background

In general, life cycle analysis methods can be divided into two approaches: the process model approach, or the economic input-output (EIO) approach. In the following paragraphs, previous research on the development and application of these two approaches is summarized, and their relative merits for the purpose of steel reuse analysis are assessed.

5.2.1 The process model approach for life cycle analysis

The process model approach to life cycle analysis is the original and most established method for quantitatively evaluating the life cycle impact of a particular product or process. In the works compiled by Curran (1996) and following ISO 14040 there are four main constituents to a life cycle analysis: (1) goal definition and scope, (2) life cycle inventory, (3) impact assessment, and (4) interpretation.

The goal definition step of a life cycle analysis establishes the reason for conducting the assessment and the desired results. When determining the scope, important considerations need to be made concerning the functional unit, system boundary, and model assumptions. The functional unit represents the quantity of production. In the case of structural steel, this is often considered to be a unit mass of steel. The system boundary defines which processes are going to be included in the analysis. It is impractical to assess every process involved, so a truncation error will exist. Every effort should be made to limit truncations to processes and products that have a small influence on the entire life cycle impact but, regardless, this results in a consistent underestimation (Lenzen, 2001). The error is largely dependent on the degree of truncation that occurs during the life cycle inventory step. Lenzen (2001) demonstrated that these errors are much greater than was previously assumed by investigating energy consumption using second-order input paths. According to Lenzen (2001), the zeroth-order represents the energy consumption of the industry sector being analyzed directly, the first-order contains 132 energy inputs; and the second-order includes 1322 inputs. The actual truncation errors for basic materials, such as steel and plastic, using second-order input paths are between 18% and 60% greater than for zeroth-order. The life cycle inventory step refers to the process of quantifying the life cycle impacts associated with the previously defined processes. Impact assessment and interpretation are the final steps, where the significance of the life cycle impacts is evaluated (ISO 14040, 2006).

5.2.2 The economic input-output method for life cycle analysis

The economic input-output (EIO) method for life cycle analysis, originally developed by Hendrickson, Lave, and Matthews (2006), simplifies life cycle analysis by aggregating economic sectors without incurring truncation errors due to ignoring higher order processes. These economic sectors have known economic inputs from and outputs to other economic sectors. Knowing this and the life cycle impacts associated with $1 of economic output from each of the sectors results in an aggregate life cycle analysis of a process based on its economic output (Hendrickson, Lave, & Matthews, 2006).

One limitation of the EIO method is that it is impossible to isolate individual processes. The other limitations of the input-output method result mainly from sources of uncertainty as outlined by Lenzen (2001) who listed seven: (1) source data uncertainty, (2) import assumption uncertainty, (3) estimation uncertainty for capital flow, (4) proportionality assumption uncertainty, (5) aggregation uncertainty, (6) allocation uncertainty, and (7) gate-to-grave truncation error. The data used in the input-output method is collected from national surveys, and while errors can be estimated, they cannot be quantitatively known. This results in source data uncertainty. The uncertainty from imports arises because the data associated with foreign goods does not necessarily follow that of their domestic counterparts, but the foreign data is not necessarily known. Worst-case errors are typically used to adjust imports, but this is a simplified approximation. If capital flow tables do not exist, they must be constructed from capital expenditure from varied sources. This is an approximation, which leads to additional uncertainty. The proportionality assumption states that there is a linear relationship between the inputs and outputs and that price is uniform across the economy (Hendrickson et al. 2006; Lenzen 2001). This means that doubling the output will require doubled input and that the cost of electricity is the same whether being purchased by the steel industry or the fabrics industry. Aggregation leads to uncertainty because multiple producers are combined into a single industry without any way of differentiating between them. The final uncertainty associated with the input-output method is the uncertainty that results from the truncation of the gate-to-grave portion of the life cycle. The IO method only accounts for the production discharges and neglects any operation, maintenance and end-of-life processes.

5.2.3 Life cycle analysis of steel production, recycling, and reuse

A considerable volume work has been reported on the life cycle analysis of structural steel production. The World Steel Association (2011) has published an extensive methodology report for their life cycle analysis of steel products, which utilizes the process model approach. This methodology assesses the life cycle impact of structural steel from the harvesting of virgin resources until the steel leaves the factory (i.e., a cradle-to-gate analysis). The process of recycling scrap steel is accounted for in this methodology but a similar methodology for reusing steel is not presented. The benefits of utilizing scrap steel are also explored by Yellishetty et al. (2011), who report up to a 67% reduction in energy requirements.

The effect of design for deconstruction on life cycle impact has been investigated by Tingley and Davison (2012) who propose a methodology for handling the reuse of materials by distributing their life cycle impact over the multiple uses of the component. This methodology utilizes the concept of embodied carbon, and therefore does not assess non-carbon life cycle impacts such as water usage.

Life cycle impacts have been effectively unified into a single metric to compare complex alternatives. This has been done (for example) to compare alternative management strategies for roads and bridges (Adey et al., 2010; Walbridge, Fernando, & Adey, 2013). This type of analysis is referred to as Total Life Cycle Cost Analysis. In these works, a number of metrics, including closure time, vehicle accidents, public discomfort, noise, and pollution are unified into a single cost. This unification facilitates a simple comparison between alternatives.

5.3 Methodology

The nature of life cycle analysis of capital facilities (e.g., buildings, power plants, etc.) is heavily dependent on the specific facility being analyzed, because the results are dependent on the sub-processes and products used for that particular facility. For this reason, the analysis results for one comparative life cycle analysis may not be representative of other, similar processes – even if the differences appear to be minor. Therefore, a comparative life cycle analysis methodology, which drastically reduces the scope of the analysis, is required to enable researchers and industry members to decide when to employ reuse as an alternative to recycling.

The methodology presented in this study for performing a life cycle analysis is essentially a simplified adaptation of ISO 14040, but focuses only on the first three steps of a life cycle analysis: (1) defining a goal and scope, (2) performing a life cycle inventory analysis, and (3) performing a life cycle impact assessment. The methodology for performing Steps (1) through (3), as they specifically apply to assessing reuse versus recycling at the end of a capital facility structure's service life, are explored in detail in the following sections.

5.3.1 Defining analysis goals and scope

This step of the life cycle analysis can be further divided into four areas: (1) goal definition, (2) scope definition, (3) functional unit definition, and (4) system boundary definition.

The goal of performing a life cycle analysis of reuse and recycling processes may appear to be obvious, but it is important that this step is not overlooked. The goal of most life cycle analyses is to produce a quantitative list of life cycle impacts that result from the analyzed process. In the case of comparing reuse and recycling processes, this is not the case. In comparative life cycle analyses, it is the difference in life cycle impacts that result from the respective processes that is important. This critical aspect is essential for establishing accurate and efficient system boundaries for the analysis.

The most important aspect of scope definition is establishing the set of assumptions that will be followed for all analyses in the comparative study. When comparing reuse with recycling, it is recommended that the following assumptions (and the associated arguments that follow) are utilized:

- higher order processes can be ignored on the basis that they will have proportional impacts to those of the zeroth-order process from which they originate, and
- generalized daily outputs for construction, demolition, and deconstruction sub-processes from RSMeans Building Construction Cost Data (RSMeans 2009) are adequate for representing activities to be analyzed.

Higher order processes are eliminated from the analysis due to their increasing complexity and computational requirements with diminishing impact on the results of the analysis. Although truncation errors exceeding 50% have been observed when eliminating higher order processes (Lenzen, 2001), it is hypothesized that the net error that results from this comparative study will be significantly lower. The reason for this hypothesis is that many of the higher order processes that have been truncated from the analysis will exist in both analyses in proportional quantities. For example, diesel fuel production produces zeroth order impacts (i.e., exhaust emissions) that are proportional to the amount of fuel consumed. The higher order impacts that result from harvesting oil, refining oil, transportation, etc. will be present and proportional to the amount of fuel consumed for all processes involving diesel fuel consumption.

The sub-processes and their associated daily outputs from RSMeans represent low order processes, for example hauling construction waste. RSMeans collects data from across the construction industry and calculates an average as a representation of the daily output that can be expected for a sub-process (RSMeans, 2009). The generalized daily outputs in RSMeans are thus considered to be accurate and representative of the actual activities.

The functional unit for practical applications should always be defined as the entire structure that has reached the end of its service life. This means that both analyses will be performed on the same tonnage of steel, with the same building volume and square footage. Defining the functional unit in this way may result in additional analysis, by means of identical processes on the reuse portion and the recycling portion of the analysis, but this additional analysis will be minor. The advantage of this choice for the functional unit is the guarantee that the scale of the reuse analysis matches the scale of the recycling analysis.

The main advantage of a comparative analysis is that the system boundary is heavily constrained. All processes that are deemed equal in both type and quantity in the reuse analysis and recycling analysis do not need to be analyzed. The elimination of these processes significantly limits the system boundary of the analysis. Figure 5-1 presents a typical overview of a recycling process model from the extraction of virgin resources to steel entering the waste stream. In this figure, each box represents a sub-process. By and large, it would be reasonable to consider the recycling process as representative of the current industry practice, as much of the new structural steel that is currently being produced contains a significant percentage of recycled content. The American Iron and Steel Institute reports that in 2012 an average of 88% of steel, across all industries, is eventually recycled as scrap steel (AISI, 2015).

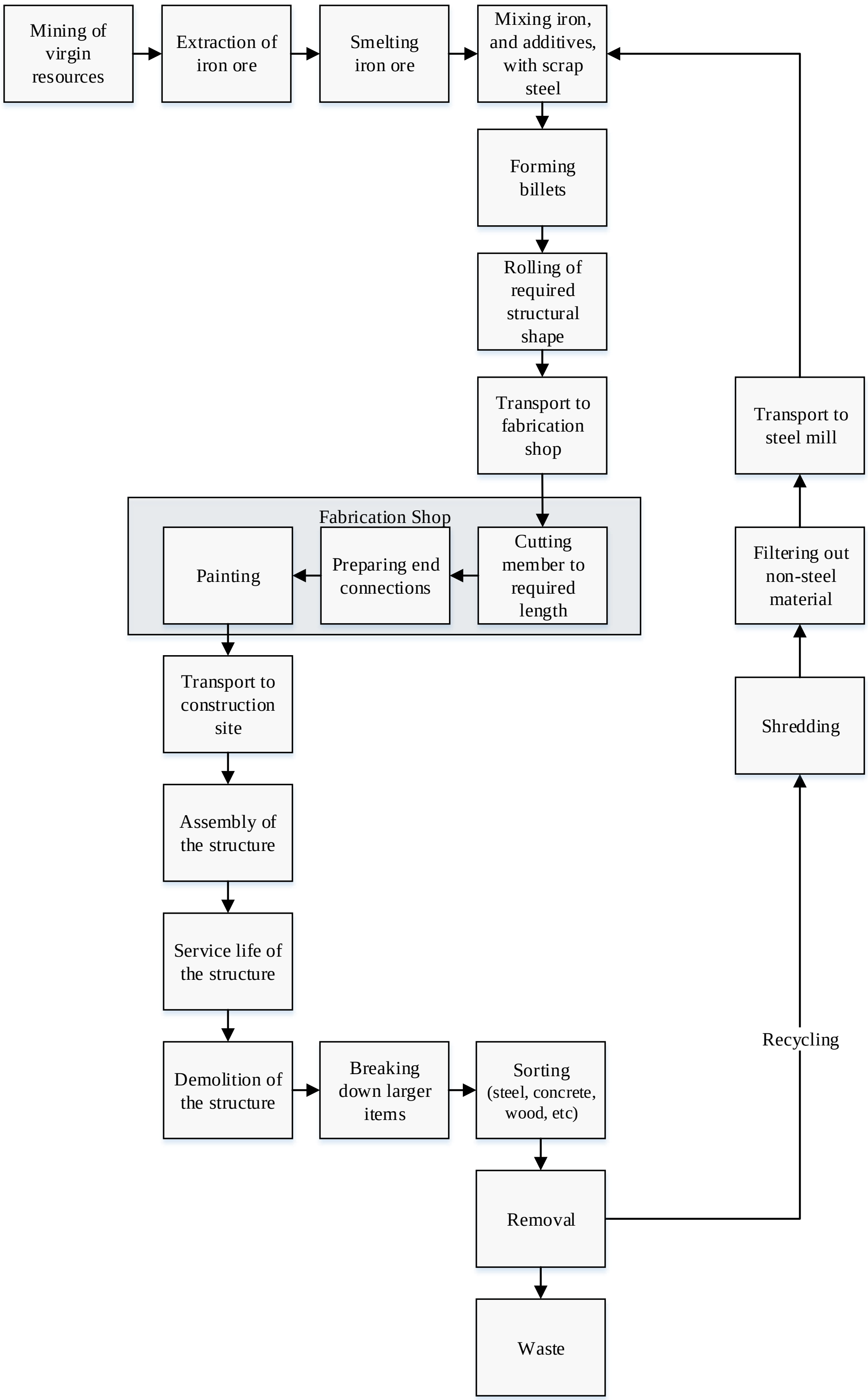


Figure 5-1: Overview of a typical steel production process model utilizing recycling

The recycling process model (Figure 5-1) begins with mining virgin resources, extraction of iron ore (Figure 5-2), and smelting iron ore. These three processes result in raw iron metal, which is then mixed with additives and scrap steel to produce steel. Additives, which are added to raw iron, include: carbon, chromium, and manganese but are dependent on the desired characteristics of the final steel product. Alternatively, electric arc furnaces (Figure 5-3) are used to melt scrap steel. In this case, scrap steel is nearly 100% of the material required. Next, billets are formed at the steel mill, which are then heated and rolled, hence hot rolled, into their required shape. These steel members are then transported to a fabrication shop where they are prepared to be assembled into a structure. Preparation at a fabrication shop involves cutting the steel members to length, preparing end connections, and painting (if required). Preparing end connections is dependent on the structural design and can include drilling bolt holes, coping member ends, or welding cleats. Next, the members are transported to site where they are assembled and will remain until the end of the structure's service life. The demolition of a low-rise steel structure involves hydraulic shears, which are used to cut members and pull sections of the building to the ground (Figure 5-4). The demolition waste is then broken down into easily manageable pieces. These pieces are then sorted by material and removed from site. The majority of structural steel that is removed from site is recycled, but inevitably a small amount of steel is lost to construction waste.

Figure 5-2: Typical iron ore mining

Figure 5-3: Electric arc furnace for steel production

Figure 5-4: Excavator with hydraulic grapple being used for the demolition of a structure

Figure 5-5 presents an equivalent process model for structural steel reuse. The main differences for this process model are the demolition or deconstruction of the structure. For reuse, the first step in deconstruction is removing the finishings of the structure to expose the structural steel. Then, depending on the type of connections, steel members are either unbolted (for bolted connections) or flame cut (for welded connections) and gently lowered to the ground. After all the steel members that have been identified for reuse have been removed, demolition of the remaining structure can proceed as per the recycling process model. The salvaged members need to be cleaned (sandblasted), inventoried to create a database of available salvaged members, and then stored until they are needed (Figure 5-6). Members with bolt holes can be reused without changing their end connection geometry. For these members, they can be incorporated into a design, painted (if required), and then transferred directly to site. Alternatively, members without reused end connections need to have their end connections prepared at a steel fabrication shop.

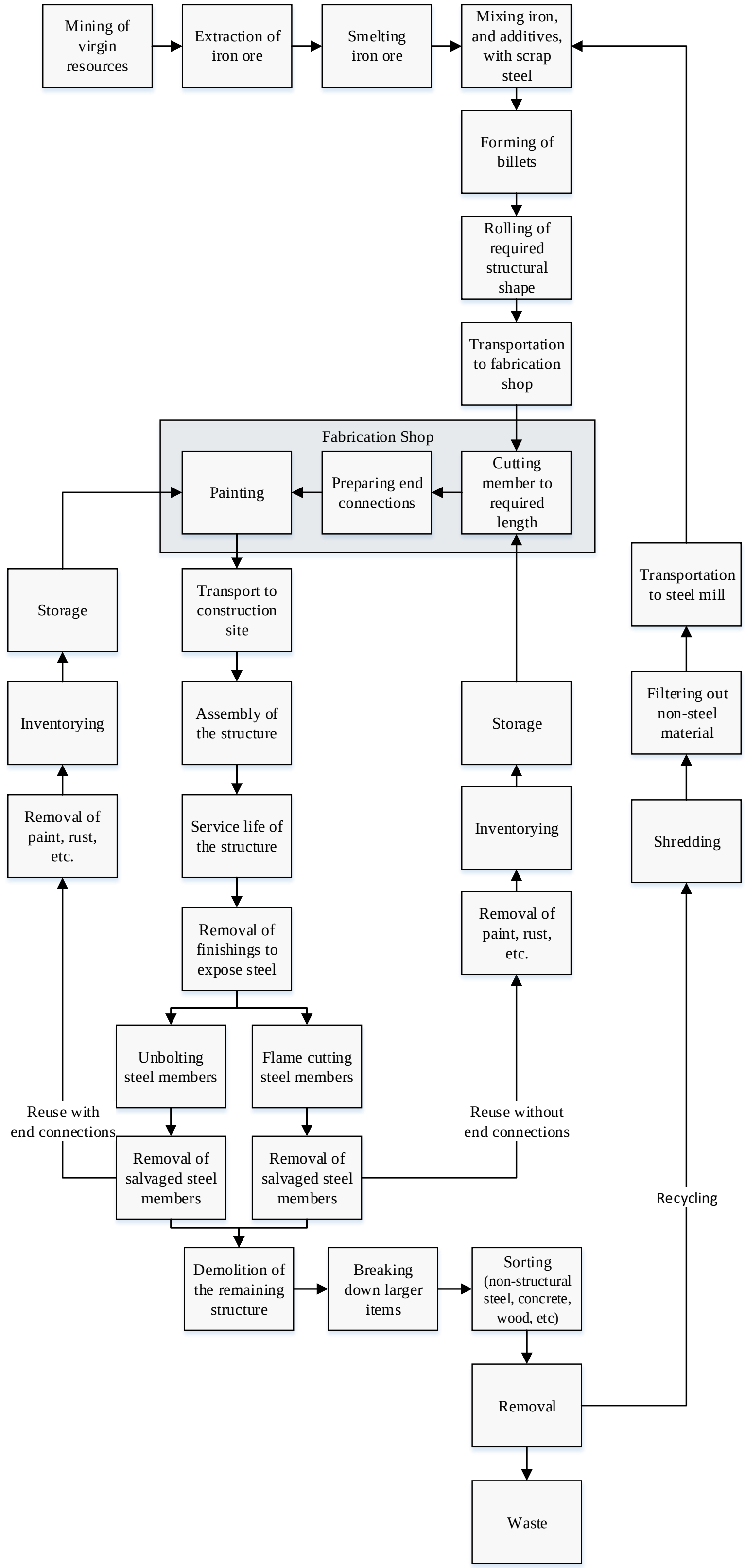


Figure 5-5: Overview of a typical steel production process model utilizing reuse

Figure 5-6: Structural steel salvage yard (Breslau, ON)

It can be observed that many of the sub-processes involved are identical when comparing the two process models. For example, transportation to the construction site, assembly, and the service life of the structure are identical regardless of the origin of the structural member.

After all equivalent sub-processes have been eliminated, the system boundary for the recycling process model includes, only: demolition, sorting, removal from site, shredding, and steel mill processes. These sub-processes have been expanded in Figure 5-7 to highlight the emission producing activities associated with each sub-process.

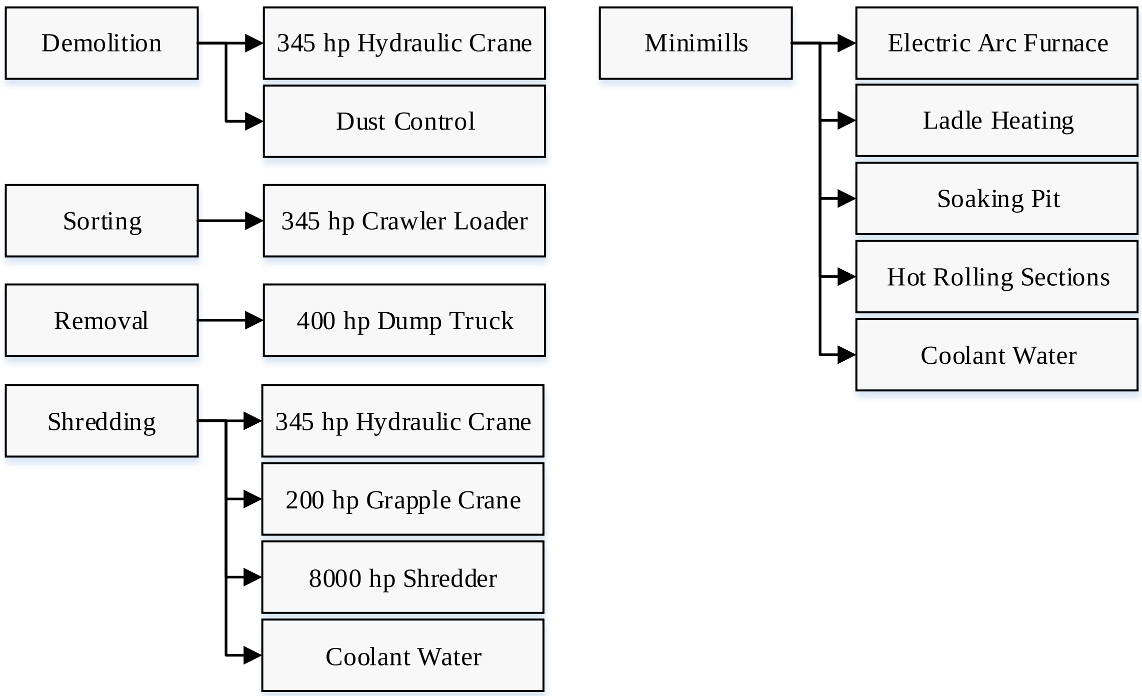


Figure 5-7: Sub-processes unique to the recycling process

Similarly, the system boundary for reuse includes the following sub-processes only: deconstruction, removal, transportation, and cleaning. Again, these sub-processes have been expanded in Figure 5-8 to highlight the emission producing activities.

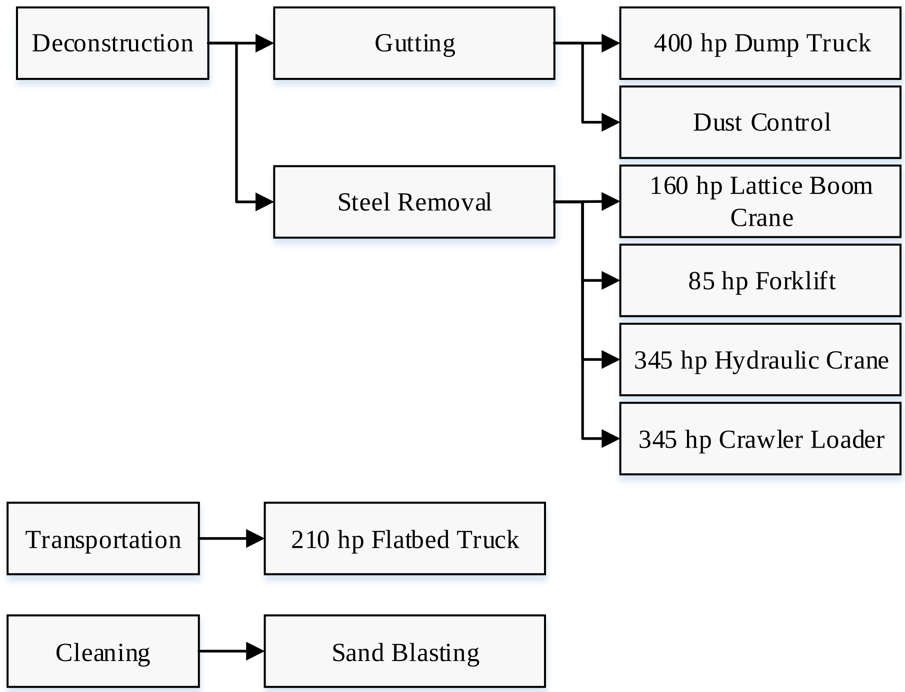


Figure 5-8: Sub-processes unique to the reuse process

5.3.2 Life cycle inventory analysis

The life cycle inventory analysis begins by determining the quantity of products and sub-processes required to accomplish the main process, in this case the reuse or recycling of steel. Then, the environmental impacts associated with a single unit of those products and sub-processes are determined. These two values (the quantity and the emissions per unit quantity) are used to determine the total emissions associated with reuse and recycling.

Generalized quantities from a common source are used to determine the quantities of the sub-processes required in the reuse and recycling processes. Maintaining consistency in the definition of these sub-processes and their quantities is critical to the accuracy and validity of the resulting analysis. For this study, RSMeans Building Construction Cost Data (RSMeans, 2009) was used to determine the quantity of each sub-process required for reuse and recycling. For example, one crew can perform a standard demolition of a steel frame building at 2,000 m^2 (21,500 ft^3) per day.

The life cycle inventory data used for the comparative impact assessment in this study was a simplified dataset consisting of emissions from three sources: diesel fuel consumption, electricity production, and steel minimills. In the context of this study, a steel minimill refers to non-integrated steel mills that utilize electric arc furnaces to make steel products, and therefore do not possess the ability to produce iron from iron ore. This simplification is made possible due to the earlier assumption that higher order processes result in insignificant changes in the comparative life cycle analysis results, and can thus be ignored. In other words, the life cycle impacts from zeroth order processes can be representative of the entire process. Examples of emissions from zeroth order processes are burning diesel fuel for construction equipment, the use of electric arc furnaces, electricity production, and using water to cool hot rolled steel beams. Emissions from higher order processes would include, among many others, burning diesel fuel in the construction equipment that is required for the mining of iron ore.

There were two main criteria when selecting life cycle inventory datasets: accuracy and practicality. To ensure the accuracy of the emissions datasets, only measured emission data were used rather than estimates based on theoretical emission rates and mass balance equations.

The life cycle emission rates used in this study can be seen in Table 5-1. This data set consisted of measured carbon monoxide (CO), ammonia (NH_3), mono-nitrogen oxides (NO_x), particulate matter (PM), water withdrawals, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and sulphur dioxide (SO_2).

Table 5-1: Life cycle analysis emission factors

Emission Source	CO	NH_3	NO_x	PM_{10}	Water	CO_2	CH_4	N_2O	SO_2	Source
	g/kWh	g/kWh	g/kWh	g/kWh	L/kWh	g/kWh	g/kWh	g/kWh	g/kWh	
Diesel Fuel	0.62	0.23	2.27	0.02		189				Frey, Rasdorf, & Lewis, 2010
	4.06		18.9	1.34		699				USEPA, 1996
	3.42	3.34	11.1	0.85		818				Gautam & Carder, 2002
Steel Mills					1600[a]					Suvio et al., 2012
	1000[b]		100[b]	29.52[b]					110[b]	USEPA, 2009
						80,000[a]				USEPA, 2012
Electricity Production			0.51			558	10.9	8.28	1.20	USEPA, 2014a
			1.29	0.18		869	0.01	0.01	3.74	CEC, 2011
					36.2					Macknick et al., 2011

[a]Water withdrawal in litres per tonne of steel produced
[b]Emissions per tonne of steel produced

Measured emission rates from Frey, Rasdorf and Lewis (2010) were calculated based on emission rates for 39 pieces of equipment and machinery with varying power (kW), diesel engines. These values were averaged and normalized to provide the emission rates in Table 5-1 as grams of emission per kW of engine power per hour of usage.

Gautam and Carder (2002) performed emission testing on loaders, sweepers, excavators, and track-type tractors. The emissions used in this study represent the emission rates measured from the excavator and have been normalized to account for the varying engine power of vehicles used.

Suvio et al. (2012) present survey results for water withdrawals and water consumption of steel mills using electric arc furnace technology. Water withdrawal refers to water that is withdrawn from a water source for steel mill use, whereas water consumption refers to the water withdrawal less the water that is returned to the water source after use (i.e., water that is evaporated). Water withdrawal rates were used for this study because water that is returned to the water source will not be returned in its original state because of increased temperature or increased pollutant concentration.

The United States Environmental Protection Agency (USEPA, 2014a) published data on the emission rates for diesel engines, steel minimills, and electricity production. The emission rates for electricity production were reported as weighted averages from across the USA and include all production types (coal, nuclear, etc.).

The Commission for Environmental Cooperation (CEC, 2011) published the emissions for various North American power plants. The total energy production of each plant was then used with the emissions to calculate a weighted average for North American power plant emission rates.

Macknick et al. (2011) presented a survey of water consumption and withdrawals for electricity generating technologies (i.e., coal, nuclear, natural gas, etc.). Again, a weighted average of water withdrawals was used based on the North American proportion of each technology's contribution to the total North American power production.

5.3.3 Life cycle impact assessment

In the life cycle impact assessment phase of the analysis, the total quantities of emissions are compared. For the proposed methodology, this is a direct comparison between reuse and recycling for the nine metrics identified in the life cycle inventory analysis phase: (1) CO, (2) CO_2, (3) PM_{10}, (4) NH_3, (5) NO_x, (6) CH_4, (7) N_2O, (8) SO_2, and (9) water usage. These metrics were selected based on the availability of emission rate data as well as the significant health and environmental risks that they pose.

Carbon monoxide (CO) poses a health risk by lowering the ability of the blood to carry oxygen and at high concentrations can lead to death (USEPA, 2015a). Carbon dioxide (CO_2) is the most common greenhouse gas created by human activity. In the United States, CO_2 makes up 82% of all greenhouse gas emissions (USEPA, 2015b). Particulate matter (PM_{10}) is particularly harmful when the diameter of the particle is less than ten micrometres. At this size, particulate matter in the air can lead to heart and lung disease, heart attacks, asthma, and respiratory difficulties (USEPA, 2015c). Hydrocarbons (HC) can be highly toxic to the human body resulting in damage to many of the body's organ systems, such as the nervous system, digestive system, circulatory system, immune system, etc. (Abha & Singh, 2012). NO_x is comprised of NO and NO_2. NO_x can react with other compounds in the air to form harmful secondary pollutants (e.g., particulate matter and ozone) that can increase the rate of heart disease, respiratory disease, and even death (USEPA, 2015d). Methane (CH_4) is the second most common greenhouse gas that results from human activities in the United States and has a global warming potential 28-36 times larger than that of carbon dioxide (USEPA, 2015e). Nitrous oxide (N_2O) is a greenhouse gas that is much less commonly produced from human activities but has a significantly greater impact on global warming; with a global warming potential of 298 times that of carbon dioxide. Sulphur dioxide (SO_2) is an air pollutant that can cause respiratory illness and can react with molecules in the air to form particulate matter (USEPA, 2015f). Finally, while water remains readily available, large amounts of water usage is not a problem, but significant health concerns arise as water, particularly fresh drinking water, becomes scarce. According to Bartram et al., 1.6 million deaths per year world-wide can be attributed to a lack of access to clean drinking a proper sanitation (Bartram et al., 2005).

5.3.4 Total Life Cycle Cost

The methodology for performing a total life cycle cost can be summarized in three steps: (1) determining the cost of impacts, (2) calculating the total life cycle cost, and (3) assessing the uncertainty in the results. Each of these steps is outlined in the following sections.

All monetary values presented in the following sections are 2016 USD. A conversion rate of 1.00 CAD to 0.76 USD was used for all appropriate conversions. This conversion rate approximately represents economic conditions at the time of publication.

5.3.4.1 Component costs

The first step in performing a total life cycle cost analysis is to determine the monetary component costs associated with reuse and recycling processes. These costs represent the relative attractiveness to perform either reuse or recycling. For the example of demolition costs, all other costs being equal, the more attractive alternative is the one with the smaller demolition cost.

The costs that are investigated as a part of this study are: construction activities, damages from air pollution, damages from greenhouse gas production, water usage, and the value of scrap and reused steel. A summary of the component costs can be seen in Table 5-2. A description of each component cost can be seen in the paragraphs following this table. The cost “type” refers to the stakeholder expected to incur the cost. Private costs are costs that would typically be incurred by the owner, whereas it is assumed that public costs are paid for by society. The emission costs from Shindell (2015) account for the economic damages associated with climate change and air pollution, and their impact on agricultural productivity, human health, property damage, flood risk, and ecosystem services.

Table 5-2: Component costs for total life cycle analysis

Component	Cost[a]	Unit	Type	Source
Demolition	Project specific		Private	RSMeans, 2009
Deconstruction	Project specific		Private	RSMeans, 2009
Scrap Steel	\$ -62.34[b]	per tonne	Private	Premier Recycling Ltd., 2014; BMI Ltd., 2016; AIM Ontario, 2009; Three D Enterprises, 2015
Reused Steel	\$ -331.65[b]	per tonne	Private	The Recycler's Exchange, 2016
CO	\$ 727.02	per tonne	Public	Shindell, 2015 [c]
NH_3	\$ 28,850.00	per tonne	Public	Shindell, 2015 [c]
NO_x	\$ 77,318.00	per tonne	Public	Shindell, 2015 [c]
BC + OC	\$ 311,580.00	per tonne	Public	Shindell, 2015 [c]
SO_2	\$ 48,468.00	per tonne	Public	Shindell, 2015 [c]
CO_2	\$ 93.94	per tonne	Public	Shindell, 2015 [c]
CH_4	\$ 5,308.40	per tonne	Public	Shindell, 2015 [c]
N_2O	\$ 42,698.00	per tonne	Public	Shindell, 2015 [c]
Water	\$ 1.60	per m^3	Private	CWF, 2011

[a] Dollars reported as 2016 USD
[b] negative costs represent the benefit of selling scrap or reused steel
[c] Reported costs are based on the median total costs with a 3% discounting rate

Construction activity costs

One of the outputs from the life cycle analysis discussed previously is a list, including quantities, of the construction activities required to demolish or deconstruct a structure. The component cost for these construction activities is found by using a set of industry averages. The source used in this study to establish those industry averages was RSMeans (2009). Estimating the cost of construction activities is one of the primary functions of this reference guide. RSMeans contains the unit prices for a wide variety of construction activities. The breadth of this reference guide makes it ideal for this use because it ensures fair cost comparison between different construction activities, compared to say a document produced by one industry stakeholder.

RSMeans (2009) provides average construction costs and productivity rates based on a 30 city average from across the USA. These values can vary greatly between countries and cultures, thus, it is important to select costs for construction activities based on the location of the project.

Damages from air pollution and greenhouse gas production

The reuse or recycling of steel contributes to environmental damages including air pollution and climate change. The quantities of these emissions are output from the life cycle analysis, discussed previously. Thus, to calculate the total life cycle cost associated with air pollution and greenhouse gas emissions, a unit cost of each metric is required.

A comprehensive investigation into the cost of air pollution and climate change gases has been performed by Shindell (2015). In this study, the valuation of damages per unit mass are presented for a number of life cycle impact metrics, including CO_2, CH_4, N_2O, black carbon (BC), organic carbon (OC), SO_2, NO_x, and NH_3. The damages associated with fine particulate matter (particulate matter under 2.5 micrometers in diameter, also known as $PM_{2.5}$), are presented as the sum of BC and OC. However, the damages associated with NO_x, SO_2 and NH_3 additionally account for their contribution to secondary $PM_{2.5}$. Secondary organic aerosols are not included, which may understate the mass of PM_{10} by 20-90% (Jimenez et al, 2009). The valuations presented in this study assume that PM_{10} is comprised entirely of $PM_{2.5}$. This assumption may lead to an overestimation of the damages from particulate matter. The presented valuations are designed for marginal emissions changes, and are applied in this study to a case representing a small emissions change compared to total emissions. The valuations include climate damages and impacts on human health from a global perspective. It has been concluded that a global measure for the impacts of air pollution and greenhouse gases is preferable because of the global nature of the damages from greenhouse gases in the environment (Greenstone et al., 2007). The use of global damages in wealthy nations may both understate (through the use of a global Value of Statistical Life) and overstate (through food security) these effects. One key aspect in the valuation calculation is the discount rate, which accounts for the time dependant value of money and the diminishing impact of a pollutant as the time from the release date increases. Shindell (2015) presents four different discount rates as part of the study; 5%, 3%, 1.4%, and a declining rate. The discount rate of 3% was used for this study based on the recommendations provided by the US EPA (2014b).

Cost of water usage

The total life cycle cost analysis presented in this study treats water as an important public good. As such, water usage is a direct cost (market value) during the process of reusing or recycling steel. The cost of using water around the world for industrial purposes has been compiled (Canada West Foundation, 2011). These costs only represent the cost of purchasing water in their respective country and do not reflect the full cost of the environmental damages associated with water usage. The market value of water should be thought of as a lower bound for the full cost including environmental damages. Calculating the total value of water is a regionally dependant and environment dependant process. Studies have shown that the value of water can vary greatly from year to year depending on the scarcity of water (Ast et al., 2013). For the purposes of this study, the purchase cost for water was used in lieu of more accurate data.

Similar to the cost of carbon, the cost of water varies greatly from region to region. For example, industrial water in the United States is $0.51 per cubic metre whereas in the United Kingdom it is $1.68 per cubic metre, a difference of 329% (Canada West Foundation, 2011). Thus, when determining the unit cost for water usage it is important to consider the geographic location of the project. For this study, the market value of industrial water in Canada was used at $1.60 per m^3. This value is subsequently varied in a sensitivity analysis.

Value of scrap and reused steel

Being endlessly recyclable is one of the main benefits of steel construction (Yellishetty, 2011). Thus, there is value in scrap steel, which serves to reduce the overall cost of the recycling process. Similarly, the resale value of reused steel components also serves to reduce the overall cost of the reuse process. To account for these benefits, a unit value (rather than a unit cost) is associated with the quantity of reused and recycled steel.

For the recycling process and scrap steel, the industry is large enough that an average unit cost of scrap steel can be calculated from many sources. For use in this study, an average unit price for scrap structural steel was calculated at approximately $62 per tonne from four sources across North America (Premier Recycling Ltd., 2014; BMI Ltd., 2016; AIM Ontario, 2009; Three D Enterprises, 2015). This translates to a component cost of -$62 per tonne to account for the benefit of selling it. It is important to select a value for the cost of scrap steel that represents the local economic conditions. For example, in China where the demand for steel is higher, scrap prices can reach upwards of $240 per tonne (Scrap Register, 2015).

A similar argument can be made about the reuse process and reused steel components. The market for reused steel is much smaller than for scrap steel but it is equally important to find local values for the cost of reused steel. Unlike scrap steel, the capacity, length, and condition of reused components are important factors in determining their value. For this reason, the cost of reused steel was determined based on the average price offered for reusable structural steel on

North American steel exchange websites. In the current study, a value of $331 per tonne has been associated with reused steel, thus the component cost of reused steel is -$331 per tonne (The Recycler's Exchange, 2016). Again, this parameter is varied in a subsequent sensitivity analysis to assess its influence on the conditions that would favour reuse.

5.3.4.2 Calculating the total life cycle cost

The third, and final, step in performing a total life cycle comparison for reuse and recycling is calculating the total life cycle cost of each process. The total life cycle cost is calculated by:

Equation 5-1: $C = \sum_{ALL\ m}\left(C_{c,m} \times Q_m\right)$

where, *'C'* is the total life cycle cost of the process; *'$C_{c,m}$'* is the unit component cost of impact *'m'*; and *'Q_m'* is the quantity of impact *'m'*. When the total cost of reuse and the total cost of recycling are calculated a comparison can then be made. Percentage based comparisons should not be made using the proposed methodology. Many products and processes are ignored in the life cycle analysis methodology, which means that a percentage based comparison can only be used to the extent of determining which process has a lower cost. When the ratio of recycling costs to reuse costs is equal to 1.0, the processes have equal costs. Ratios larger than 1.0 favour reuse and ratios lower than 1.0 favour recycling.

5.4 Case study

In this section, a case study is presented to demonstrate the proposed methodology. The structure, as seen in Figure 5-9 after exposing the structural steel, is a 5800 m^2, single storey, steel framed structure containing approximately 114 tonnes of structural steel. A complete list of input parameters used for this analysis can be found in Table 5-3. The transportation time refers to the round trip time associated with the transportation sub-process. This process accounts for the additional process required to transport salvaged to a processing plant prior to it being reused. The proposed methodology was used to analyze the comparative life cycle impact of reuse versus recycling.

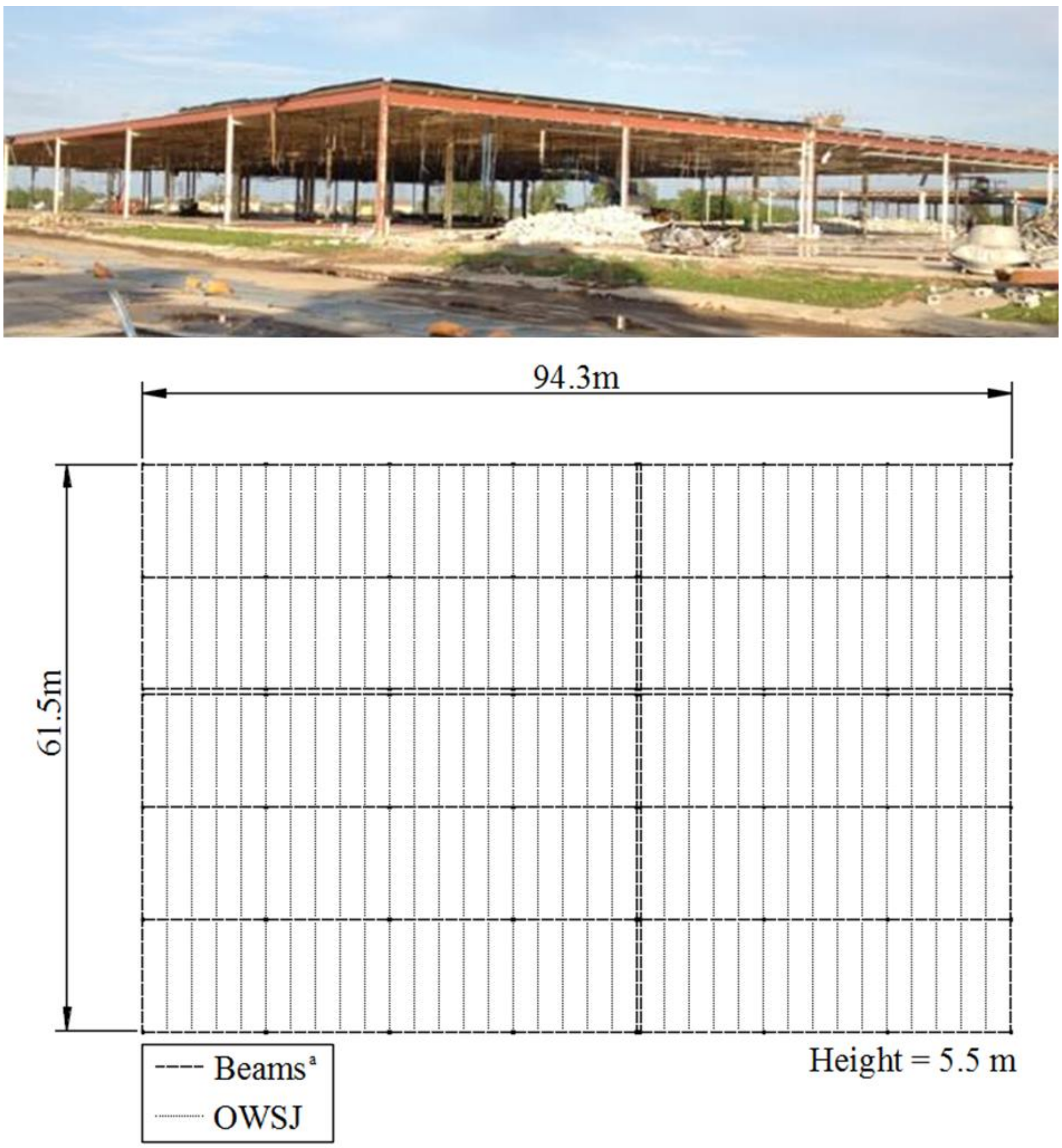


Figure 5-9: Structural steel case study structure (photograph and floor plan)
[a]Beams along horizontal gridlines are used in a Gerber system

Table 5-3: Life cycle analysis input parameters for the case study

Parameter	Quantity
Mass of steel	114 tonnes
Transportation time[a]	3 hours
Building volume	31,800 m^3
Building footprint	5,800 m^2
Surface area of steel[b]	2,500 m^2
Demolition time	418 hours
Gutting time	1416 hours

[a]round trip time for the transportation sub-process
[b]used for calculating sandblasting requirements for cleaning steel

5.4.1 Life cycle analysis for recycling

Table 5-4 presents the life cycle inventory for the demolition sub-processes for recycling. These sub-processes contain items for hydraulic shears, which are used for the demolition of the structure, and for a dust control unit. Both of these pieces of machinery result in emissions due to burning diesel fuel. The dust control unit also consumes water during its operation. As recommended by RSMeans (2009) hydraulic shears were required to complete this process. A dust control unit is included based on field observations and best practices. The flow rate for the dust control unit is taken as a typical value from commercially available systems.

Table 5-5 presents the life cycle inventory for the sorting sub-processes for recycling. This sub-process only contains an item for a crawler loader used for separating debris into piles by material type and is recommended by RSMeans (2009) as part of demolition practices.

Table 5-6 presents the life cycle inventory for the removal sub-processes for recycling. As recommended by RSMeans (2009), this sub-process contains an item for two dump trucks, which are required to remove debris from site.

Table 5-7 presents the life cycle inventory for the shredding sub-processes for recycling. This sub-process contains items for hydraulic shears and a grapple crane, which are required to provide a steel shredder with material. The requirement of these items is assumed based on industry practices and technical specifications for industrial “mega-shredders”.

Table 5-8 presents the life cycle inventory for the steel mills sub-processes for recycling. Items in this sub-process include: ladle preheating, soaking pit, rolling, electric arc furnace electricity requirements, emissions directly from minimills, and water withdrawals directly associated with minimills. The electricity requirements for ladle preheating, the soaking pit, rolling, and the electric arc furnace were provided by the Energy Solutions Center (2016). Emissions associated with minimills can be found in Table 5-1.

Table 5-9 presents a summary of the total life cycle inventory for the process of recycling. This table is calculated by summing the items from each sub-process.

Table 5-4: Life cycle inventory for the demolition sub-process of recycling (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Hydraulic Shears	257			418	hours	291	192	1,155	79		61,265			
Water for Dust Control		75	liters / minute	418	hours									1,883
Dust Control Unit	19.8			418	hours	22	15	89	6		4,715			

Table 5-5: Life cycle inventory for the sorting sub-process of recycling (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Crawler Loader	257	418	hours	291	192	1,155	79		61,265			

Table 5-6: Life cycle inventory for the removal sub-process of recycling (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.	CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Dump Truck	298	418	hours	2	674	445	2,679	183		142,064			

Table 5-7: Life cycle inventory for the shredding sub-process of recycling (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Hydraulic Shears	257	0.022	hours / tonne	114	tonne	2	1	7			368			
Grapple Crane	151	0.022	hours / tonne	114	tonne	1	1	4			217			
Shredder	5966	0.004	hours / tonne	114	tonne	7	4	27	2		1,422			
Shredder Coolant Water		0.556	litres / tonne	114	tonne									434

Table 5-8: Life cycle inventory for the steel mills sub-process of recycling (for 114 tonne steel building)

Sub-Process	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Ladle Preheating	4	kWh / tonne	114	tonne					1	326	3	2	17
Soaking Pit	323	kWh / tonne	114	tonne			33	7	91	26,307	202	153	1,333
Rolling	44	kWh / tonne	114	tonne			5	1	12	3,591	28	21	182
Electric Arc Furnace	524	kWh / tonne	114	tonne			54	11	148	42,638	327	248	2,161
Minimill Emissions			114	tonne	114		11	3	13	9,118			
Minimill Water Withdrawal	1600	litres / tonne	114	tonne									182

Table 5-9: Summary of the life cycle inventory for the process of recycling (for 114 tonne steel building)

Process	CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Demolition	313	207	1,244	85		65,980			1,883
Sorting	291	192	1,155	79		61,265			
Removal	674	445	2,679	183		142,064			
Shredding	10	6	38	3		2,007			434
Steel Mills	114		103	22	265	81,980	559	423	3,875

5.4.2 Life cycle analysis for reuse

Table 5-10 presents the life cycle inventory for the gutting and removal sub-processes for reuse. The items for this sub-process include a dump truck for removing debris from site and a dust control unit. The flow rate for the dust control unit was reduced from the manufacturer's specifications to match the volume of water used in the recycling process. This is a valid assumption because similar levels of dust will be experienced as the buildings being gutted and demolished are the same. It should be noted that this is an upper limit of the amount of water that would be required for dust control because gutting is a more controlled process and would therefore generate less dust.

Table 5-11 presents the life cycle inventory for the deconstruction sub-processes for reuse. The items for this sub-process are divided into three categories: (1) deconstruction of OWSJs, (2) deconstruction of structural steel sections, and (3) sorting and loading deconstructed material. The items for deconstruction of OWSJs and structural steel sections are recommended in RSMeans (2009). The additional machine time for the 25-ton (22.7 tonne) hydraulic crane and the crawler loader were added based on the recommendation of an industry expert.

Table 5-12 presents the life cycle inventory for the transportation sub-processes for reuse. The only item included in this sub-process is a flatbed truck. This item was included to account for the additional activity associated with transporting salvaged steel to a processing facility where it will be cleaned, inventoried, and stored.

Table 5-13 presents the life cycle inventory for the cleaning sub-processes for reuse. The item for this sub-process is sandblasting with productivity rates recommended by RSMeans (2009). This item is required in order to produce steel products that are in a state that can be used by steel fabricators in the same way that a new steel product would be used.

Table 5-14 presents a summary of the life cycle inventory for the process of reuse. This table is calculated by summing the items from each sub-process.

Table 5-10: Life cycle inventory for the gutting and removal sub-process of reuse (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Dump Truck	298	1416	hours	1,140	753	4,532	310		240,308			
Water for Dust Control		22	litres / minute									1,877
Dust Control Unit	20	1416	hours	76	50	301	21		15,952			

Table 5-11: Life cycle inventory for the deconstruction sub-process of reuse (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
OWSJ - 20 ton lattice boom crane	120	4.5	members / hour	180	members	13	9	52	4		2,732			
OWSJ - Fork lift	64			40	hours	7	5	27	2		1,457			
Structural Steel - 25 ton hydraulic crane	257	3.8	members / hour	129	members	24	16	95	6		5,037			
Structural Steel - Fork lift	64			34	hours	6	4	24	2		1,253			
25 ton hydraulic crane	257			40	hours	28	18	110	8		5,856			
Crawler Loader	257			40	hours	28	18	110	8		5,856			

Table 5-12: Life cycle inventory for the transportation sub-process of reuse (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Flatbed Truck	157	3	hours	8	tonnes / truck	18	12	72	5		3,809			

Table 5-13: Life cycle inventory for the cleaning sub-process of reuse (for 114 tonne steel building)

Sub-Process	Power (kW)	Units		Qty.		CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Sandblasting	3.9	11.6	m^2 / hour	2500	m^2			1		2	600	5	3	30

Table 5-14: Summary of the life cycle inventory for the process of reuse (for 114 tonne steel building)

Process	CO (kg)	NH_3 (kg)	NO_x (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Gutting incl. Removal	1,216	803	4,833	330		256,260			1,877
Deconstruction	105	70	419	29		22,191			
Transportation	18	12	72	5		3,809			
Cleaning			1		2	600	5	3	30

5.5 Results

The results for conventional air pollutants, greenhouse gases, and water usage for the entire structure can be seen in Figure 5-10, Figure 5-11, and Figure 5-12.

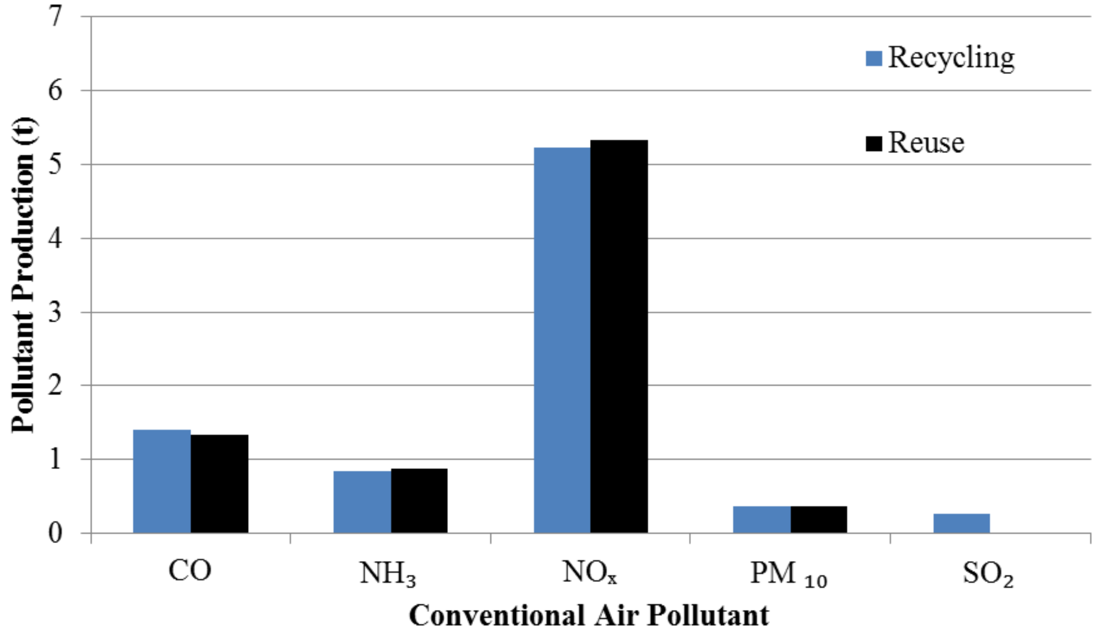


Figure 5-10: Conventional air pollutant comparison between recycling and reuse

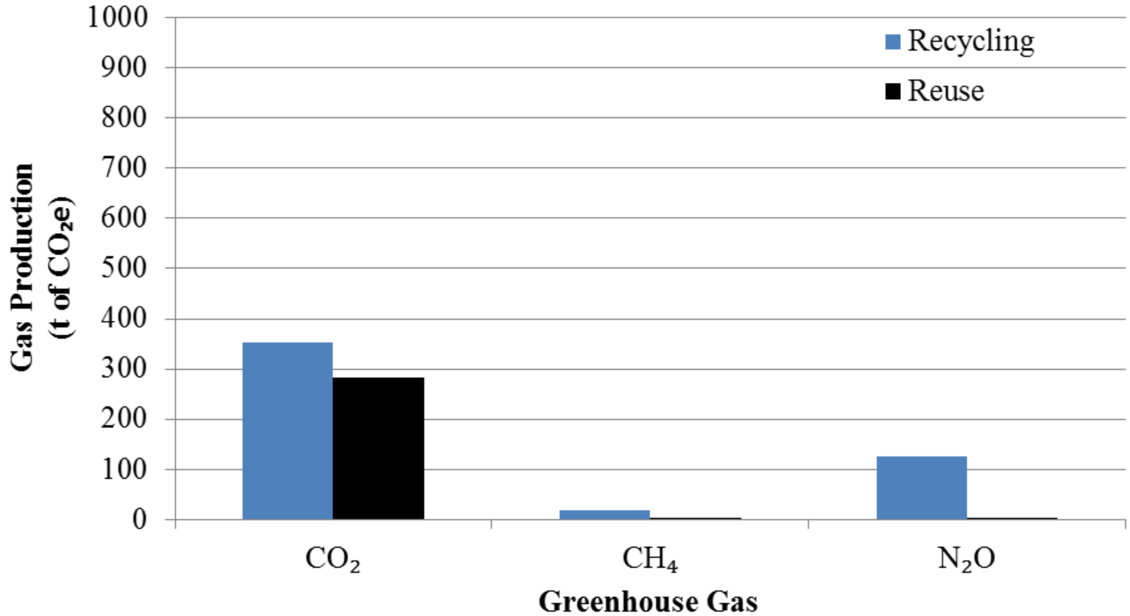


Figure 5-11: Greenhouse gas emission comparison between recycling and reuse

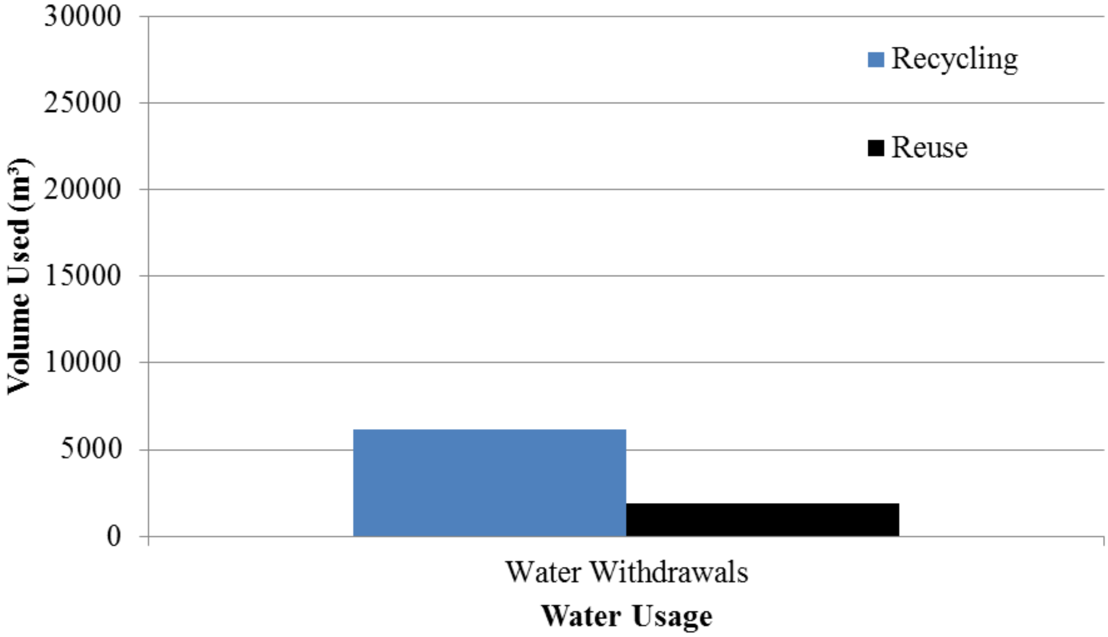


Figure 5-12: Water usage comparision between recycling and reuse

The comparative life cycle analysis shows that reuse is not strictly superior to recycling and vice versa. Reuse was the superior alternative for sulphur dioxide, the greenhouse gas metrics of carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), and for water withdrawal. Recycling was the superior alternative for the metric of carbon monoxide (CO), ammonia (NH_3), mono-nitrogen oxides (NO_x), and particulate matter. Table 5-15 quantifies the benefit of reusing structural steel per tonne of steel for the given case study.

Table 5-15: Emission reduction for steel reuse compared to recycling

Metric	Emission Reduction kg/tonne
CO	0.55
NH_3	-0.30
NO_x	-0.91
PM_{10}	0.07
SO_2	2.30
CO_2	618
CH_4	156
N_2O	1100
Water (L/tonne)	37,600

When analyzed on a sub-process level for life cycle impacts, the results in Figure 5-13 are observed for recycling and Figure 5-15 for reuse. These figures show the relative contribution from each sub-process towards the total amount of each impact metric for a given process. Similarly, Figure 5-14 and Figure 5-16 display a heat map for recycling and reuse, respectively, which highlights the most significant contributor for each emission.

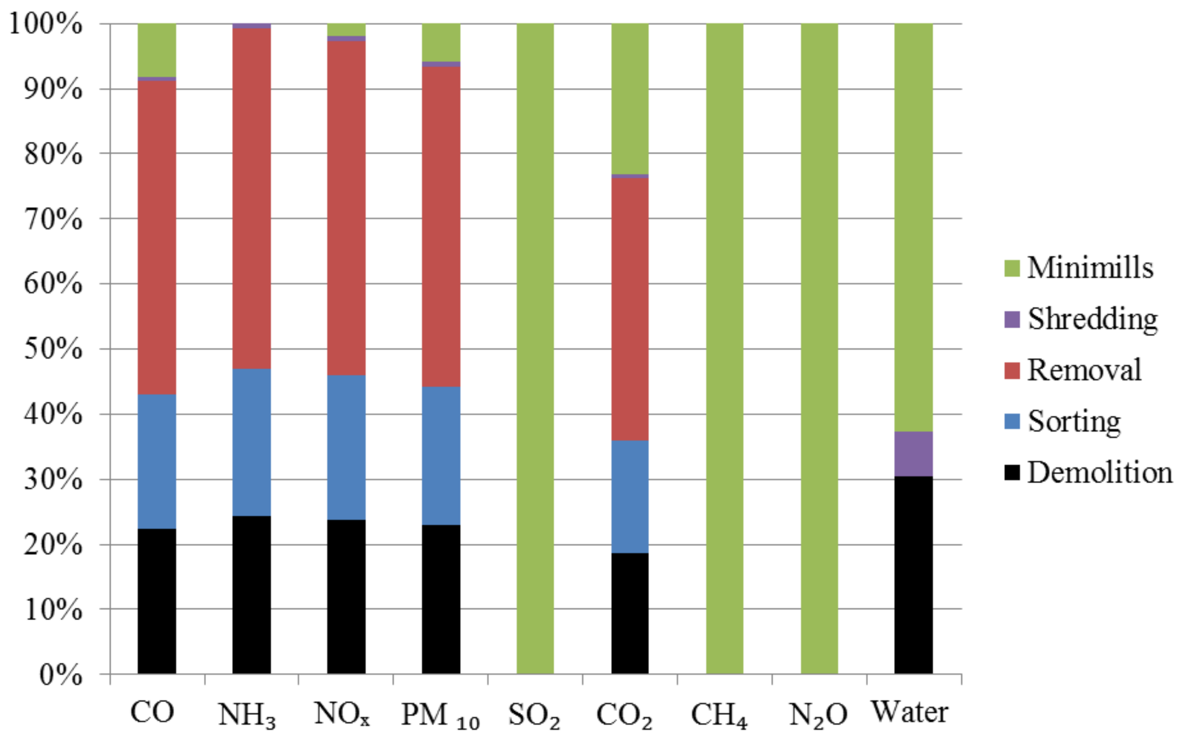


Figure 5-13: Impact contributions for sub-processes in steel recycling

Process	CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Demolition	313	207	1244	85	0	65980	0	0	1883
Sorting	291	192	1155	79	0	61265	0	0	0
Removal	674	445	2679	183	0	142064	0	0	0
Shredding	10	6	38	3	0	2007	0	0	434
Steel Mills	114	0	103	22	265	81980	559	423	3875

Figure 5-14: Heat map for impact contributions for sub-processes in steel recycling

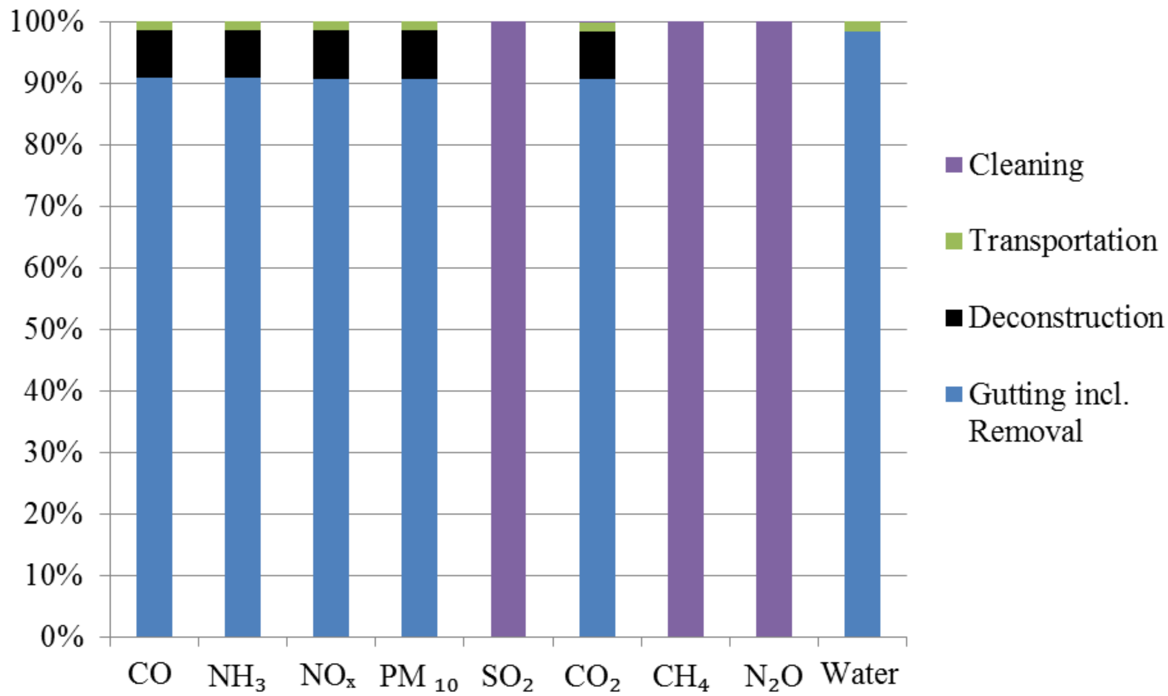


Figure 5-15: Impact contributions for sub-processes in steel reuse

Process	CO (kg)	NH_3 (kg)	NOx (kg)	PM_{10} (kg)	SO_2 (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)	Water (m^3)
Gutting and Removal	1216	803	4833	330	0	256260	0	0	1877
Deconstruction	105	70	419	29	0	22191	0	0	0
Transportation	18	12	72	5	0	3809	0	0	0
Cleaning	0	0	1	0	2	600	5	3	30

Figure 5-16: Heat map for impact contributions for sub-processes in steel reuse

5.5.1 Sensitivity Analysis

Previously, all results have been based off of average, North American emission rates from the values in Table 5-1. Figure 5-17 and Figure 5-18 show the sensitivity for the emission rates for conventional air pollutants and greenhouse gases, respectively. The error bars on these graphs indicate the upper and lower bounds for total emissions that are calculated from the maximum and minimum emission rates in Table 5-1. In other words, the maximum emission rate for each metric from Table 5-1 was used to generate the upper bound for each error bar, and similarly the minimum emission rate was used to generate the lower bound. These graphs highlight the high variability in the results based on the emission rate data used. Without presenting statistical distributions and standard deviations, it is impossible to draw conclusions regarding the likelihood of given emissions but these graphs stress the importance of acquiring accurate emission rates when performing a life cycle analysis.

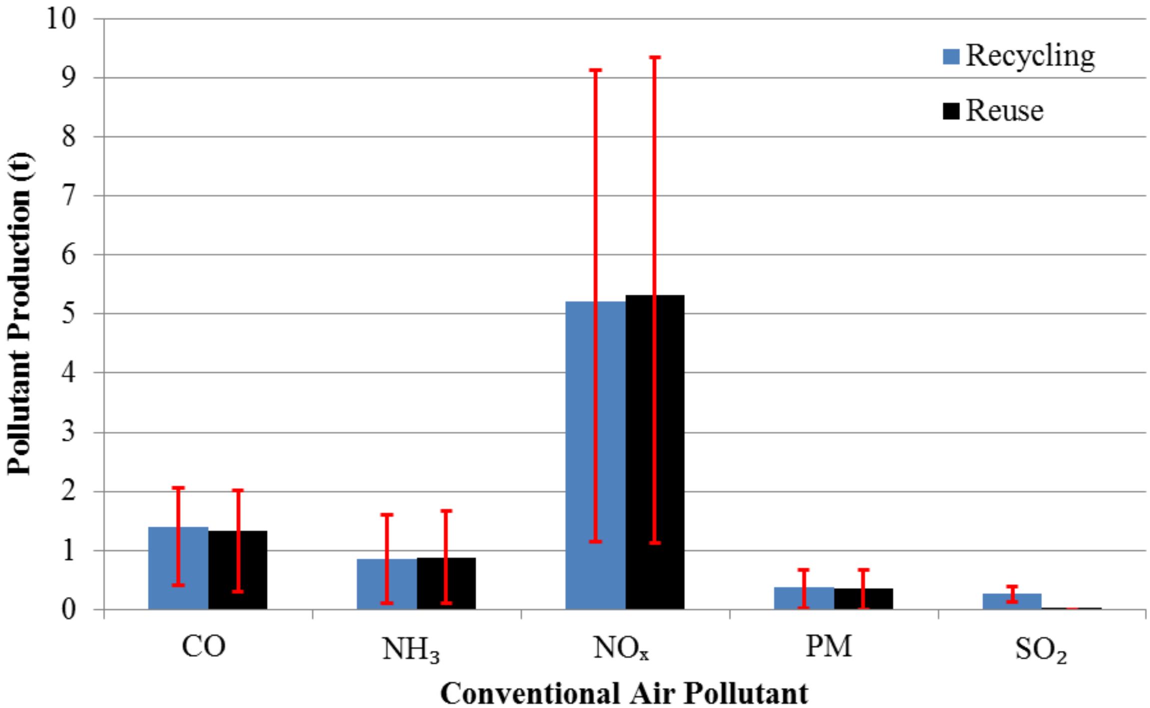


Figure 5-17: Sensitivity analysis for emission rates of conventional air pollutants

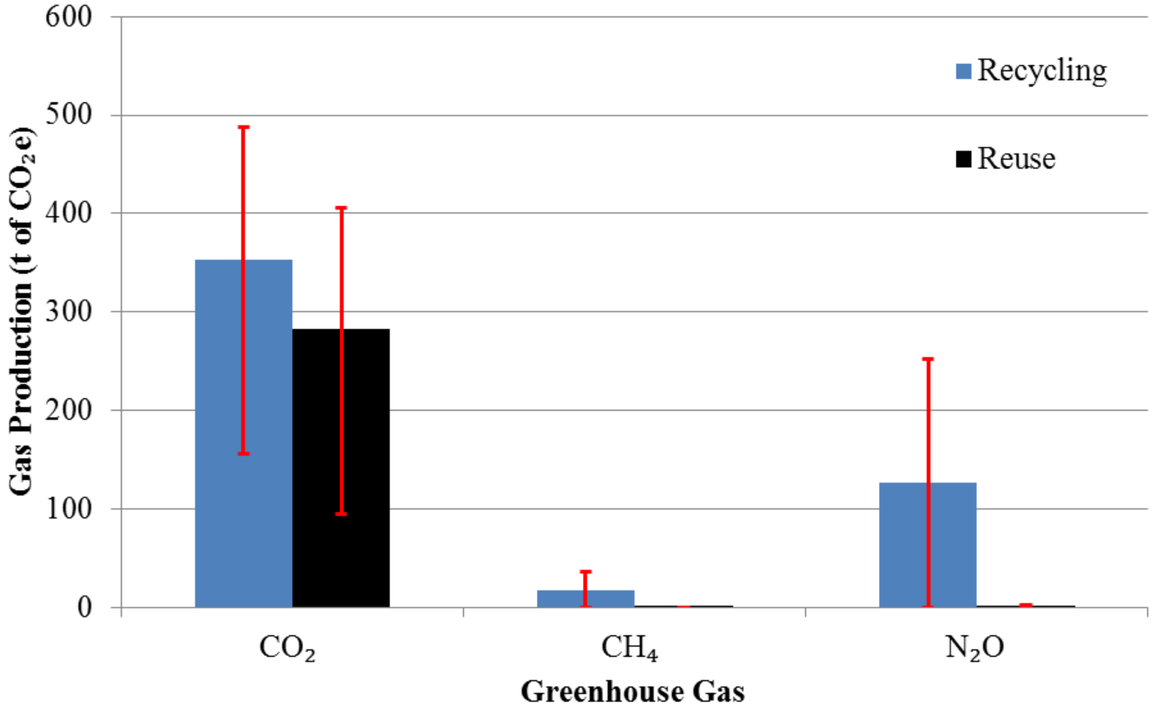


Figure 5-18: Sensitivity analysis for emission rates of greenhouse gases

5.5.2 Total life cycle cost

A breakdown of the construction activities associated with recycling and reuse can be seen in Table 5-16. These costs represent the total costs to the owner to have the sub-process completed. This includes materials, labour, equipment, and overhead and profit for the contractor. The total emission values for recycling and reuse (Table 5-9 and Table 5-14, respectively) and the component costs (Table 5-2) combine, using Equation 5-1, to produce the total life cycle costs in Table 5-17. For the analysis, it was assumed that 100% of the available structural steel was reused or recycled. The construction, water, and resale costs are in the context of North American and European prices, while the environmental costs are considered on a global impact basis. Market conditions in other regions of the world will vary with these numbers substantially, especially in internally relative terms.

Table 5-16: Cost breakdown for construction activities (for 114 tonne steel building)

Process	Sub-process	Cost
Recycling	Demolition	$ 386,960.40
Reuse	Gutting incl. removal	$ 433,422.56
	Deconstruction	$ 40,549.96
	Transportation	$ 2,129.19
	Cleaning	$ 88,203.55

Table 5-17: Breakdown of total life cycle costs from emissions, water usage, and the resale value of steel (for 114 tonne steel building)

	Recycling	Reuse
Construction Activities	$ 386,960.40	$ 564,305.26
CO	$ 1,018.93	$ 973.76
NH_3	$ 24,515.48	$ 25,504.29
NO_x	$ 403,621.81	$ 411,660.90
BC + OC	$ 114,765.58	$ 112,411.36
SO_2	$ 12,825.11	$ 100.68
CO_2	$ 34,247.18	$ 27,419.32
CH_4	$ 2,967.51	$ 24.45
N_2O	$ 18,066.29	$ 148.88
Water	$ 9,881.95	$ 3,044.49
Scrap Steel	-$ 8,167.67	$ -
Reused Steel	$ -	-$ 43,418.36
Total	$ 1,000,702.56	$ 1,102,175.02

For this case study presented in this study, the cost of recycling is $101,500 less than the cost of reuse, which corresponds to an overall cost ratio (recycling cost: reuse cost) of 0.91.

5.5.2.1 Uncertainty and sensitivity analysis

Uncertainty in the results can arise from a number of different origins. For this case study, the uncertainties are summarized in

Table 5-18, which is followed by a brief justification for the uncertainties associated with each metric. Uncertainties also exist in the emission rate data, which can be seen in Table 5-1.

Table 5-18: Uncertainties in total life cycle cost data

Cost metric	Maximum valuation	Minimum valuation	Units	Source
Labour	$ 63.36	$ 2.10	$ per hour	US BLS, 2013
Value of scrap steel	$ 240.00	$ 19.00	$ per tonne	Scrap Register. 2015; BMI Ltd., 2016
Value of reused steel	$ 3,638.00	$ 19.00	$ per tonne	RSMeans, 2009; BMI Ltd., 2016
CO	$ 2,155.02	$ 291.56	$ per tonne	Shindell, 2015
NH_3	$ 49,438.60	$ 13,944.22	$ per tonne	Shindell, 2015
NO_x	$ 139,442.22	$ 34,226.73	$ per tonne	Shindell, 2015
BC + OC	$ 1,001,448.64	$ 192,683.79	$ per tonne	Shindell, 2015
SO_2	$ 84,932.99	$ 24,085.47	$ per tonne	Shindell, 2015
CO_2	$ 431.00	$ 15.21	$ per tonne	Shindell, 2015
CH_4	$ 17,747.19	$ 1,774.72	$ per tonne	Shindell, 2015
N_2O	$ 202,825.04	$ 5,197.39	$ per tonne	Shindell, 2015
Water	$ 1.78	$ 0.54	$ per m^3	CWF, 2011

Labour

When demolition and deconstruction activities are sub-divided into material costs, labour costs, and equipment costs, it was found that 43% of the demolition costs and 59% of the deconstruction costs were a result of labour. These labour costs would vary from one country to another, thus, uncertainty is introduced into the cost of construction activities for recycling and reuse. Norway has one of the highest labour costs at $63.36 per hour, and the Philippines has one of the lowest, at $2.10 per hour (US BLS, 2013). It should be noted that China and India were not included as part of this study due to data gaps and methodological issues, thereby producing results that were not directly comparable.

Although labour costs vary from country to country, it should not be concluded that effective reuse can be performed in countries with low labour costs before transporting the salvaged steel to countries with higher labour costs. This is because the cost of transportation, which includes the private cost to the owner and the public cost to the environment, is assumed based on local transportation distances and does not apply to situations where salvaged steel is being relocated internationally.

Value of scrap steel

The value of scrap steel varies depending on the purchaser and the economic conditions in the purchasing country. The maximum valuation for the value of scrap steel is from China at $240 per tonne (Scrap Register. 2015) and the minimum valuation is based on a Canadian buyer at $19 per tonne (BMI Ltd., 2016).

Value of reused steel

Reused steel components are not common when compared to scrap steel. As such, reliable uncertainty in the value of reused steel is unavailable. To account for variability in the value of reused steel, the maximum valuation is $3,638.00 per tonne and is based on the value of new steel (RSMeans, 2009) and the minimum valuation is $19 per tonne and is based on the lowest value for scrap steel.

Air pollution and greenhouse gases

The maximum and minimum valuations for air pollution and greenhouse gases are based on the uncertainty analysis provided in supplemental material to the original paper by Shindell (2015). The values used in the present study also incorporate uncertainty in which discount rate is most applicable. Combined, this means that the maximum valuation is based on the 95th percentile with a 1.4% discounting rate and the minimum valuation is based on the 5th percentile with a 5% discounting rate.

Water

The market value of water varies from country to country. The Canada West Foundation (CWF, 2011) lists the maximum value of water in the United Kingdom at \$1.78 per m^3 and the minimum in the United States at \$0.54 per m^3. It should be noted again that the market value of water does not account for the full cost of water, including environmental damages. Also, variation in the full cost of water is expected to be much greater than that of its market value.

The results in Figure 5-19 are calculated when the uncertainties from

Table 5-18 and the uncertainties in emission rates from Table 5-1 are incorporated into the calculation for the cost ratio between recycling and reuse. The “average” line represents the cost ratio analysis presented in Table 5-17, which represents average, North American emissions and costs, and the “1.0” line where the alternatives are equal is highlighted. For example, the uncertainty in labour costs is produced by calculating the cost ratio when labour costs vary from \$2.10 per hour, in the Philippines, to \$63.36 per hour, in Norway. From this figure, it can be seen that the greatest uncertainty is in labour costs and price of reused steel. Uncertainty in the reused steel price could result in the cost ratio becoming significantly more favourable for reuse, whereas uncertainty in emission rates could result in the cost ratio becoming less favourable for reuse.

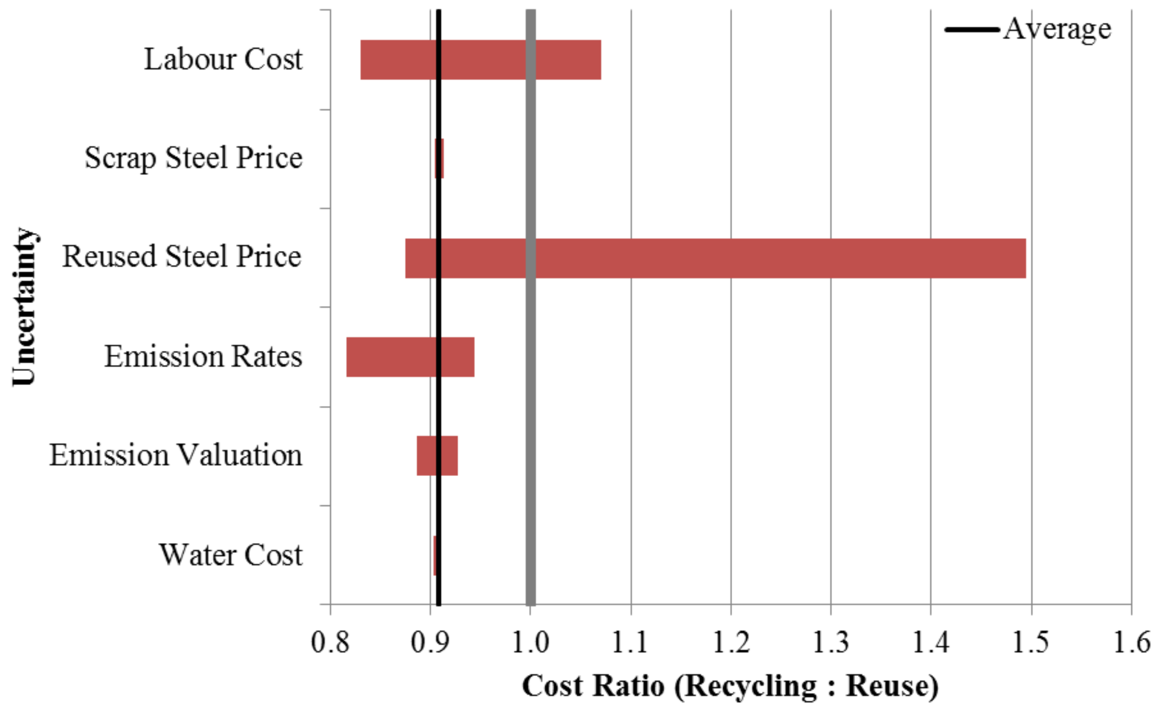


Figure 5-19: Impact of the uncertainties on the cost ratio

Similarly, these uncertainties can be applied to the comparative costs rather than the cost ratio, as seen in Figure 5-20. In this case, the difference in the cost of each metric is presented. The uncertainty in the difference in cost between recycling and reuse is displayed with the “average” line based on the results in Table 5-17, which represents average, North American emissions and costs. This figure shows that in the most favourable conditions, reuse can be the less expensive alternative by $760,000, for the given case study.

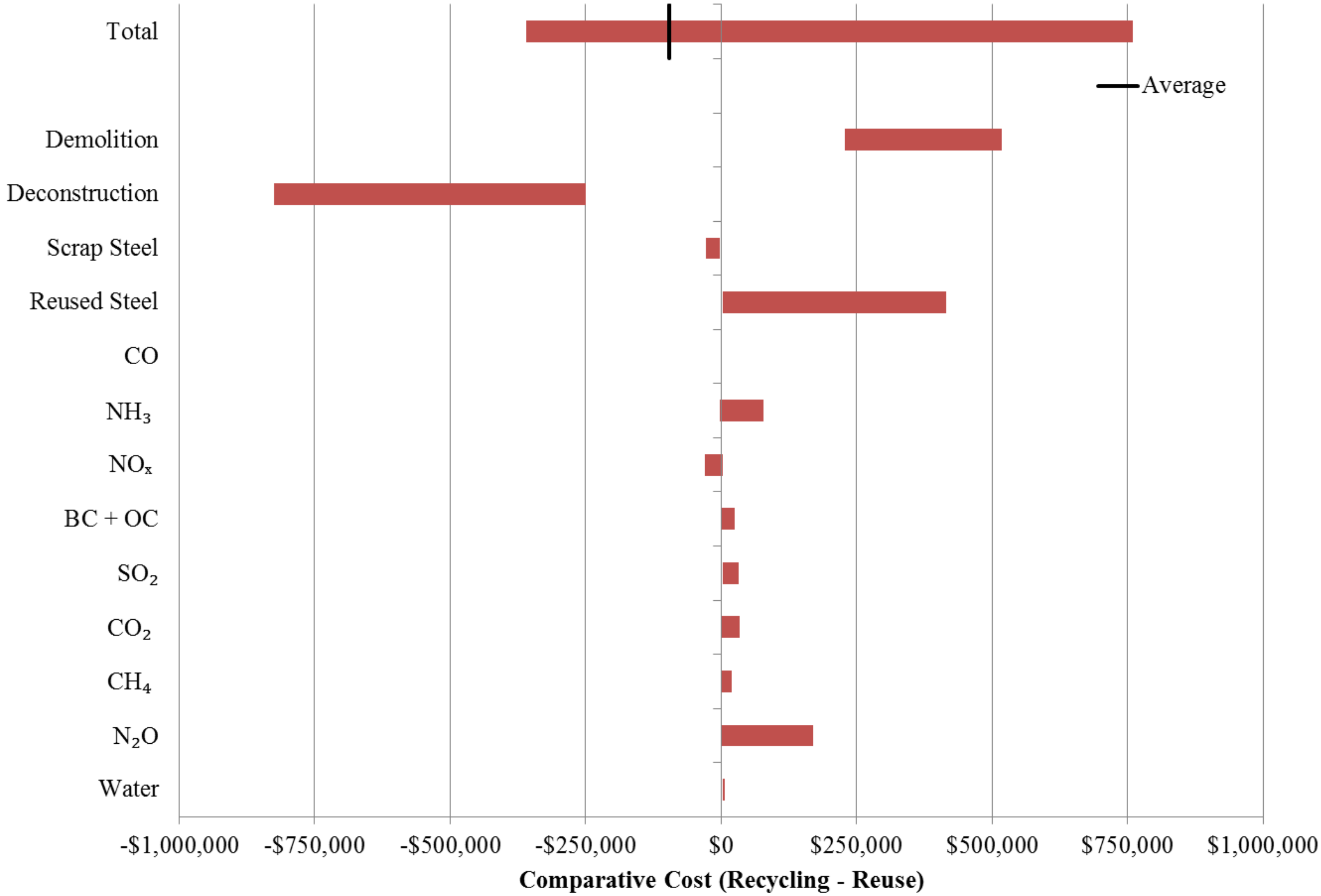


Figure 5-20: Impact of uncertainty on the comparative costs

An important characteristic of the analysis is the point at which the optimum process changes from recycling to reuse or vice versa (i.e., when the cost ratio equals 1.0). A sensitivity analysis was conducted to investigate how varying component costs impacts the overall cost ratio. For this analysis, a single component cost was varied from zero to 20 times its “average” value while the other component costs were held constant at their “average” value. A range of zero to 20 was used for each analysis to account for the uncertainty in current valuations, which suggest that component cost factors range between 0.06 and 11, and for the uncertainty of future valuations of each metric. The resulting cost ratios can be seen in Figure 5-21, Figure 5-22, and Figure 5-23. Additionally, it is reasonable to conceive that the impact of multiple metrics would increase or decrease simultaneously. For this sensitivity analysis, the component cost factor for all air pollutants, all greenhouse gases, and scrap and reused steel was varied. The results of this analysis can be seen in Figure 5-24.

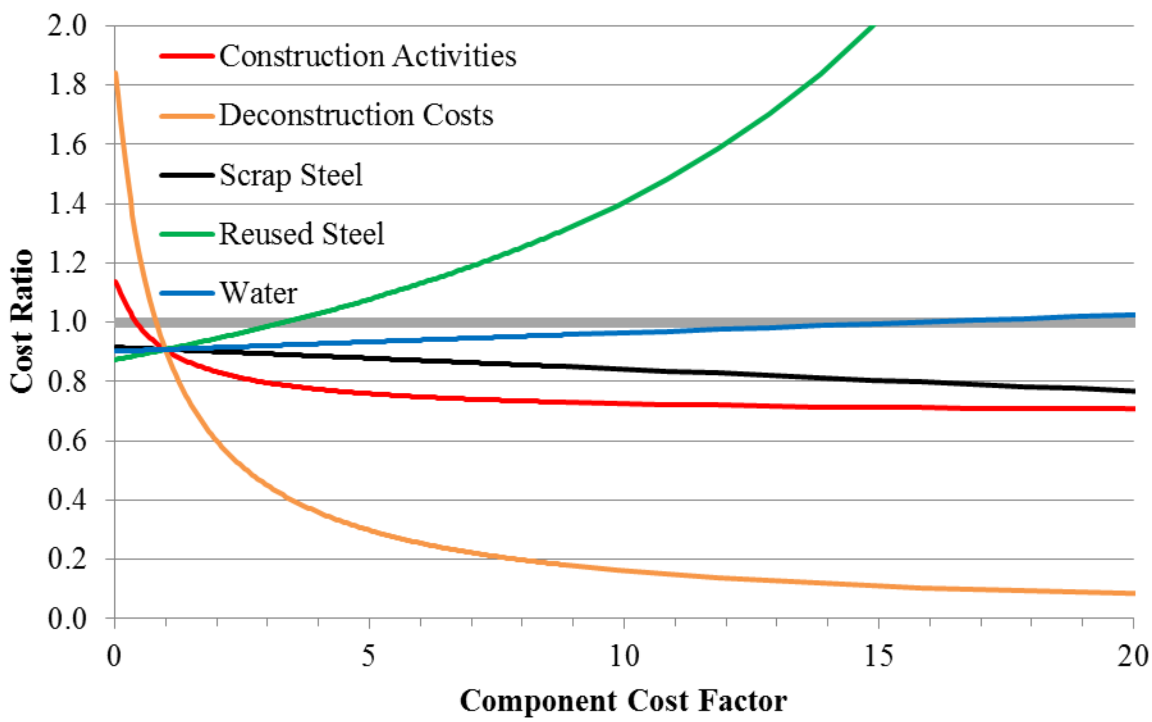


Figure 5-21: Sensitivity analysis for component costs of non-emission metrics

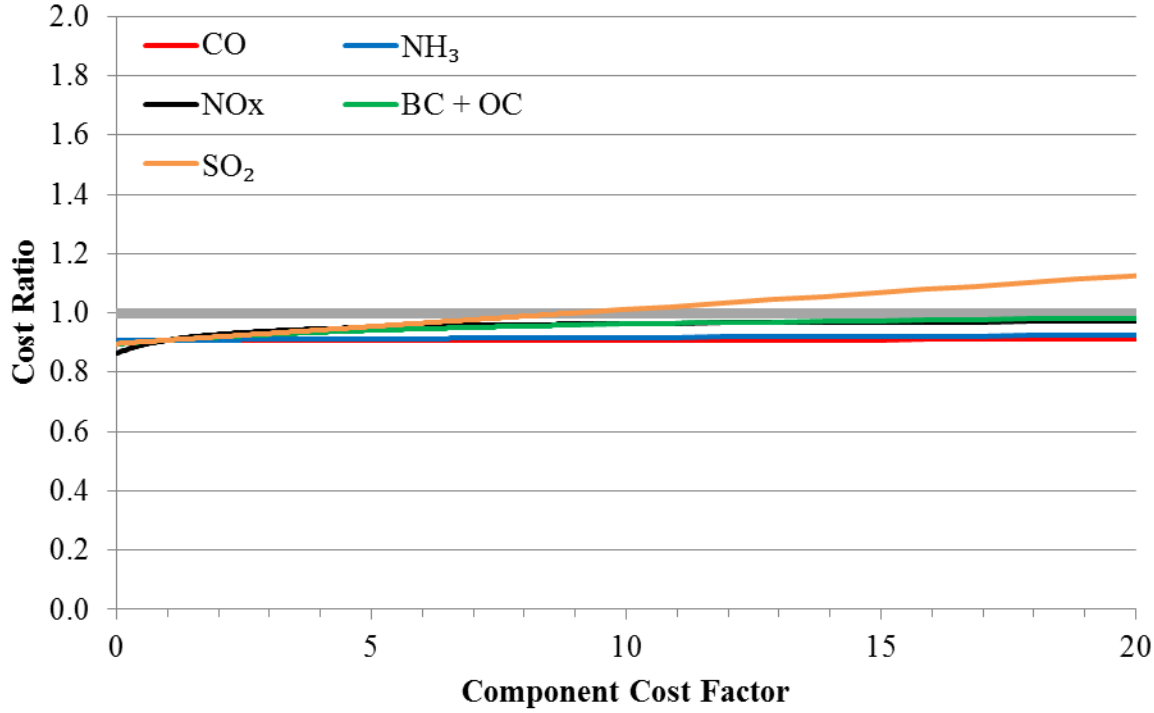


Figure 5-22: Sensitivity analysis for component costs of air pollution metrics

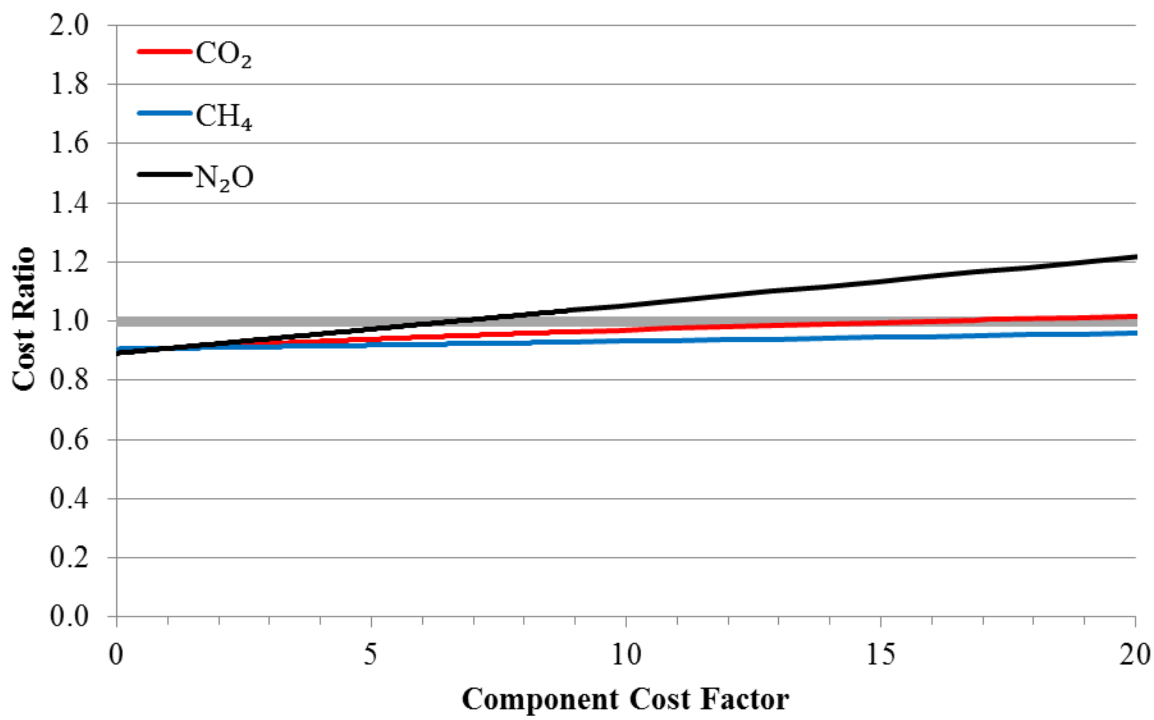


Figure 5-23: Sensitivity analysis for component costs of greenhouse gas metrics

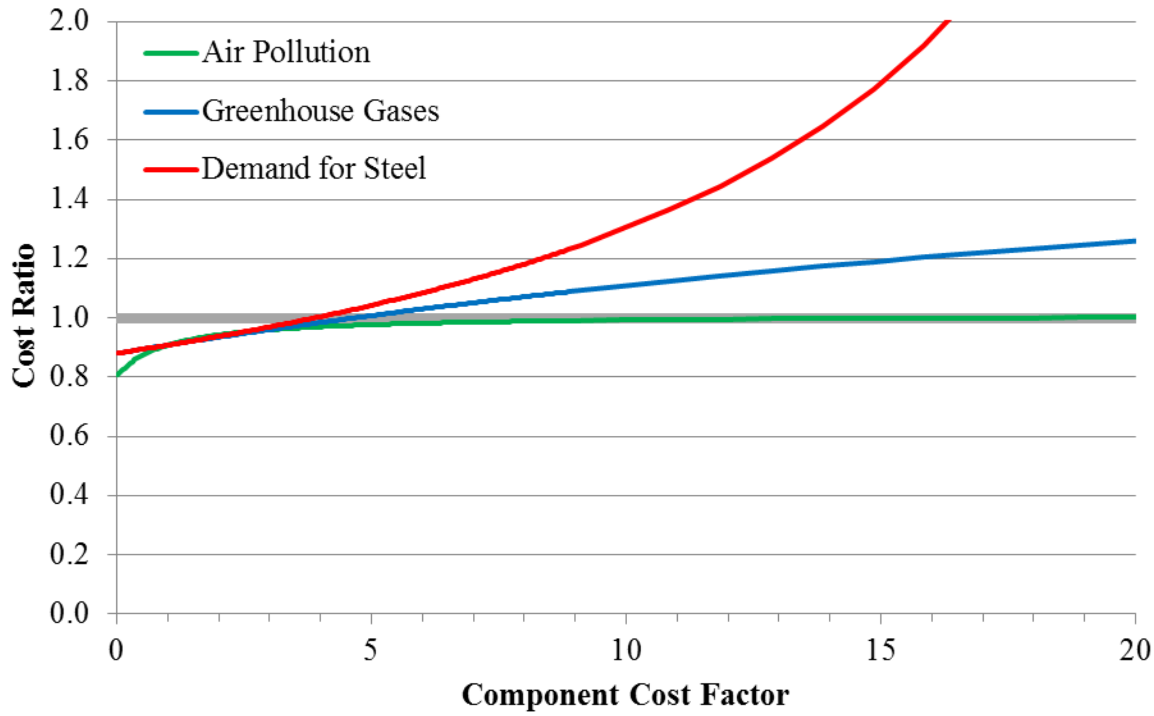


Figure 5-24: Sensitivity analysis for component costs of combined metrics

Figure 5-21 shows that the cost ratio is sensitive to deconstruction costs, the cost of construction activities and the value of reused steel components. The break-even point for deconstruction costs is at a component cost factor of 0.80. This means that if deconstruction processes were improved such that the cost of deconstruction were 80% of what it currently is, reuse would be equally appealing as recycling. Similarly, if construction activities cost 40% of their current value, or if reused steel components were 3.3 times their current value, reuse and recycling would be equally appealing.

Figure 5-22 shows that the cost ratio is not sensitive to air pollution. Only SO_2 has a large enough impact to equate the cost of reuse and recycling for component cost factors less than 20. The break-even point for SO_2 is 9.0.

Figure 5-23 also shows that the cost ratio experiences little sensitivity towards greenhouse gases with the exception of N_2O. The break-even point for N_2O was at a component cost factor of 6.7.

Figure 5-24 shows that all of the combined metrics can have a significant impact on the cost ratio. The break-even component cost ratios for “Demand for Steel”, “Greenhouse Gases”, and “Air Pollution” are 3.9, 4.7, and 17.6, respectively.

The break-even points for the sensitivity studies presented in Figure 5-21 through Figure 5-24 are summarized in Table 5-19.

Table 5-19: Break-even component cost factors for total life cycle cost metrics

Metric	“Break-even” component cost factor
Construction activities	0.40
Deconstruction costs	0.80
Scrap steel	< 0.0
Reused steel	3.3
Water	15.9
CO	> 20
NH_3	> 20
NO_x	> 20
BC + OC	11.3
SO_2	9.0
CO_2	15.9
CH_4	> 20
N_2O	6.7
Air pollution	17.6
Greenhouse gases	4.7
Demand for steel	3.9

5.6 Discussion

Based on the analysis results, reuse demonstrates clear benefits for reducing greenhouse gas emissions, with a reduction of 1,870 kg of CO_2e per tonne of steel. Reuse also demonstrates clear benefits for conserving water with a water withdrawal reduction of 38 m^3 / tonne of steel. The benefits of reuse are not as clear when it comes to air pollution. Reuse practices resulted in a reduction of SO_2 by 2.3 kg / tonne but resulted in increased NO_x and NH_3 emissions. Qualitatively, reuse of steel would intuitively reduce emissions due to the significant energy and water savings associated with avoiding the process of melting and reforming the steel. The increase in NO_x and NH_3 emissions can be explained by examining the demolition process versus the deconstruction process. Deconstruction is a much slower and more labour intensive process, which requires the use of diesel powered machinery for a much longer time than the demolition process. The increase in NO_x and NH_3 emissions is a direct result of the increased consumption of diesel fuel, which is the main contributor of these emissions. Table 5-20 summarizes the most significant sub-processes for each life cycle analysis impact metric. Reductions in these sub-processes will have the greatest benefit on the life cycle impact they are associated with. It is important to note that the most significant sub-processes are relative to an individual impact metric, rather than the process as a whole. This means that the Cleaning sub-process is identified as the main contributor to three life cycle impact metrics but these metrics contribute very little to the total life cycle impact of the reuse process.

Table 5-20: Most significant sub-processes for life cycle impacts in steel recycling

Life Cycle Impact Metric	Recycling Most Significant Sub-Process	Reuse Most Significant Sub-Process
CO	Removal	Gutting incl. removal
NH_3	Removal	Gutting incl. removal
NO_x	Removal	Gutting incl. removal
PM_{10}	Removal	Gutting incl. removal
SO_2	Minimills	Cleaning
CO_2	Removal	Gutting incl. removal
CH_4	Minimills	Cleaning
N_2O	Minimills	Cleaning
Water	Minimills	Gutting incl. removal

The emission reductions presented in this study cannot be compared to the life cycle analysis results for recycling steel from Yellishetty et al. (2011). The proposed methodology and life cycle analysis results for recycling represent only the life cycle impacts for sub-processes and products that differ from that of reuse, and thus do not fully represent the life cycle impacts of recycling steel.

5.6.1 Comparison to the economic input-output method

To perform a "reality check" of sorts, the economic input-output method was used to perform a similar comparative analysis. The EIO method for life cycle analysis has been applied to the comparison between reuse and recycling (Yeung, Walbridge, & Haas 2015). In this methodology, the EIO method is used by analyzing the life cycle impacts associated with producing a particular mass of steel and of salvaging that same mass. Detailed calculations for the EIO method can be found in Appendix C. Analyzing the life cycle impacts for producing steel (or another product) is a common practice for the EIO method, thus the methodology was followed as prescribed by Hendrickson, Lave and Matthews (2006). For the life cycle impacts associated with salvaging a mass of steel, alterations to the methodology needed to be employed. First, it was assumed that construction processes were equivalent to deconstruction processes in terms of resources required, except that instead of constructing a structure that contains a particular mass of steel, that mass of steel was salvaged during deconstruction. This meant that the EIO methodology could be followed as prescribed. Finally, life cycle impacts associated with material production were eliminated from the results. For example, life cycle impacts for steel production are included in the analysis of construction practices. These impacts were removed to better represent deconstruction processes. It should be noted that very few comparisons between the EIO and process model methods can be found in the literature, especially quantitative comparisons. The results from the EIO method can be seen in Figure 5-25b, Figure 5-26b, and Figure 5-27b. These results were produced using the same functional unit as the results for the current study, which can be seen in Figure 5-25a, Figure 5-26a, Figure 5-27a.

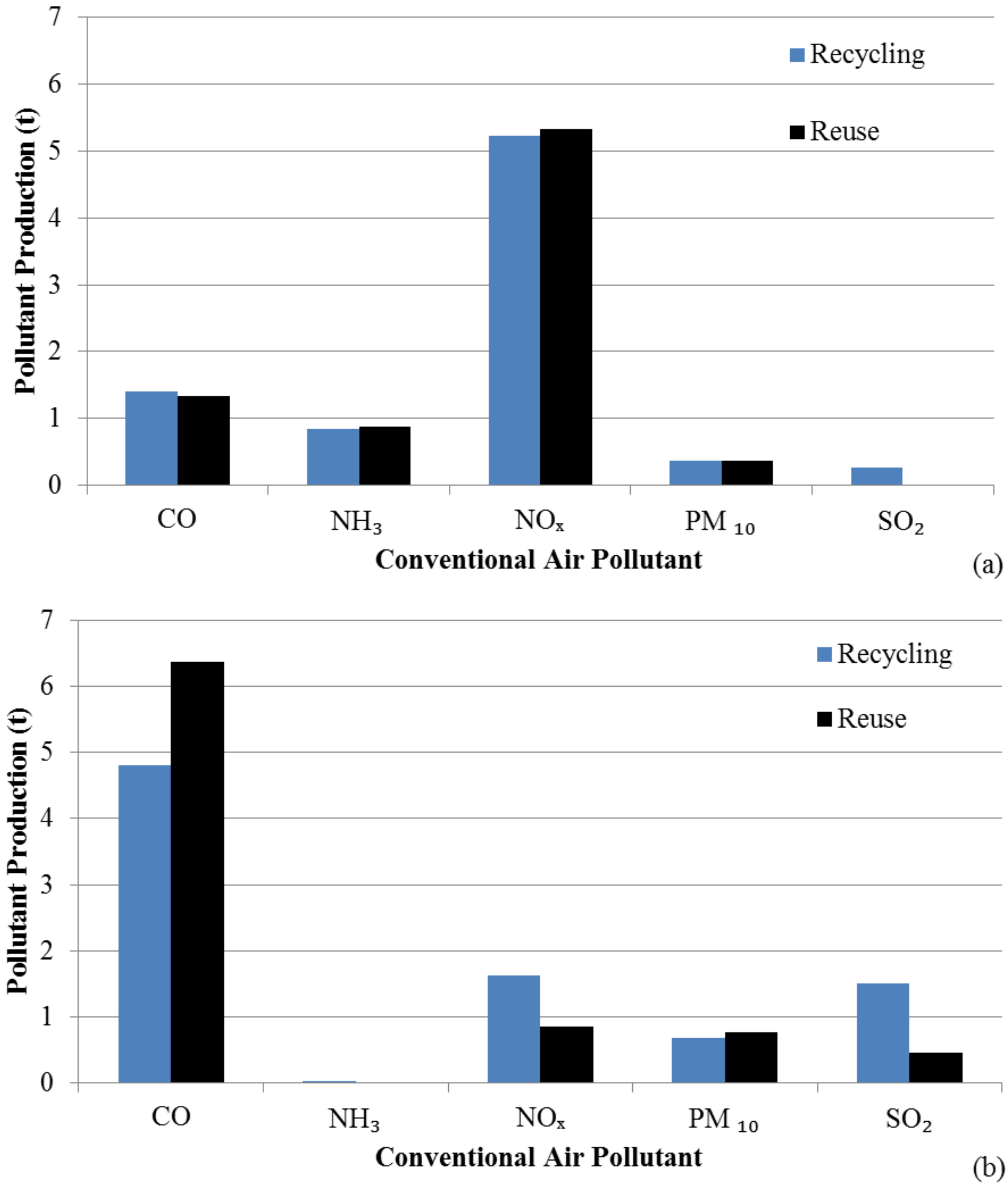


Figure 5-25: Conventional air pollutant comparison between recycling and reuse using the current study (a) and the EIO method (b) (Yeung, Walbridge & Haas, 2015)

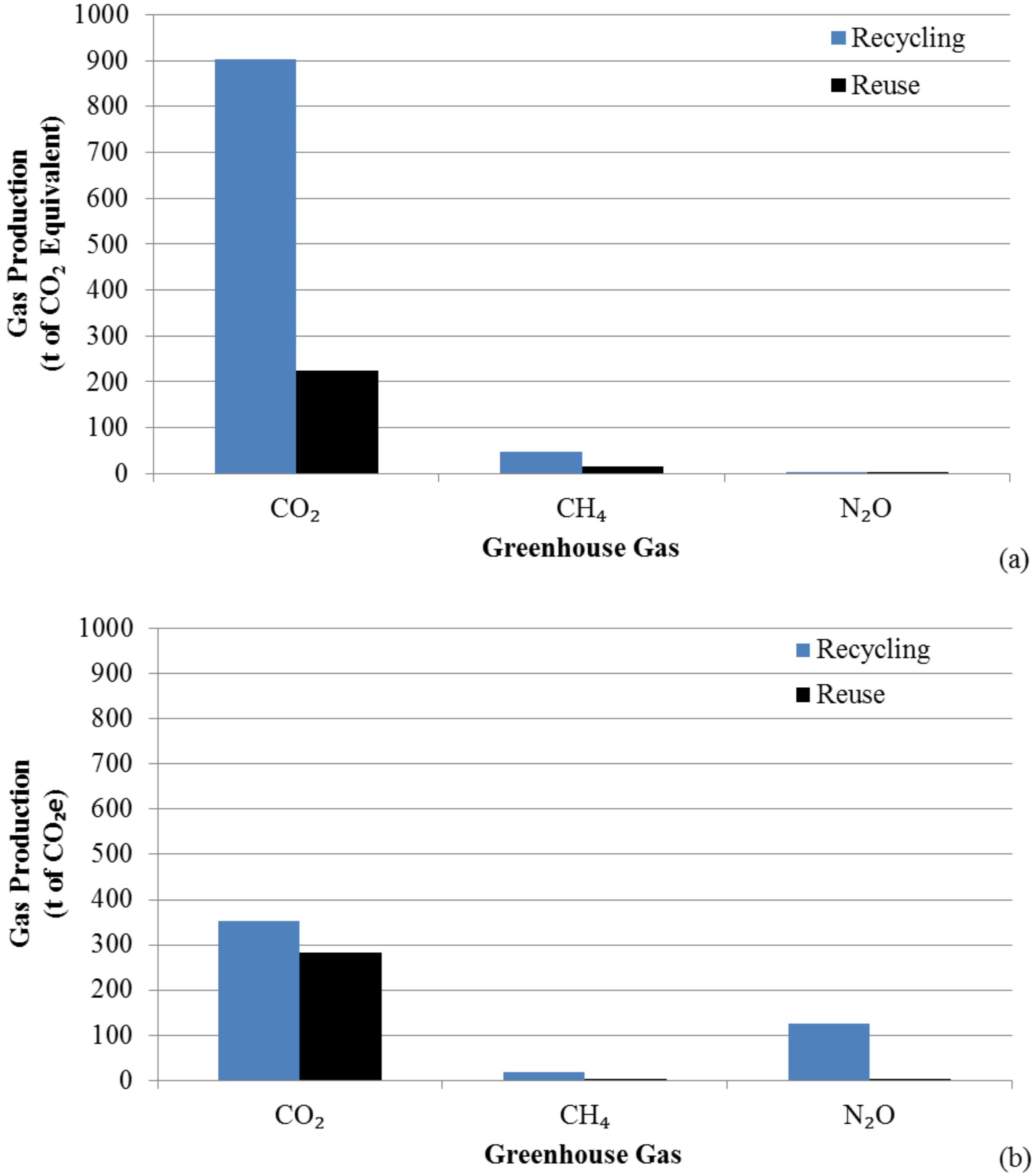


Figure 5-26: Greenhouse gas emission comparison between recycling and reuse using the current study (a) and the EIO method (b) (Yeung, Walbridge & Haas, 2015)

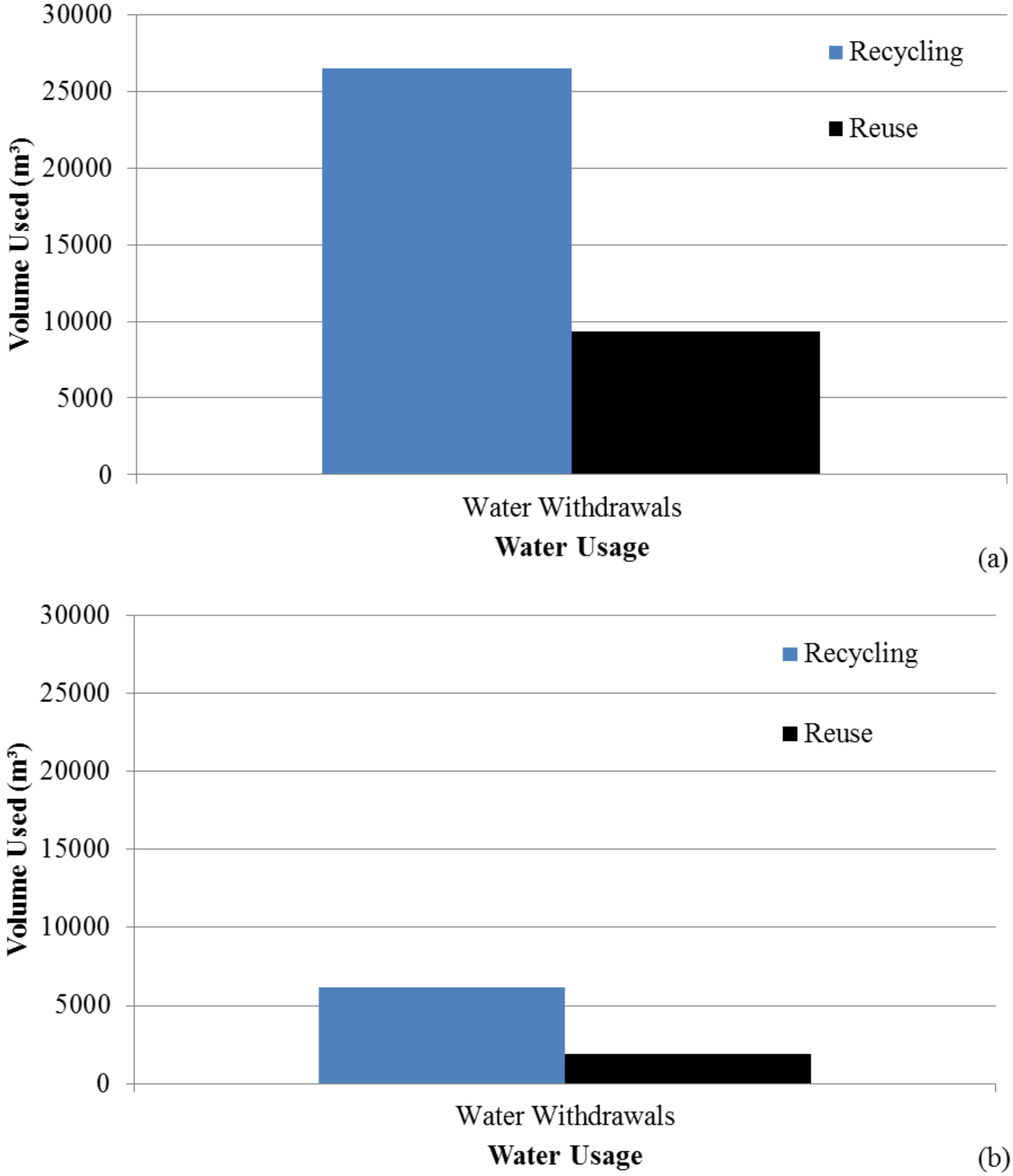


Figure 5-27: Water usage comparision between recycling and reuse using the current study (a) and the EIO method (b) (Yeung, Walbridge & Haas, 2015)

It can be observed that the trend between reuse and recycling (i.e., reuse superior vs. recycling superior) for a given metric remains the same with the exception of NO_x. For example, both approaches suggest that reuse produces more carbon monoxide than recycling. The difference between the two methods is in the quantity of each metric. For example, the EIO method suggests that approximately 26,500 m^3 of water is consumed when recycling, whereas the current study suggests that less than 7,000 m^3 would be used during this process. There is also a difference when comparing the relative scale of each metric. For example, the EIO method suggests that significantly more carbon monoxide is produced than nitrogen oxide whereas the opposite trend exists in the current methodology. These differences can be explained by the system boundary used in the current study. The comparative methodology also ignores all equivelant process and all higher order processes, which is not the case in the EIO method. The life cycle analysis in the current study also analyzes a different set of processes than the EIO method. Figure 5-28 highlights the difference between these processes. The EIO method, outlined in red, includes processes for the extraction of virgin material but does not include demolition, due to its cradle-to-gate nature. The LCA in the current study, shown outlined in blue in Figure 5-28, does not include the extraction of virgin material but does include demolition.

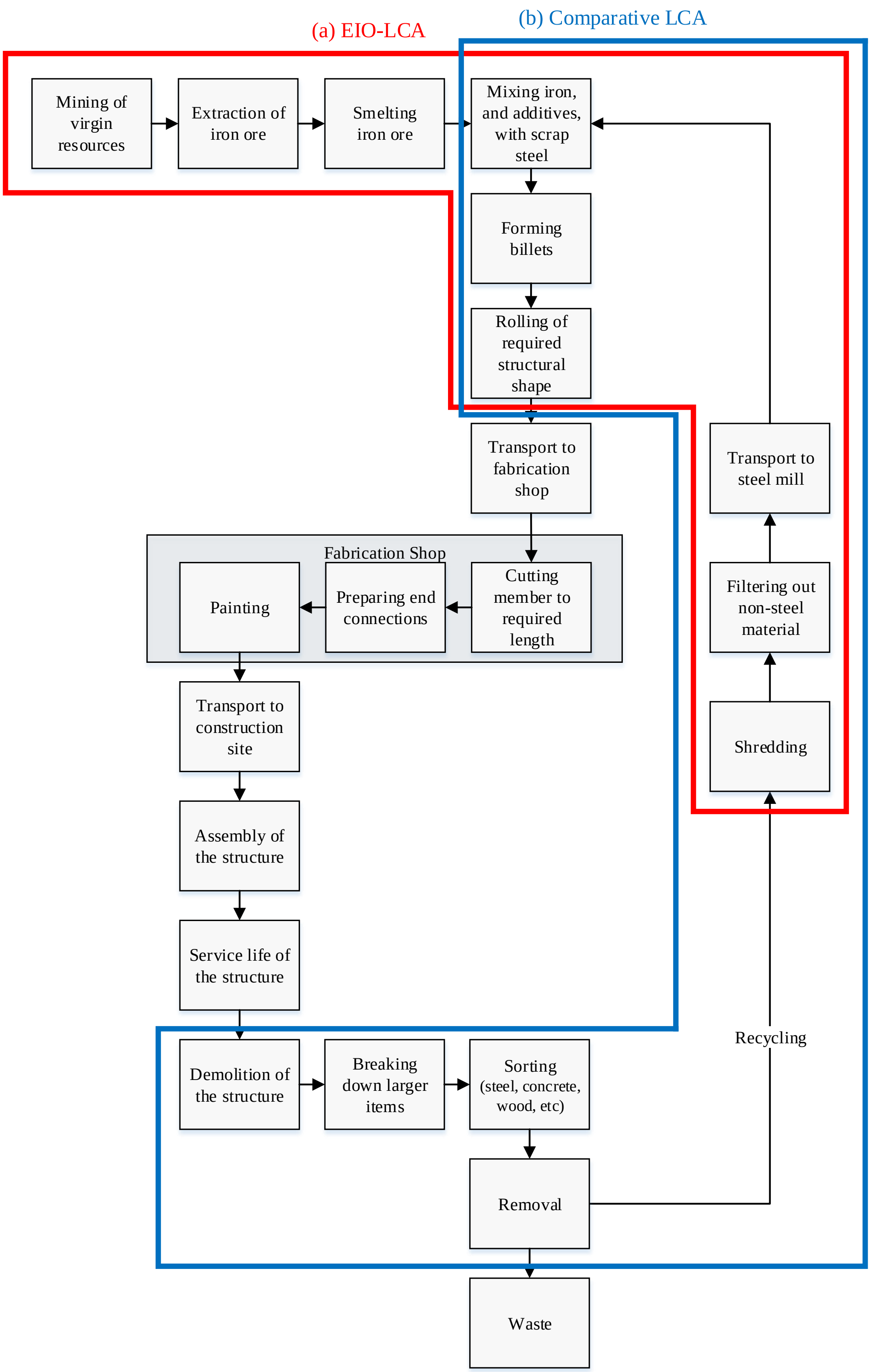


Figure 5-28: Differences in the processes analyzed between the EIO-LCA method (a), and the comparative analysis in the current study (b)

The proposed methodology is a superior alternative for comparative life cycle analysis of reuse and recycling for two reasons: (1) assumptions, and (2) transparency. The assumptions that allow the EIO method to be used for a comparative life cycle analysis of reuse and recycling are significant, and their impact on the accuracy is important. The error introduced by assuming that construction and deconstruction processes are equivelant could be significant. For this reason, the EIO method should not be used for in-depth analysis, but rather just as a reality check for other methods. The second limitation is transparency of the method. The EIO method does not provide results for sub-processes and thus, does not allow for analysis of areas for improvement.

One key question remains: if reuse has less life cycle impact than recycling, why is it not more prevalent? At least in North America, the cost of water and environmental impacts are not yet high enough or made endogerous to the processes, while labour and equipment rates are high. For now, recycling simply costs less for companies in North America in most cases and the low value of reused steel is not enough to overcome this.

5.6.2 Total life cycle cost

The results of the case study suggest that the recycling of structural steel is the less expensive alternative in the framework of a total life cycle cost analysis. This corroborates common practices in the structural steel industry, which are primarily focused on recycling structural steel rather than reusing it.

Uncertainty analysis suggests that in the data the results are highly susceptible to variation in the cost of labour and the value of reused steel components. The variation is large enough to suggest that for the case study in extreme cases, reuse could be the less expensive alternative by $760,000.

Nevertheless, the current economic and social conditions, which make recycling less expensive, will not last indefinitely. The sensitivity analysis provides decision makers with a tool that enables them to identify when these conditions will begin to favour reuse over recycling and where market costs can be reduced most feasibly, if the objective is to make reuse most attractive. It has been demonstrated that the most impactful metrics on the total life cycle cost comparison between reuse and recycling are deconstruction costs and the value of reused components. One possible method for reducing the cost of construction activities for reuse activities is to incorporate design for deconstruction into the initial design of structural steel structures. This will result in a more efficient deconstruction of the structure at the end of its life. Currently, design for deconstruction is not common practice so significant improvements could be realized through its implementation.

Design for deconstruction will also positively impact the value of reused steel components. Steel structures that are designed with efficient deconstruction as a design consideration will allow for the removal of longer and less damaged components. The deconstruction principles will allow for longer components because end connections can be unattached, preserving the entire length of the component (Silverstein, 2008). Components will be less damaged because demolition practices can be avoided, for example cutting a beam with hydraulic shears. It is noteworthy that the potential reduced capacity of reused components is not taken into consideration in the presented life cycle cost analysis, and it therefore follows that 1 kg of reused steel is equivalent to 1 kg of recycled steel. This assumption results in a more favourable total life cycle cost of reused components, but further investigation would be required to quantify the difference.

Another method for increasing the rated resistance of reused components is to perform structural reliability analysis on the reused components using measured geometries, such as the methodology proposed by Yeung, Walbridge, and Haas (2015). Structural reliability analysis on reused components allows engineers to design using the maximum resistance of the reused component. Without the use of reliability analysis, a discounted resistance needs to be used to ensure the safety of the reused component. An internet based exchange for reused steel, if properly structured, might also reduce transaction costs and improve the rate of "perfect information" required to make markets work effectively.

5.7 Summary

The work presented in this study proposes a methodology for the comparative life cycle analysis of structural steel reuse and recycling. This comparative LCA provides a quantitative comparison using nine common life cycle analysis metrics. The LCA has been developed in such a way as to provide decision makers with a practical way of approaching the problem of performing a life cycle analysis for the purpose of determining when it makes sense to consider reuse as opposed to recycling. This was accomplished by limiting the system boundary to the processes that are unique to each end-of-service life strategy and by ignoring the higher order processes, which add increasing complexity and decreasing impact as the order of the process increases.

The methodology is demonstrated through the use of a case study, which suggested that reuse practices could save more than 1870 kg of greenhouse gases (CO_2e) and more than 37,500 L of water per tonne of reused steel.

When the proposed methodology was compared to similar results produced with the economic input-output (EIO) method, significant differences in the results were found. These differences can be explained by the different system boundaries between the methods and the truncation of higher order processes in the comparative LCA.

The comparative LCA in the current study provides decision makers and life cycle analysts with a fast and easy method, relative to the standard process model approach, for quantitatively computing the difference in life cycle impacts between reuse and recycling processes. This facilitates a more complete assessment of reuse as an end-of-life alternative for structural steel structures.

This study develops an analysis tool for performing a total life cycle cost comparison between the reuse and recycling of structural steel. This methodology is demonstrated using a case study that supported the current, recycling dominated, practice in steel construction. Uncertainty analysis demonstrates that, under extreme conditions, reuse has the potential to be the superior alternative by nearly $760,000 for the case study presented.

A sensitivity analysis was presented to explore the economic and social conditions that would favour structural steel reuse. It was found that if cost of deconstruction were 0.80 times its current cost or less, reuse would be the less expensive alternative. Also if the value of reused structural steel were more than 3.2 times its current value, reuse would be less expensive.

6 Conclusions and recommendations for future work

The following chapter is divided into two main sections: (1) conclusions, and (2) recommendations for future work. The conclusions section presents a brief description of the major conclusions that have stemmed from the research performed in this study. The recommendations for future work section presents ideas and areas of research that could be expanded upon following the conclusion of the current study.

6.1 Conclusions

The conclusions presented in this chapter are separated into four distinct areas, each reflecting a main research area of the current study: (1) the decision making framework, (2) semi-automated cross-section identification, (3) reliability analysis, and (4) comparative life cycle analysis.

6.1.1 Decision making framework for structural steel reuse

A complete decision making framework that is integrated into an existing structural steel reuse process model has been proposed, leading to the following conclusions:

- The first decision that should be made at the end of a steel structure's service life is whether or not deconstruction is an option. If it is, members should be identified for reuse prior to deconstruction. If it is not, members should be identified for reuse after demolition.
- A visual inspection can serve to identify the possibility of reuse, but more information is required to make an informed decision regarding the value of reusing steel.
- Many inputs into the structural steel reuse decision making process do not involve the steel to be reused. These inputs include but are not limited to: market value of scrap steel,

market value of reused steel, life cycle impact comparison between reuse and recycling processes, costs of impacts on the environment, and impact on schedule.

- Low-rise structures are particularly attractive for structural steel reuse, as these structures typically lack steel fireproofing, which can be difficult to remove.

6.1.2 Semi-automated cross-section identification

17 structural steel members were analyzed as part of the semi-automated cross-section identification study. The geometry of these members was captured using 3D laser scanning technology. This geometric data was then analyzed to relate it to structural capacity. The following conclusions are drawn from these results:

- The proposed methodology demonstrates the feasibility of semi-automatically identifying the geometric characteristics of structural steel sections using 3D laser scanning data.
- Utilizing filters based on the geometry of known structural steel sections is a valid approach to determining the section properties of laser scanned data.
- The proposed methodology resulted in a conservative estimate of a cross-section's capacity; on average a 10% underestimation of the capacity. These results are more conservative on average than the values used for code calibration for new construction, although the coefficient of variation was more than seven times larger.

6.1.3 Reliability analysis of reused components

A reliability analysis was performed to calculate resistance factors for reused steel members with cross-section geometries identified by 3D laser scanning. The results from the semi-automated cross-section identification analysis were used to characterize the accuracy and precision of the geometric data. A line fitting technique was also utilized for the same purpose. The following conclusions are drawn from the results of this study:

- The methodology proposed in Chapter 3 can identify structural steel sections in such a way as to provide a resistance factor approximately half that of values that have been suggested for new steel ($\phi = 0.42$ vs. $\phi_{\text{new steel}} = 0.95$).
- Line fitting can result in a resistance factor very similar to values used for new steel ($\phi = 0.93$ vs. $\phi_{\text{new steel}} = 0.95$). This implies that the current capabilities of 3D laser scanners would facilitate very accurate geometric identification.
- Sensitivity analysis reveals that changes to the coefficient of variation of the geometric parameter of interest (e.g., area, section modulus) have a much greater effect on the resistance factor than changes to the mean value.

6.1.4 Life cycle analysis comparison of reuse and recycling

A methodology for performing a comparative life cycle analysis between reuse and recycling was presented. This analysis results in a quantified list of life cycle impacts that result from each process. These impacts are then unified into a total life cycle cost. This study and its application to a case study project result in the following conclusions:

- Comparative life cycle analysis significantly reduces the scope of the life cycle analysis (and therefore the required complexity and time involved) by eliminating identical processes and products that are common to reuse and recycling.
- The life cycle impact metrics of NH_3, and NO_x, were increased as a result of reusing steel but all other metrics (CO, PM_{10}, SO_2, CO_2, CH_4, N_2O, and water) were reduced. Some of

the most significant improvements were for N_2O and water usage, which were reduced by 1100 kg (of CO_2e) / tonne and 37,600 L / tonne (of steel), respectively.

- Total life cycle cost analysis supports real-world observations of reuse and recycling frequency because reuse was found to be the more expensive process even when life cycle impacts were monetized and accounted for.
- Uncertainty analysis suggests that feasible values for the cost of labour, and the value of reused steel, individually, could result in reuse being the less expensive alternative.
- In certain cases, reuse has the potential to be the superior alternative by nearly $760,000 for the presented case study.
- Reuse would be the superior alternative if deconstruction costs were reduced to 0.80 times their current cost or reused steel was valued at 3.3 times its current value, without modifying input values such as transportation distances.

6.2 Recommendations for future work

The recommendations for future work presented in this chapter are similarly separated into four distinct areas: (1) the decision making framework, (2) semi-automated cross-section identification, (3) reliability analysis, and (4) comparative life cycle analysis.

6.2.1 Decision making framework for structure steel reuse

Expansion of the decision making framework developed in this thesis could come in the form of a framework could be developed to aid companies seeking to control all aspects of the reuse process. These aspects include: inventory acquisition, storage, and certification; and design; fabrication. This would reduce or eliminate many of the logistical problems currently associated with steel reuse.

6.2.2 Semi-automated cross-section identification

Further advancements in the automatic geometric characterization of structural steel and in the remote sensing technology are required to facilitate widespread implementation of the methods developed herein. Specifically, the following major advancements are needed:

1. the development of more robust and accurate cross-section identification algorithms,
2. the development of software for automatically characterizing connection geometry, and
3. the development of software to assist in automatically locating joints in building frames.

The results presented in this thesis suggest that such advancements have strong potential to further reduce the cost and uncertainty associated with structural steel reuse, and would therefore enable an increased rate of reuse by the building construction industry.

6.2.3 Reliability analysis of reused components

Material properties are a very important aspect of the capacity of a steel component, along with geometry. Further development of the reliability analysis should begin with a more in-depth treatment of material properties, and consideration of the various ways that material properties can be measured or estimated, in the event that the steel grade is not known.

Additionally, the concept of proof load testing could be used to improve the resistance factors of reused components by eliminating the lower tail of the resistance curve based on the fact that these components are known to have safely carried a certain load.

Finally, it is recommended that the implications of varying the target beta values be investigated in a future study. The purpose of this study would be to investigate the possibility of using reused components more effectively in low occupancy structures than in regular occupancy structures.

6.2.4 Life cycle analysis comparison of reuse and recycling

Further development of the life cycle analysis is recommended with the goal of convincing decision makers to utilize higher rates of structural steel reuse. Some particularly promising directions of focus for future developments are outlined as follows:

1. Refinement of the life cycle emission data would result in a more accurate analysis, which would be more representative of current conditions.
2. Schedule delays should be incorporated into the total life cycle cost analysis. Reuse processes require a longer schedule than demolition processes and should therefore be accounted for as a cost of the reuse process in the total life cycle cost analysis.
3. Development of easy-to-use software applications would provide individuals and parties with a means of performing similar life cycle analyses for their specific projects. Each construction project is unique and therefore each comparison between reuse and recycling will be unique. Developing a software application would give decision makers the confidence that the results directly apply to their project.
4. Refine the life cycle analysis model by including partial reuse and partial recycling. Then, investigate the impact that varying the level of reuse versus recycling has on the total life cycle cost of end-of-life processes. This modified model can then be used to make recommendations about the optimum level of reuse.
5. Modify the current life cycle analysis model to explore the impact that the material cost to labour cost ratio has on the total life cycle cost of end-of-life processes. Different sized members and buildings of different types (low rise industrial, multi-storey commercial, etc.) will result in different material cost to labour cost ratios. The current model could be

modified to explore these different ratios and present total life cycle cost ratios for a wide array of situations.

6. Modify the current life cycle analysis model to incorporate the benefits that concepts like design for deconstruction could have on the total life cycle cost of reuse practices. Design for deconstruction provides an opportunity to reduce the deconstruction costs associated with reuse. Practical applications of design for deconstruction could be investigated to quantify the reduction in deconstruction costs and, therefore, the reduction in total life cycle cost of reuse.
7. Modify the current total life cycle cost analysis to incorporate the impact of reduced capacities for reused components due to uncertainty in geometric and material properties.

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networks", *Computer-Aided Design.* vol. 44, pp. 644-656.

Appendix A

Developed Algorithms

Cross-section Identification

```
clear
clc

%Runs the appropriate functions to perform Section ID
%on a set of data

%INPUTS
Points = importdata('Connection Tree Data\BW1.txt', '\t');
load('Filter Creation\Tenth Web\Filters1mm.mat');
PixelSize = 0.001;
SplitThickness = 0.05;


%Split the data points
Splits = split(Points, SplitThickness);

%Make binary images of the splits
Images = cell(length(Splits),1);
for i = 1:length(Splits)
    Images{i} = binaryimage(Splits{i}, PixelSize);
end

%Convolve the filter over the splits

SectionMatch = zeros(length(Filters), length(Images));
for i = 1 : length(Splits)
    for j = 1 : length(Filters)
        clc
        disp(i), disp(j)
        SectionMatch(j,i) = convolve2(Filters{j}, Images{i});
    end
end

SectionMatch = SectionMatch / max(max(SectionMatch));

disp('Done')
```

Splitting Subroutine

```
function [ ZSplit ] = split( Data, Size )
%Splits the data into sections orthogonal to the Z axis

    Data = sortrows(Data,3);
%Sorts the rows of based on the third column (from smallest to largest)
    Splits = zeros(ceil((max(Data(:,3))-min(Data(:,3)))/Size), 1);
%Array of (soon to be) locations within the data to split the data
    Splits(1) = 1;
%Sets the first split location to be the first point

    Xo = Data(:,1) - min(Data(:,1));
    Yo = Data(:,2) - min(Data(:,2));
    Zo = Data(:,3) - min(Data(:,3));
    Data = [Xo,Yo,Zo];

    p = 0;
    k = 1;
%Counter used for counting up along the data until the split location is
passed
%Determines the locations of the splits within the data array
    for i = min(Data(:,3)) + Size : Size : max(Data(:,3))
%Counts through splits from the smallest data value to the largest data
value with a step of the split size
        j = 0;
%Flag variable to keep track of when the current split is passed in the
data
        p = p + 1;
%Counter to keep track of the split number being worked on
        while j == 0
%Condition that the split has not been passed
            if Data(k,3) >= i
%Condition that the data at 'k' is greater than the split (k has gone past
the split)
                j = 1;
%Flag to exit loop is made true
                Splits(p+1) = k-1;
%Split location is saved
            else
                k = k + 1;
%Moves loop to the next data point
            end
        end
    end
    Splits(p+2) = length(Data(:,3));
%Populates the end of the Splits array with the last data point

    ZSplit = cell(length(Splits)-1, 1);
%Creates a cell to contain the data points from each split
    for i = 1 : length(Splits) - 1
%Counts through the number of splits
        ZSplit{i} = Data(Splits(i):Splits(i+1), [1,2]);
%Populates the cell with data points according to the splits
    end

end
```

Binary Imaging Subroutine

```
function [ Image ] = binaryimage( Slice, Size )
%Takes a slice and a pixel size and creates a binary image

    %Sets up the binary image as a matrix of zeros
    xp = ceil(max(Slice(:,1)) / Size) + 1;
    yp = ceil(max(Slice(:,2)) / Size) + 1;

    Image = zeros(yp, xp);

    %Reduces the input data, removing repeated rows
    Slice = floor(Slice/Size);
    Slice = unique(Slice, 'rows');

    %Maps each data point to a pixel in the Image array and sets its value
to 1

    for i = 1:length(Slice(:,1))
        Image(yp - Slice(i,2), Slice(i,1)+1) = 1;
    end
end
```

Section Match Subroutine

```
function [ BestFit ] = convolve2( Filter, Image )
%CONVOLVE2 Summary of this function goes here
%   Detailed explanation goes here

if size(Image,1) >= 3*size(Filter,1) || size(Image,2) >= 3*size(Filter,2)
%Condition that the image size is 3 times greater than the fitler size in
either direction

    BestFit = 0;
%Assumes that very small sections will have a very low match

elseif size(Image,1) >= size(Filter,1) && size(Image,2) >= size(Filter,2)
%Condition that the image is larger than the filter (to avoid crashes)

    Match = zeros(size(Image,1) - size(Filter,1) + 1, ...
%Empty array of match values for each location the filter is convolved
over the image
                  size(Image,2) - size(Filter,2) + 1);

    for i = 1 : size(Match,1)
%Counts the rows of the match locations
        for k = 1 : size(Match,2)
%Counts the columns of the match locations
            ImageOverlap = (Image(i:i+size(Filter, 1)-1, ...
%Array containing the values within the image that are overlapping with
the filter
                                  k:k+size(Filter,2)-1));
%at its current location
            Match(i,k) = sum(sum(Filter.*ImageOverlap));
%Match value calculated as the number of cells where the filter and
overlapping
        end
%image values are both equal to 1
    end

    BestFit = max(max(Match));
%Match value that is the highest (and therefore most applicable) for the
current filter

else
%Condition that the filter is larger than the image (avoids crashes)
    BestFit = 0;
end

end
```

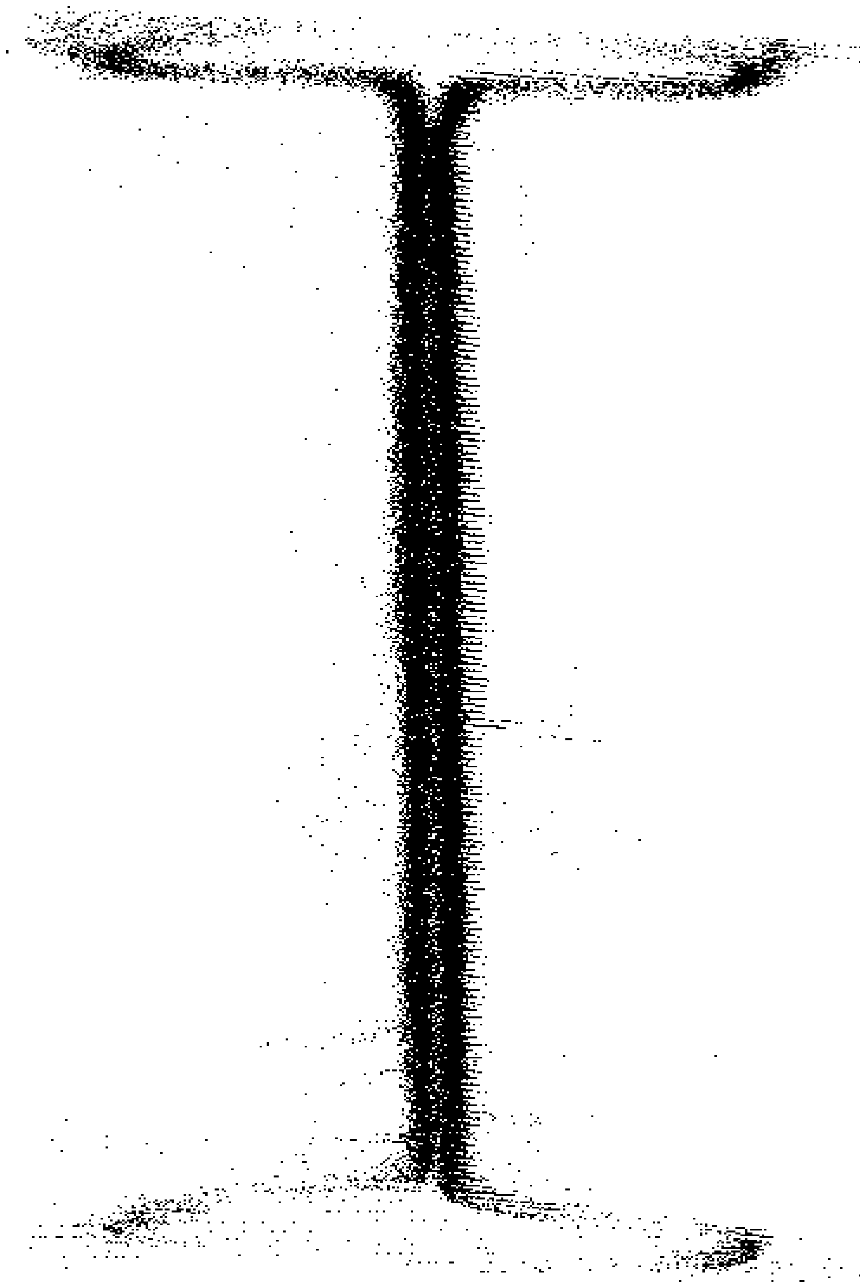
Section Match Subroutine

```
clear
clc
Trials = 500000;

M_r = 1;
phi_s = 0.4;

M_f = 1;
Alpha_L = 1.5;
Alpha_D = 1.25;

Z1_Mean = 1.060;      %Bias factor for F_y
Z2_Mean = 1.000;      %Bias factor for S
Z3_Mean = 1.090;      %Bias factor for Resistance Model
Z4_Mean = 1.030;      %Bias factor for M_D
Z5_Mean = 1.367;      %Bias factor for M_L
Z6_Mean = 0.930;      %Bias factor for Analysis Model
Z7_Mean = 1.134;      %Bias factor for Detection

Z1_STDEV = 0.05406;      %Bias factor for F_y
Z2_STDEV = 0.0;          %Bias factor for S
Z3_STDEV = 0.04905;      %Bias factor for Resistance Model
Z4_STDEV = 0.08240;      %Bias factor for M_D
Z5_STDEV = 0.05304;      %Bias factor for M_L
Z6_STDEV = 0.11160;      %Bias factor for Analysis Model
Z7_STDEV = 0.27200;      %Bias factor for Detection

M_P = M_r / phi_s;

L_D = 1.5;

M_D = M_f / (Alpha_L * L_D + Alpha_D);
M_L = M_f / (Alpha_L + Alpha_D / L_D);

Failures = 0;
for i = 1:Trials
    Z1 = logninv(rand(),Z1_Mean, Z1_STDEV);
    Z2 = 1;
    Z3 = logninv (rand(),Z3_Mean, Z3_STDEV);
    Z4 = logninv (rand(),Z4_Mean, Z4_STDEV);
    Z5 = logninv (rand(),Z5_Mean, Z5_STDEV);
    Z6 = logninv (rand(),Z6_Mean, Z6_STDEV);
    Z7 = norminv(rand(),Z7_Mean, Z7_STDEV);

    Resistance = M_P * Z1 * Z2 * Z3 * Z7;
    Load = M_D * Z4 + M_L * Z5 * Z6;

    if Load >= Resistance
        Failures = Failures + 1;
end

Beta = -norminv(Failures/Trials);

    disp(['L/D = ' num2str(L_D) ' || Beta = ' num2str(Beta)])
end
```

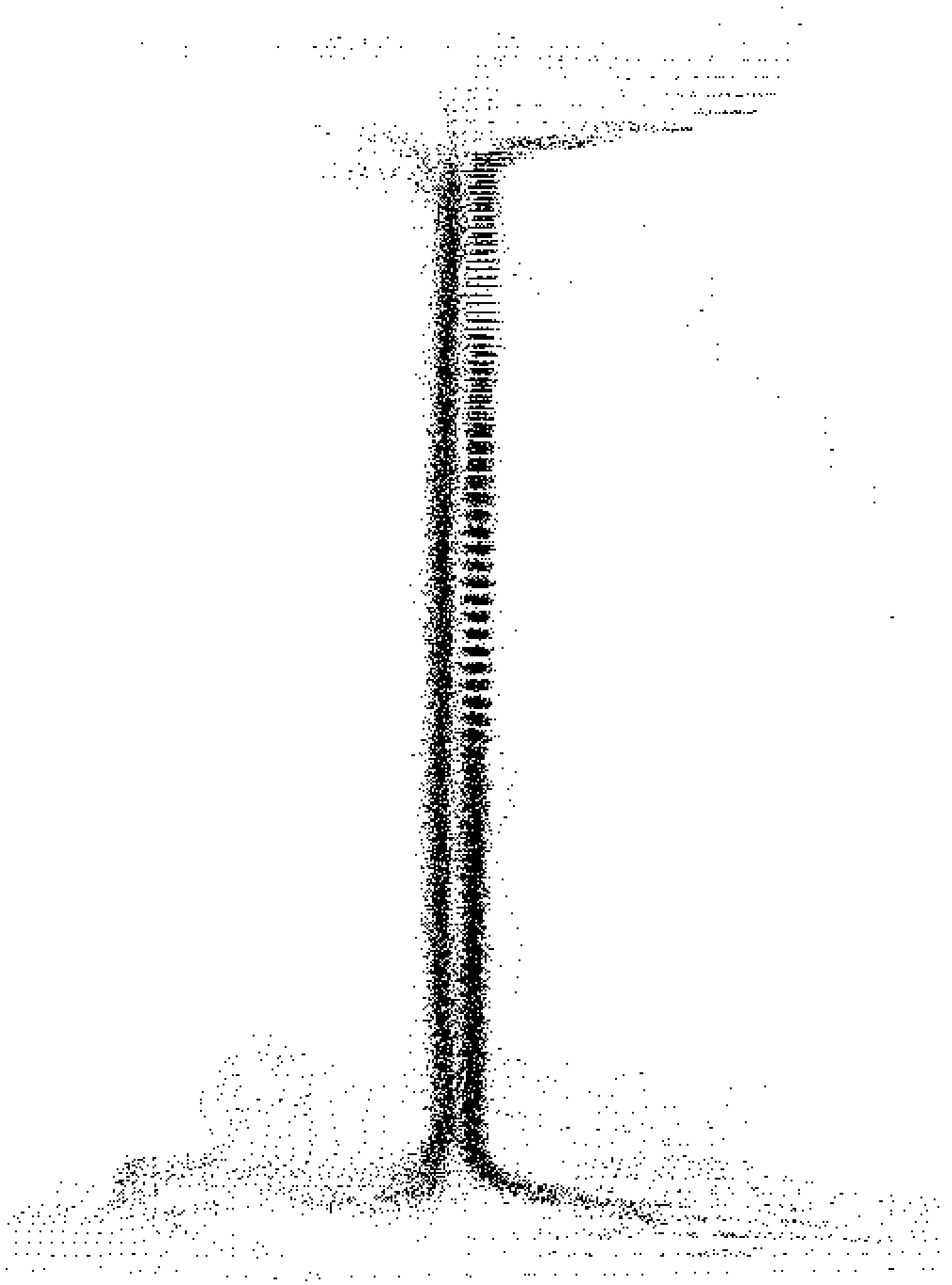
Appendix B

Automated Cross-section Identification Point Cloud Data

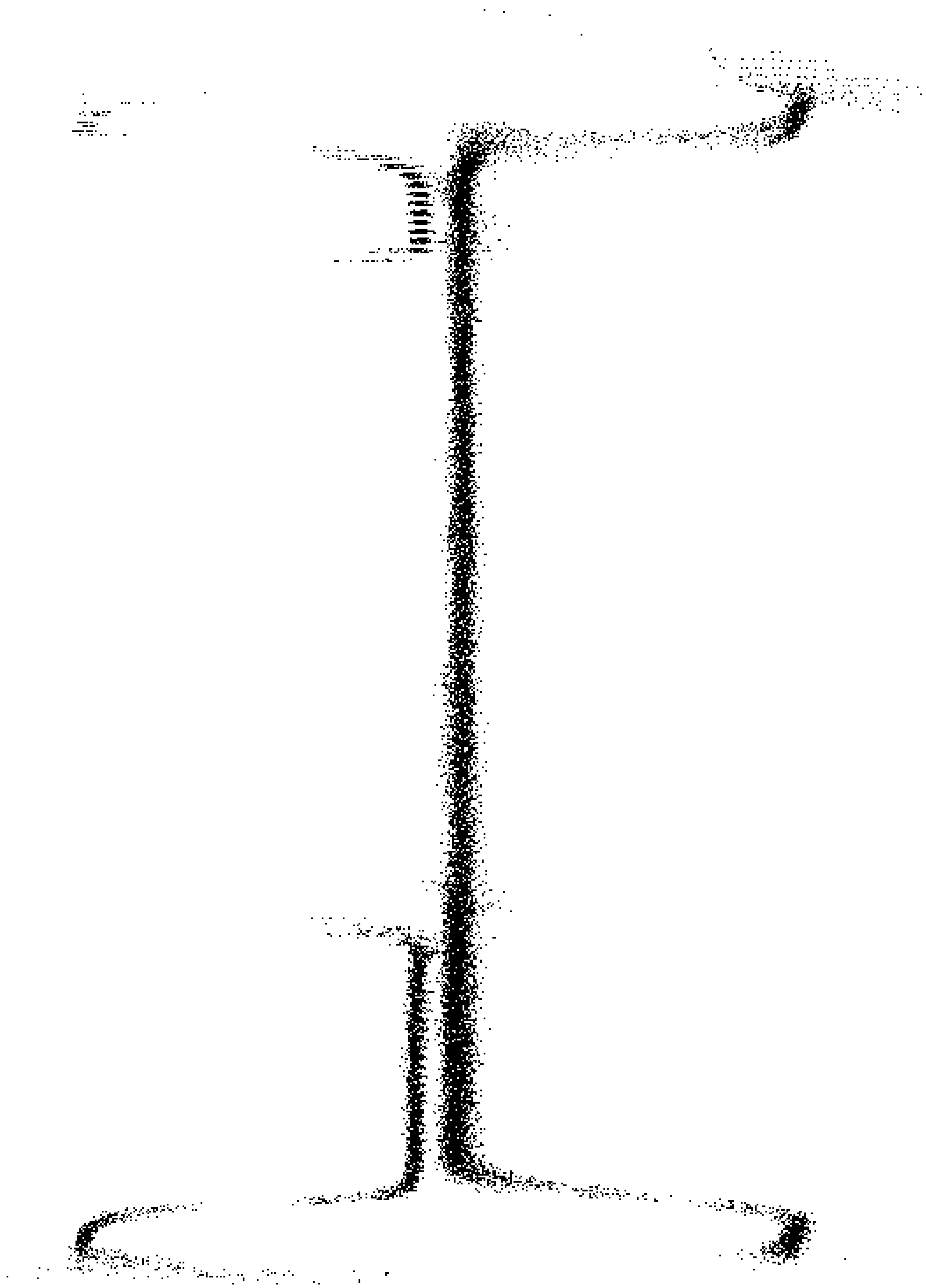
Point Cloud Data: A1



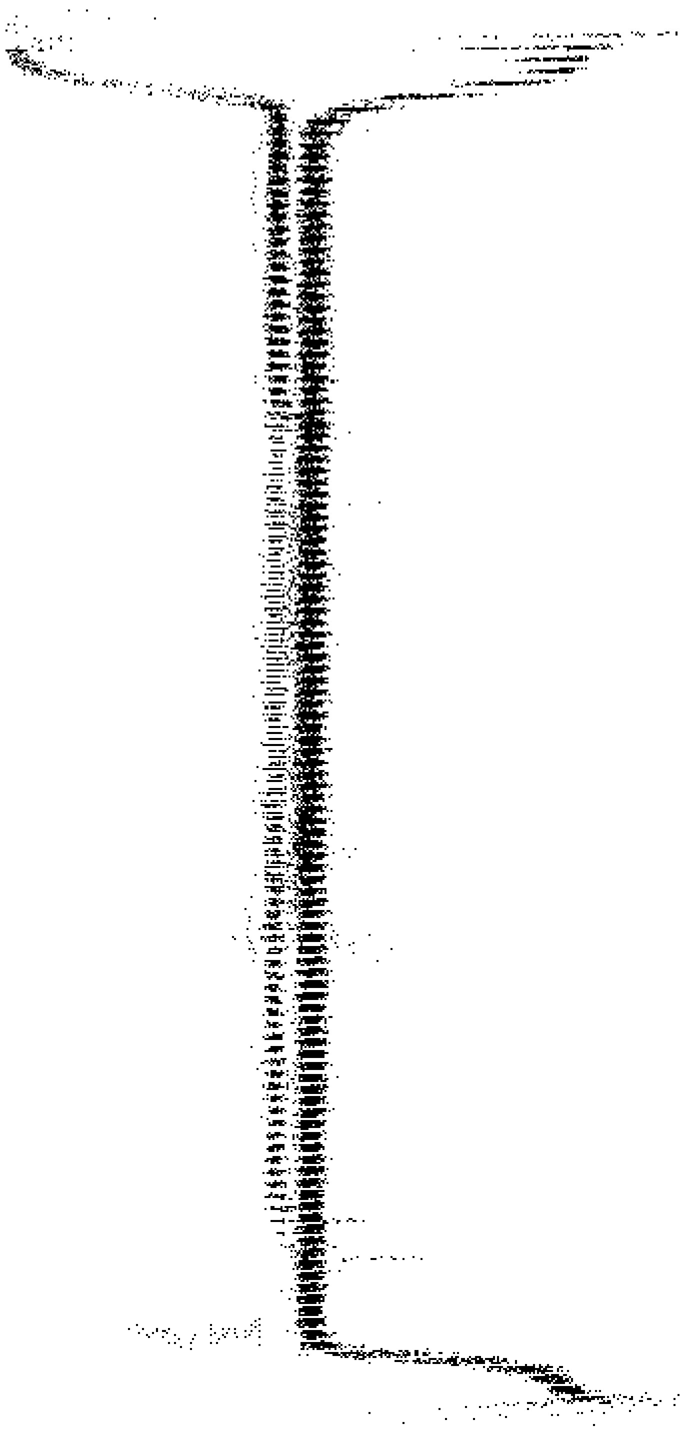
Point Cloud Data: A2



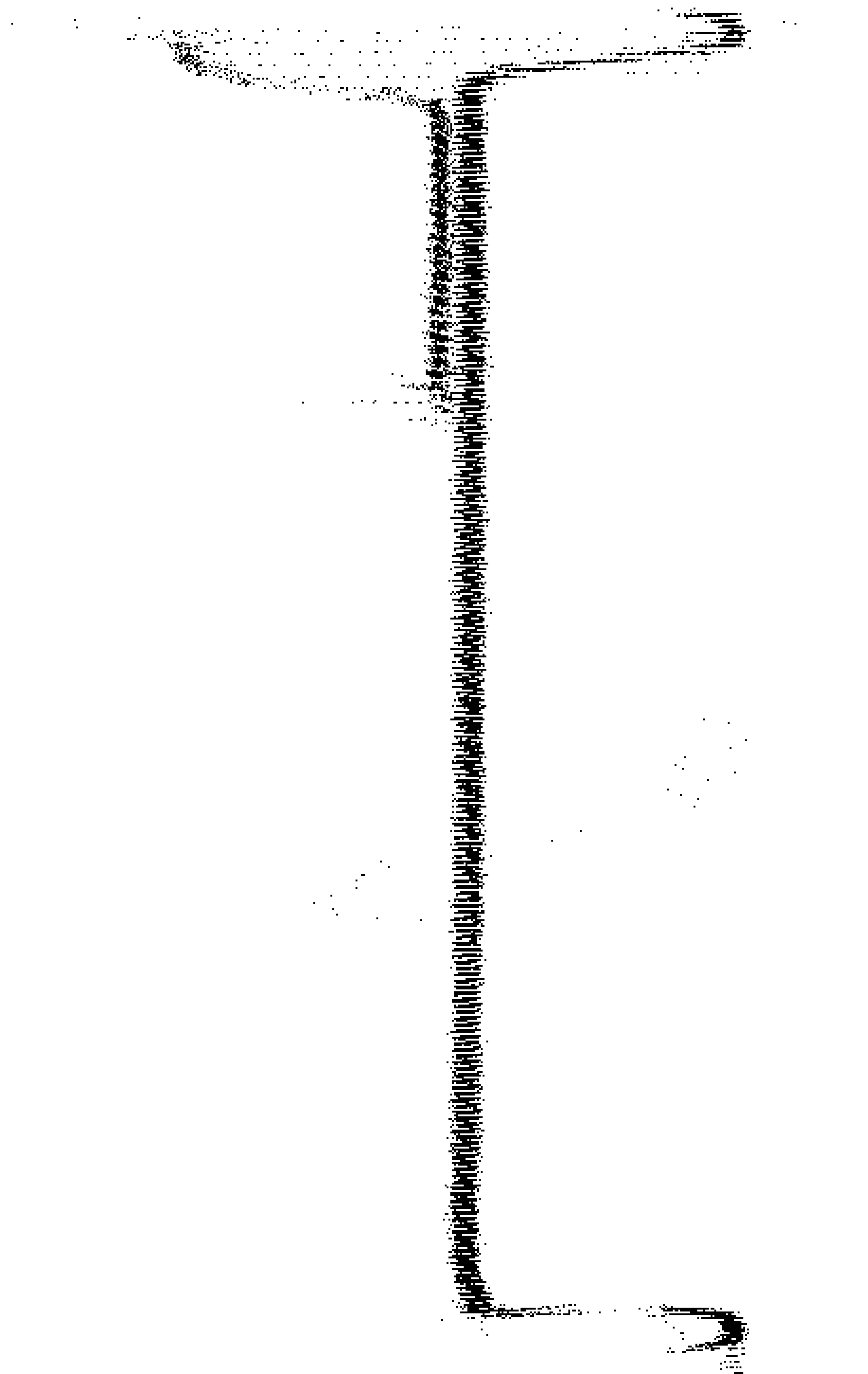
Point Cloud Data: A3



Point Cloud Data: A4

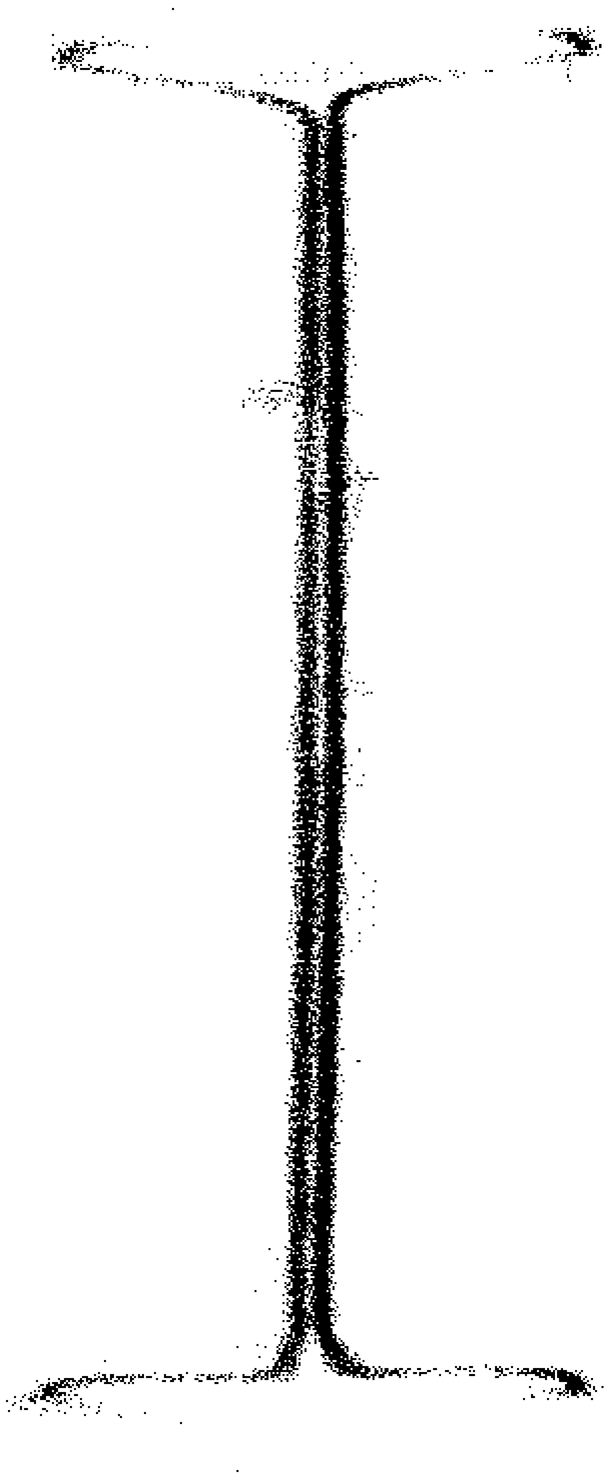


Point Cloud Data: A5



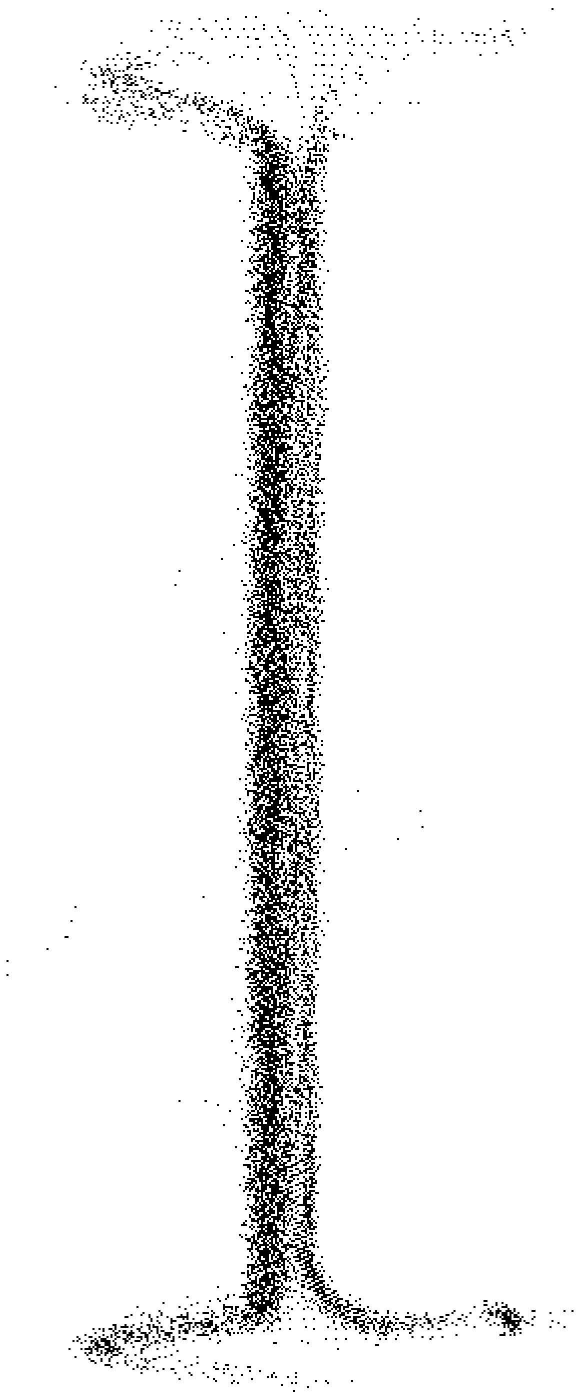
Point Cloud Data: A6

Point Cloud Data: A7

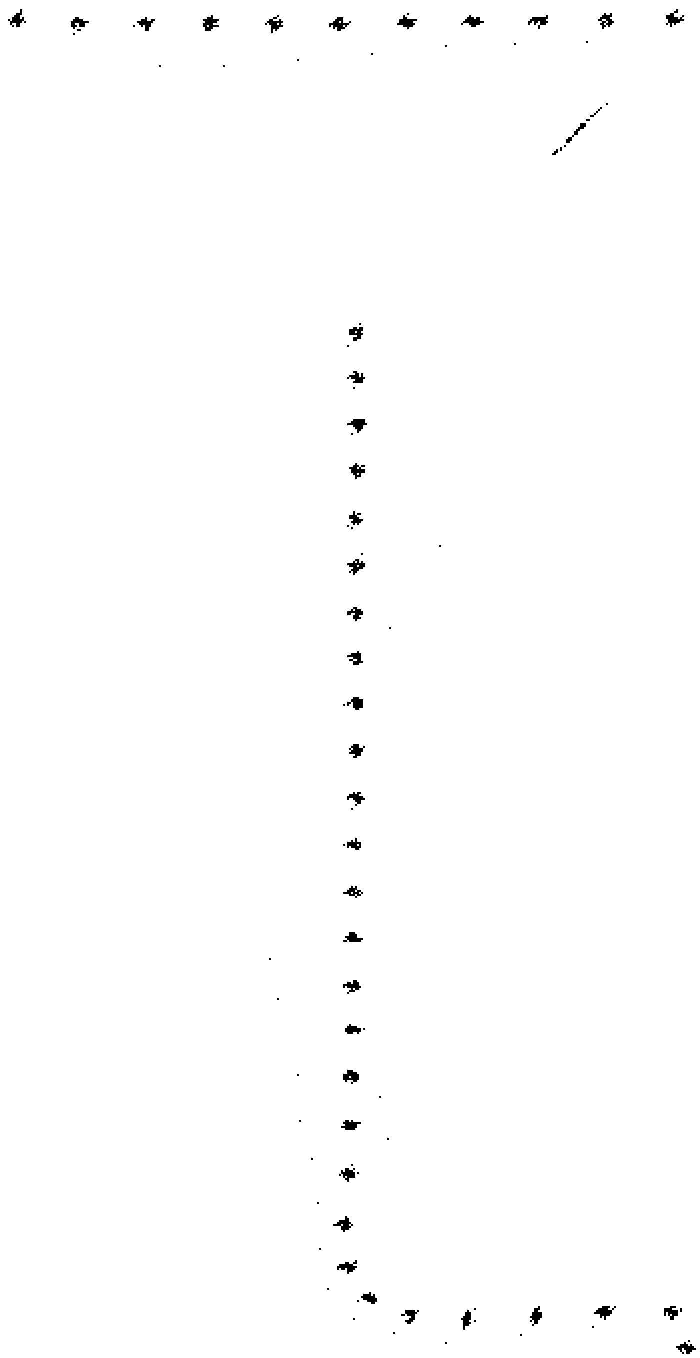


Point Cloud Data: A8

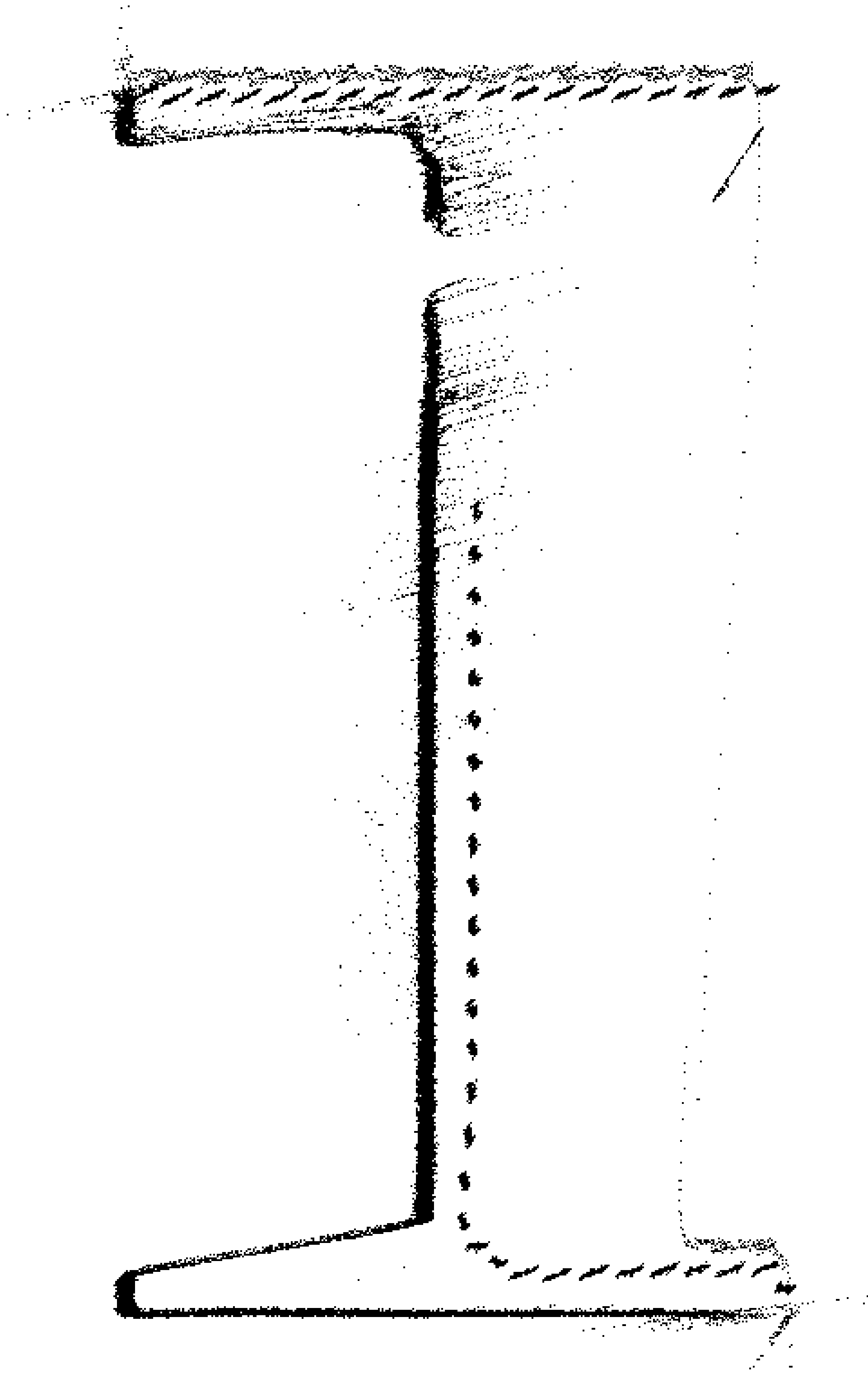
Point Cloud Data: A9



Point Cloud Data: B1



Point Cloud Data: B2



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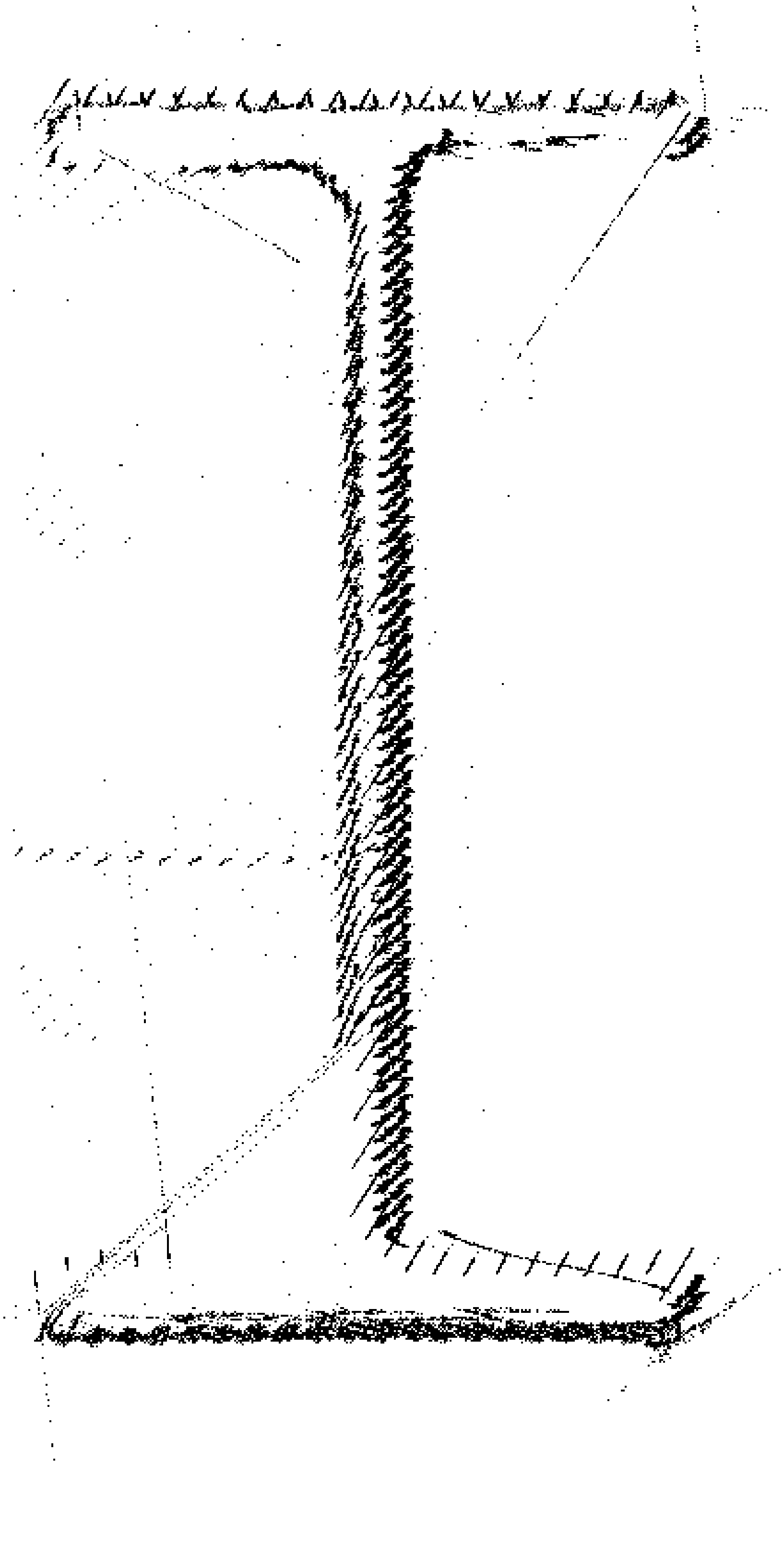

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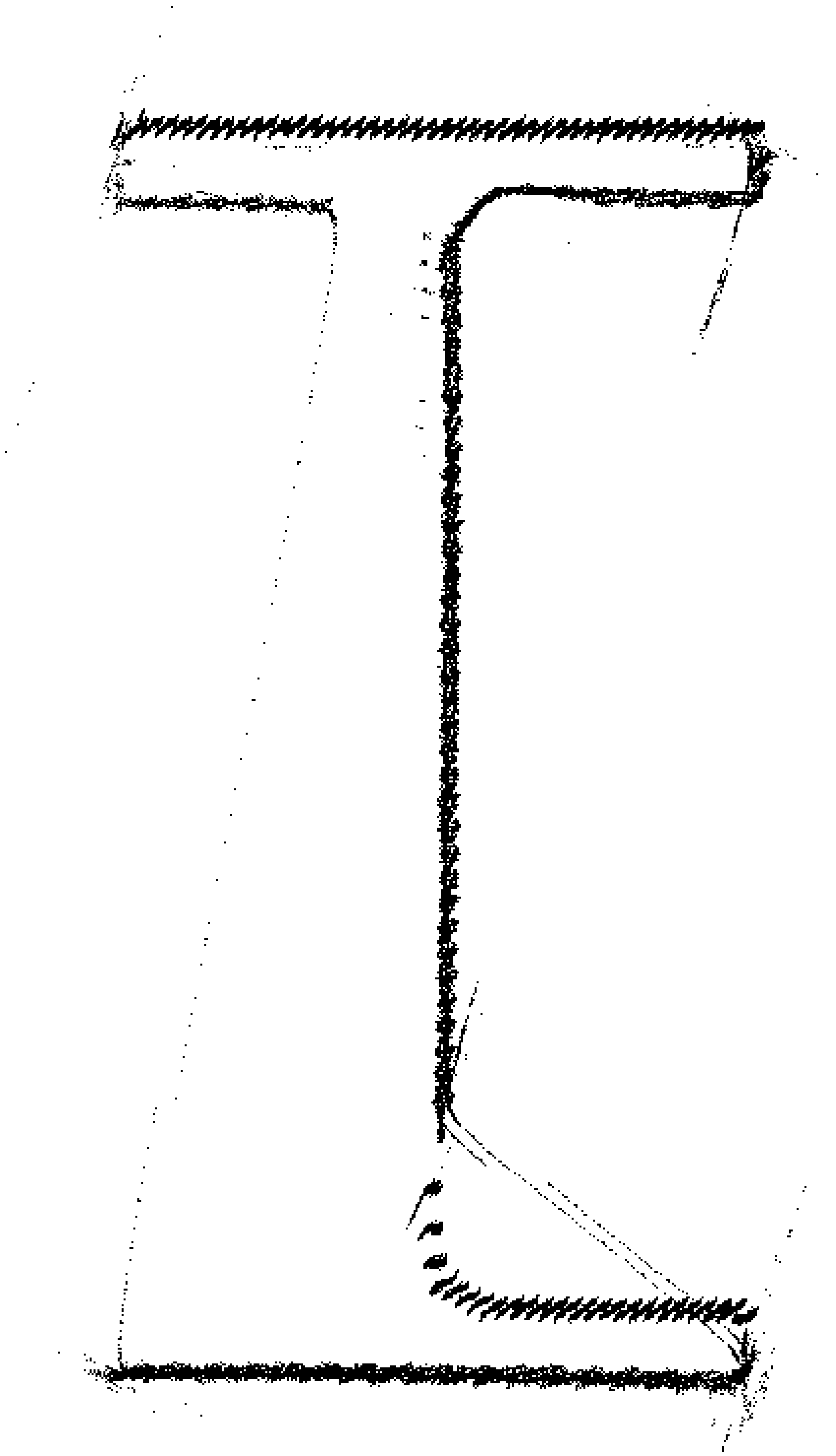

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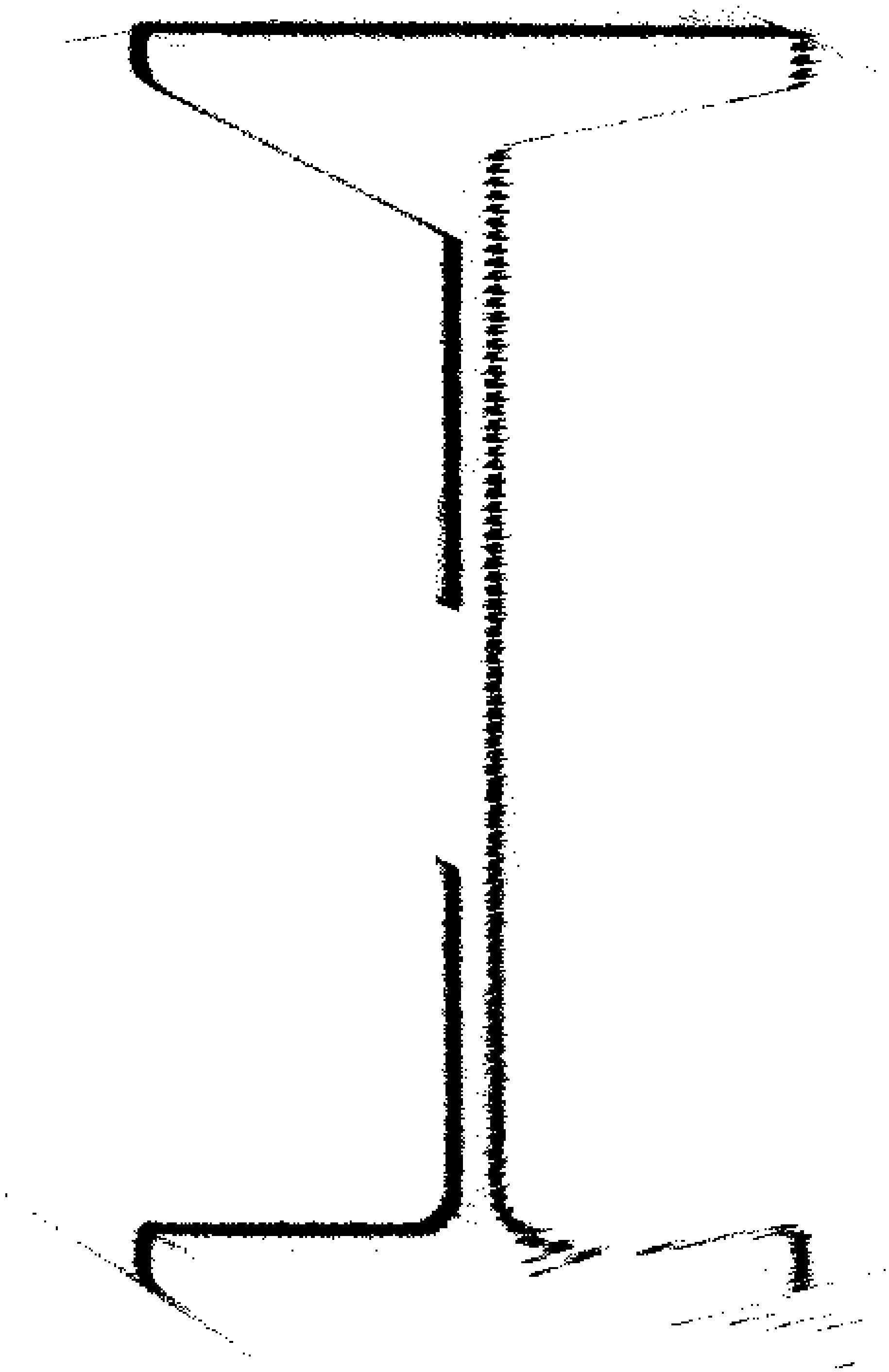

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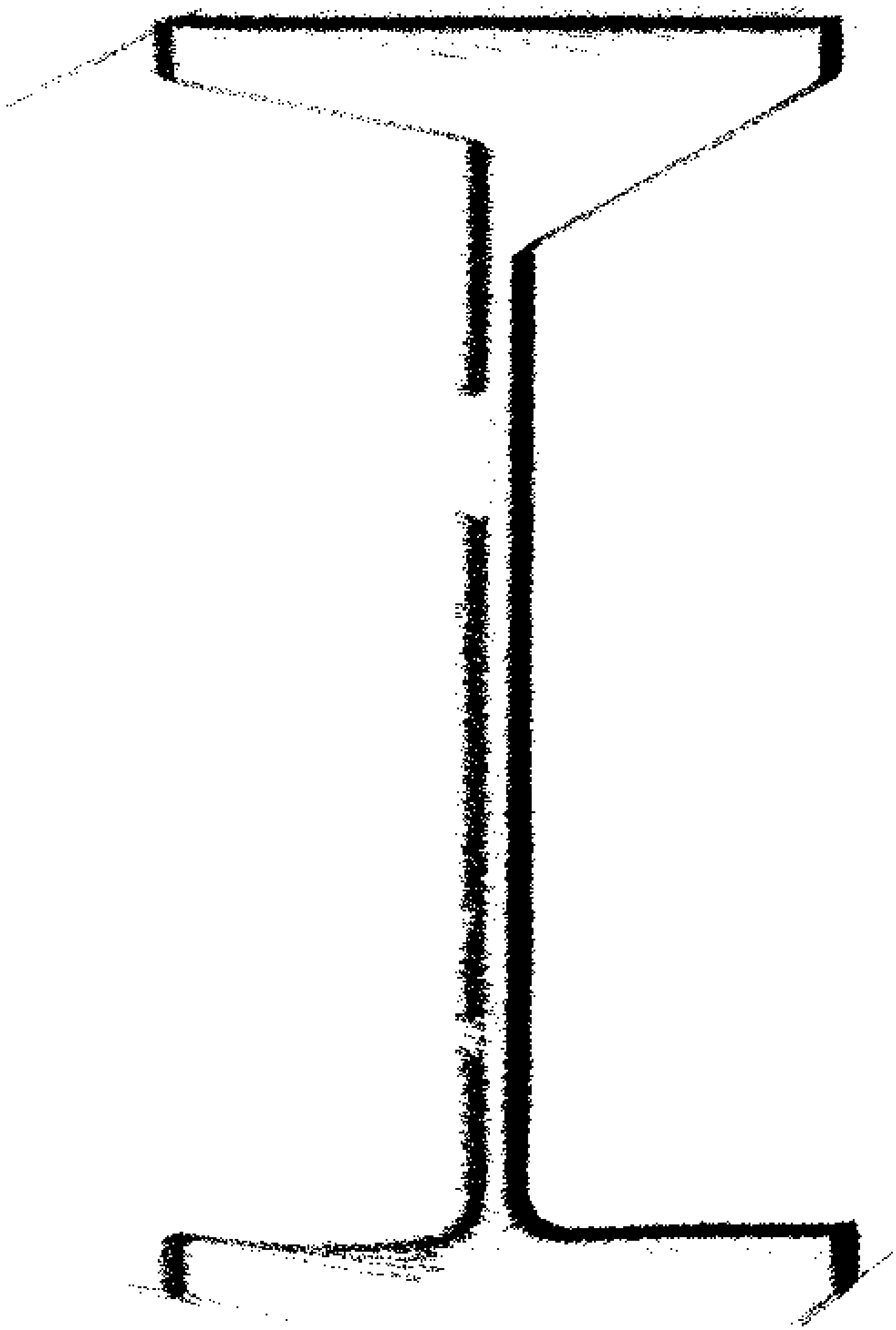

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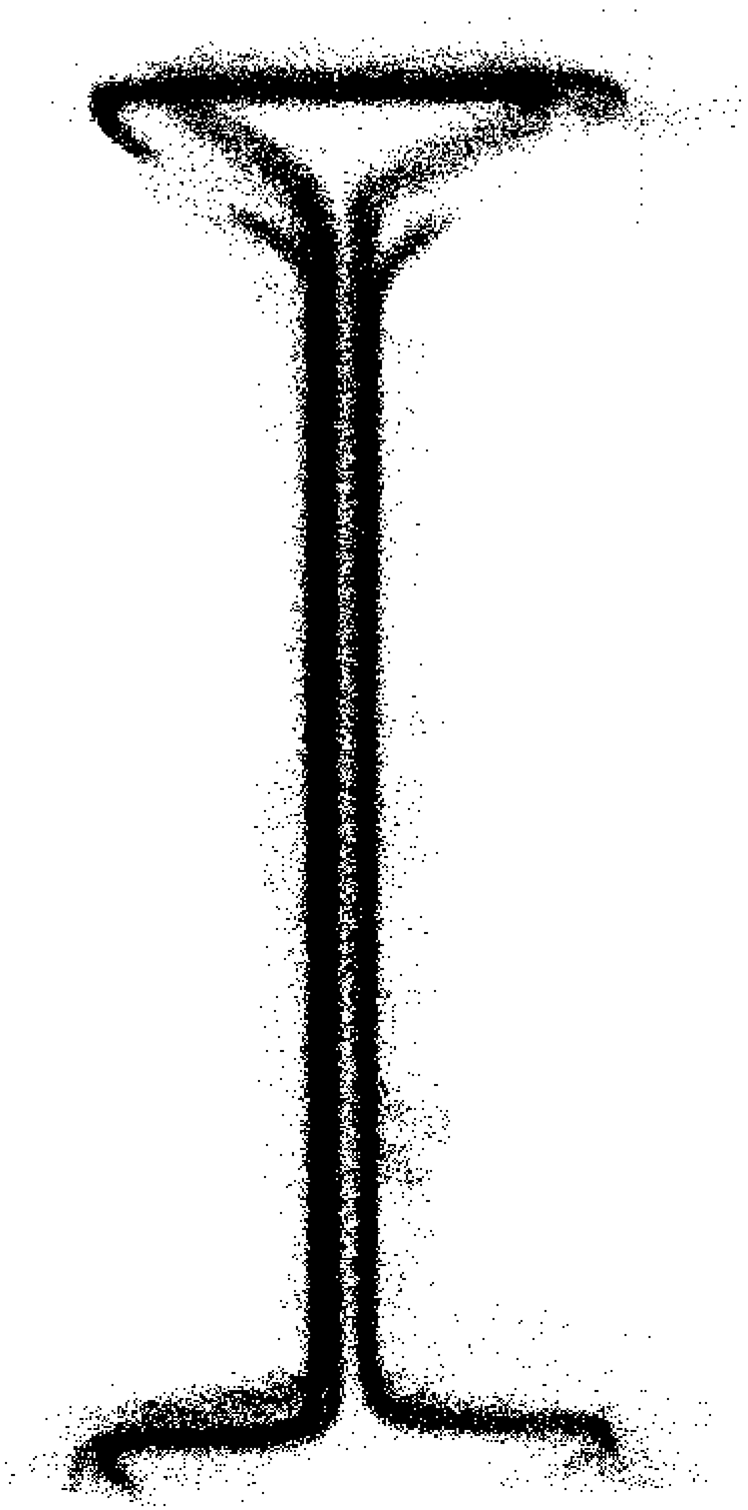

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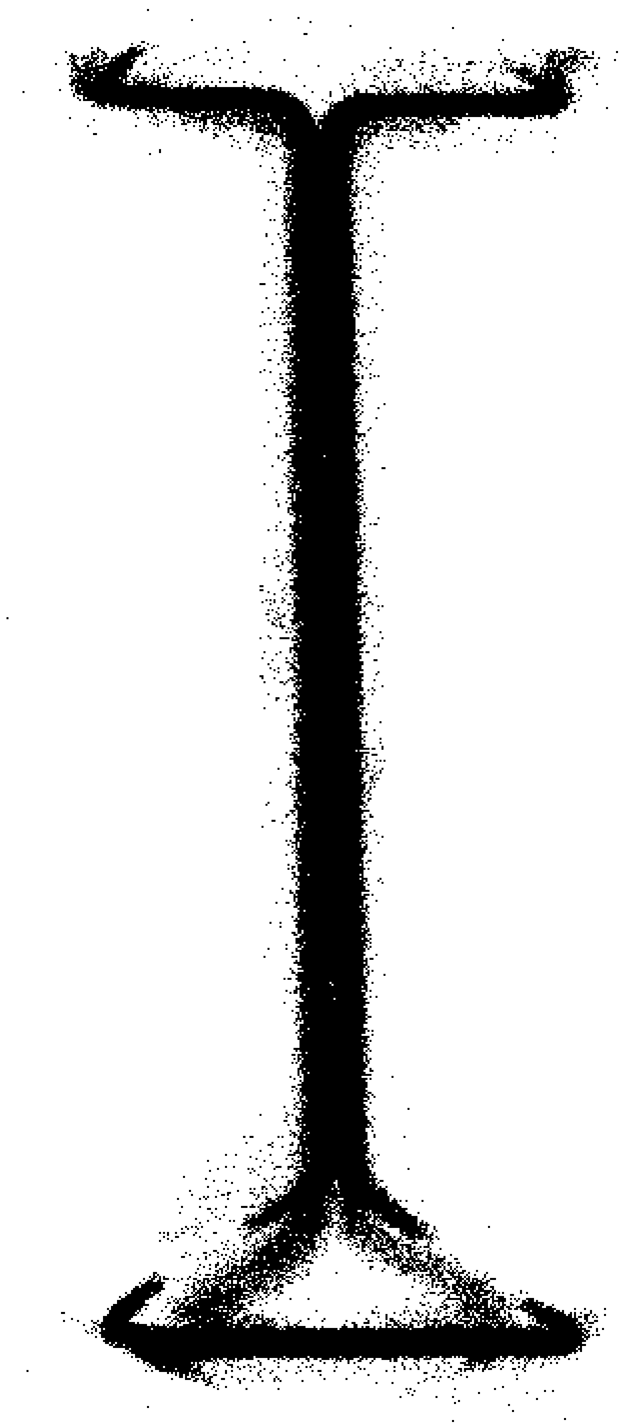

Appendix C

Economic Input-Output Method:

Detailed Calculations

Value of New Steel Produced
$ 1,000,000.00

Average Price of Steel Per kg
3.64 Dollars / kg

Average Construction Value Per kg of Steel
4.93 Dollars / kg

Value of Reused Steel Required to Offset the New Steel
$ 1,354,395.60

EIO-LCA for Current Practices of Steel Production – Conventional Air Pollutants

Sector
#331200: Iron, steel pipe and tube manufacturing from purchased steel

Economic Output
$1,000,000.00

Sub Sector	CO	NH3	NOx	PM10	PM2.5	SO2
	t	t	t	t	t	t
Total for all sectors	10.10	0.06	3.42	0.91	0.52	3.18
Iron and steel mills	6.30	0.02	0.94	0.26	0.21	0.71
Iron, steel pipe and tube manufacturing from purchased steel	1.53	0.01	0.23	0.08	0.06	0.17
Alumina refining and primary aluminum production	0.27	0.00	0.01	0.01	0.01	0.09
Truck transportation	0.27	0.00	0.29	0.08	0.01	0.01
Natural gas distribution	0.20	0.00	0.01	0.00	0.00	0.00
Coal mining	0.14	0.00	0.14	0.03	0.02	0.03
Iron ore mining	0.13	0.00	0.10	0.02	0.01	0.04
Commercial and industrial machinery and equipment rental and leasing	0.10	0.00	0.00	0.00	0.00	0.00
Power generation and supply	0.10	0.00	0.68	0.10	0.08	1.52
Oil and gas extraction	0.09	0.00	0.06	0.00	0.00	0.00
Household goods repair and maintenance	0.08	0.00	0.00	0.00	0.00	0.00
Spring and wire product manufacturing	0.07	0.00	0.05	0.01	0.01	0.02
Primary smelting and refining of nonferrous metal (except copper and aluminum)	0.07	0.00	0.01	0.01	0.00	0.14
Rail transportation	0.05	0.00	0.41	0.01	0.01	0.03
Wholesale trade	0.05	0.00	0.05	0.01	0.00	0.00
Couriers and messengers	0.04	0.00	0.05	0.01	0.00	0.00
Services to buildings and dwellings	0.04	0.00	0.00	0.00	0.00	0.00
Material handling equipment manufacturing	0.03	0.00	0.01	0.00	0.00	0.00
Ferrous metal foundaries	0.03	0.00	0.01	0.02	0.01	0.02
Copper rolling, drawing, extruding and alloying	0.02	0.00	0.01	0.01	0.00	0.02
Paperboard Mills	0.02	0.00	0.01	0.00	0.00	0.02
Lime and gypsum product manufacturing	0.02	0.00	0.02	0.01	0.00	0.01
State and local government passenger transit	0.02	0.00	0.02	0.01	0.00	0.00
Scenic and sightseeing transportation and support activities for transportation	0.02	0.00	0.05	0.00	0.00	0.00
Air transportation	0.02	0.00	0.00	0.00	0.00	0.00

EIO-LCA for Reuse Practices of Steel Production – Conventional Air Pollutants

Sector

#230102: Nonresidential manufacturing structures

Economic Output

$1,354,395.60

Sector	**CO**	**NH3**	**NOx**	**PM10**	**PM2.5**	**SO2**
	t	**t**	**t**	**t**	**t**	**t**
Total for all sectors	13.36	0.03	1.81	1.19	0.41	0.97
Nonresidential manufacturing structures	11.97	0.00	0.91	0.88	0.30	0.05
Commercial and industrial machinery and equipment rental and leasing	0.29	0.00	0.00	0.00	0.00	0.00
~~**Iron and steel mills**~~	~~0.23~~	~~0.00~~	~~0.03~~	~~0.01~~	~~0.01~~	~~0.03~~
Alumina refining and primary aluminum production	0.17	0.00	0.01	0.01	0.00	0.05
Truck transportation	0.12	0.00	0.12	0.04	0.01	0.00
Household goods repair and maintenance	0.10	0.00	0.00	0.00	0.00	0.00
Oil and gas extraction	0.07	0.00	0.05	0.00	0.00	0.00
~~**Cement manufacturing**~~	~~0.06~~	~~0.00~~	~~0.08~~	~~0.01~~	~~0.01~~	~~0.06~~
Natural gas distribution	0.06	0.00	0.00	0.00	0.00	0.00
Fluid power process machinery	0.05	0.00	0.00	0.00	0.00	0.00
Wholesale trade	0.04	0.00	0.04	0.01	0.00	0.00
Material handling equipment manufacturing	0.04	0.00	0.01	0.00	0.00	0.00
~~**Iron, steel pipe and tube manufacturing from purchased steel**~~	~~0.03~~	~~0.00~~	~~0.01~~	~~0.00~~	~~0.00~~	~~0.00~~
Power generation and supply	0.03	0.00	0.24	0.03	0.03	0.52
Couriers and messengers	0.03	0.00	0.03	0.01	0.00	0.00
Services to buildings and dwellings	0.03	0.00	0.00	0.00	0.00	0.00
Clay and non-clay refractory manufacturing	0.02	0.00	0.05	0.02	0.01	0.07
Forest nurseries, forest products, and timber tracts	0.01	0.00	0.01	0.00	0.00	0.00
Coal mining	0.01	0.00	0.01	0.00	0.00	0.00
Petroleum refineries	0.01	0.00	0.02	0.00	0.00	0.03
Synthetic dye and pigment manufacturing	0.01	0.00	0.00	0.00	0.00	0.00
State and local government passenger transit	0.01	0.00	0.01	0.00	0.00	0.00
Commercial machinery repair and maintenance	0.01	0.00	0.00	0.00	0.00	0.00
Air transportation	0.01	0.00	0.00	0.00	0.00	0.00
Paper mills	0.01	0.00	0.01	0.00	0.00	0.01

EIO-LCA for Current Practices of Steel Production – Greenhouse Gases

Sector

#331200: Iron, steel pipe and tube manufacturing from purchased steel

Economic Output

$1,000,000.00

Sector	Total	CO2 Fossil	CO2 Process	CH4	N2O
	t CO2e	t CO2e	t CO2e	t CO2e	t CO2e
Total for all sectors	2030.00	1090.00	803.00	101.00	5.92
Iron and steel mills	1260.00	477.00	780.00	7.70	0.00
Power generation and supply	368.00	362.00	0.00	1.00	2.25
Coal mining	58.20	6.57	0.00	51.60	0.00
Oil and gas extraction	33.90	9.54	6.21	18.10	0.00
Truck transportation	32.80	32.80	0.00	0.00	0.00
Spring and wire product manufacturing	25.10	25.10	0.00	0.00	0.00
Iron, steel pipe and tube manufacturing from purchased steel	20.20	20.20	0.00	0.00	0.00
Iron ore mining	19.10	19.10	0.00	0.00	0.00
Rail transportation	16.60	16.60	0.00	0.00	0.00
Industrial gas manufacturing	15.90	1.84	0.00	0.00	0.00
Petroleum refineries	14.50	14.40	0.00	0.05	0.00
Lime and gypsum product manufacturing	13.00	4.85	8.20	0.00	0.00
Pipeline transportation	11.80	5.41	0.02	6.40	0.00
Primary smelting and refining of nonferrous metal (except copper and aluminum)	10.10	1.72	2.45	0.00	0.00
Alumina refining and primary aluminum production	10.10	2.28	3.57	0.00	0.00
Waste management and remediation services	8.96	0.33	0.00	8.54	0.10
Natural gas distribution	6.64	0.60	0.00	6.04	0.00
Other basic organic chemical manufacturing	6.33	5.68	0.00	0.00	0.65
Air transportation	5.85	5.85	0.00	0.00	0.00
Plastics material and resin manufacturing	4.01	4.01	0.00	0.00	0.00
Ferrous metal foundaries	3.83	3.83	0.00	0.00	0.00
Couriers and messengers	3.77	3.77	0.00	0.00	0.00
Paperboard Mills	3.76	3.76	0.00	0.00	0.00
Nonresidential maintenance and repair	3.36	3.36	0.00	0.00	0.00
Water transportation	3.35	3.35	0.00	0.00	0.00

<u>EIO-LCA for Reuse Practices of Steel Production – Greenhouse Gases</u>

Sector

#230102: Nonresidential manufacturing structures

Economic Output

$1,354,395.60

Sector	Total	CO2 Fossil	CO2 Process	CH4	N2O
	t CO2e	t CO2e	t CO2e	t CO2e	t CO2e
Total for all sectors	515.48	456.21	12.87	34.93	5.59
Nonresidential manufacturing structures	200.45	200.45	0.00	0.00	0.00
Power generation and supply	126.64	124.60	0.00	0.34	0.77
~~**Iron and steel mills**~~	~~46.32~~	~~17.47~~	~~28.58~~	~~0.28~~	~~0.00~~
~~**Cement manufacturing**~~	~~30.07~~	~~12.54~~	~~17.47~~	~~0.00~~	~~0.00~~
Oil and gas extraction	28.85	8.13	5.28	15.44	0.00
Petroleum refineries	20.59	20.45	0.00	0.06	0.00
Truck transportation	14.09	14.09	0.00	0.00	0.00
Waste management and remediation services	8.14	0.30	0.00	7.76	0.09
Clay and non-clay refractory manufacturing	7.04	7.04	0.00	0.00	0.00
Alumina refining and primary aluminum production	6.19	1.41	2.19	0.00	0.00
Coal mining	6.08	0.69	0.00	5.39	0.00
Fertilizer Manufacturing	5.53	1.37	1.86	0.00	2.30
Pipeline transportation	5.47	2.51	0.01	2.97	0.00
Other basic organic chemical manufacturing	4.81	4.31	0.00	0.00	0.49
Air transportation	4.69	4.69	0.00	0.00	0.00
Lime and gypsum product manufacturing	3.63	1.35	2.28	0.00	0.00
Plastics material and resin manufacturing	3.39	3.39	0.00	0.00	0.00
Rail transportation	2.94	2.94	0.00	0.00	0.00
Petrochemical manufacturing	2.76	2.30	0.32	0.13	0.00
Wholesale trade	2.67	2.67	0.00	0.00	0.00
Couriers and messengers	2.57	2.57	0.00	0.00	0.00
Paperboard Mills	2.41	2.41	0.00	0.00	0.00
Lighting fixture manufacturing	2.28	2.28	0.00	0.00	0.00
Paper mills	2.13	2.13	0.00	0.00	0.00
Industrial gas manufacturing	1.92	0.22	0.00	0.00	0.00

EIO-LCA for Current Practices of Steel Production – Water Withdrawals

Sector

#331200: Iron, steel pipe and tube manufacturing from purchased steel

Economic Output

$1,000,000.00

Sector	Water Withdrawals kGal
Total for all sectors	14700.00
Power generation and supply	10500.00
Iron and steel mills	1840.00
Iron ore mining	499.00
Grain farming	350.00
Paint and coating manufacturing	204.00
Gold, silver, and other metal ore mining	157.00
Paperboard Mills	135.00
Cotton farming	112.00
Spring and wire product manufacturing	108.00
Copper, nickel, lead, and zinc mining	108.00
Iron, steel pipe and tube manufacturing from purchased steel	100.00
Industrial gas manufacturing	80.50
Sand, gravel, clay, and refractory mining	65.60
Other basic organic chemical manufacturing	43.80
Stone mining and quarrying	35.40
Secondary smelting and alloying of aluminum	31.40
All other basic inorganic chemical manufacturing	26.30
All other crop farming	24.10
Sugarcane and sugar beet farming	22.00
Alkalies and chlorine manufacturing	21.20
Paper mills	14.70
Other state and local government enterprises	14.00
Synthetic dye and pigment manufacturing	13.80
Adhesive manufacturing	11.40
Petrochemical manufacturing	10.20

<u>EIO-LCA for Reuse Practices of Steel Production – Greenhouse Gases</u>

Sector

#230102: Nonresidential manufacturing structures

Economic Output

$1,354,395.60

Sector	Water Withdrawals kGal
Total for all sectors	5174.06
Power generation and supply	3602.69
Paint and coating manufacturing	457.79
Grain farming	279.01
Nonresidential manufacturing structures	127.72
Paperboard Mills	86.14
Sand, gravel, clay, and refractory mining	77.61
~~**Iron and steel mills**~~	~~67.45~~
Cotton farming	60.68
Stone mining and quarrying	38.87
Other basic organic chemical manufacturing	33.32
All other crop farming	28.31
Synthetic dye and pigment manufacturing	26.95
Gold, silver, and other metal ore mining	19.77
Secondary smelting and alloying of aluminum	18.83
Iron ore mining	18.56
Paper mills	15.58
All other basic inorganic chemical manufacturing	15.03
Copper, nickel, lead, and zinc mining	14.76
Petroleum refineries	13.50
Fertilizer Manufacturing	9.98
Industrial gas manufacturing	9.77
Real estate	9.74
Petrochemical manufacturing	9.13
Adhesive manufacturing	9.10
Fruit farming	8.63