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Carbon Estimation and Decision Making in USAF Acquisition

Robert F. Gray

CARBON ESTIMATING AND DECISION MAKING IN ACQUISITIONS

THESIS

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Abstract

Recent executive orders and international agreements require the United States to significantly reduce its carbon and greenhouse gas emissions. The DoD is a significant contributor to the carbon emissions of the USA and will be required to reduce the emissions. Therefore, to make appropriate programmatic decisions, the DoD needs to develop an appropriate method for estimating carbon and making programmatic decisions; trading-off carbon emissions with the traditional cost-schedule-performance metrics. This thesis examines the possibility of developing a model that can estimate the carbon footprint of producing a system before detailed engineering designs have been complete. Furthermore, it examines the viability of using such an estimate in the decision-making process. While the model produced requires refinement before being used to inform quantitative and objective decisions. The output of the EIO model can certainly be used to increase awareness of the negative impacts and external costs caused by carbon emissions in acquisitions.

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Robert F. Gray

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CARBON ESTIMATING IN USAF ACQUISITIONS

I. Introduction

Background

Scientific support for anthropogenic climate change has continued to build for several decades, and the general population is increasingly aware of climate change. The body of evidence to support the notion that humans have released enough Carbon Dioxide and other Green House Gases to alter the natural climate cycle is overwhelming. In fact, according to the 2021 Intergovernmental Panel on Climate Changes 6th report "It is unequivocal that human influence has warmed the atmosphere, ocean and land. Widespread and rapid changes in the atmosphere, ocean, cryosphere, and biosphere have occurred" (Intergovernmental Panel on Climate Change, 2021). Altering the climate cycle is a grave concern because for the last 12,000 years the earth has experienced unparalleled stability of temperature and climate, known as the Holocene, which enabled the development of agriculture and human civilization. Evidence continues to grow to suggest that due to human causes the Holocene is likely to end long before its natural time. The human impact on the stability of the Holocene is so pronounced that several climate scientists are suggesting that the earth has entered a new epoch; the Anthropocene (Steffen, et al., 2018). The Anthropocene is the name given to the period, in which, humans have affected the climate of the Earth. The term is widely used but not yet officially recognized as a new era. Furthermore, the exact start of the Anthropocene is in debate; some argue that it began with the agricultural revolution while others suggest the industrial revolution.

Due to changes in the climate, there will likely be increased conflict around the world. Currently, societies have developed in a relatively stable climate. Cities and countries have borders that enable the population access to food and water. As climate changes, certain areas will flood, destroying farmland. Other areas will see increased heat and decreased rainfall. This will cause food and water scarcity in many areas and will drive national and regional conflicts. Millions of the worlds poorest will become refugees as they flee famine and war. Some may turn to terrorism as their only option. This will put a greater burden on rich countries, America in particular, to assist. However, America will likely be struggling to cope with increased drought and extreme heat. Nationally, the number of days above 90F, 100F, and 105F is set to increase from 41, 14, and 5 to 61, 36, and 24 by midcentury if no action is taken, this is highlighted in figure 1 (Dahl, et al., 2019). In other words, climate change is a threat multiplier that the DoD needs to address (Causevic, 2017). Even in developed countries, there is likely to be increased scarcity as droughts affect crop yields. There is potential that increased scarcity will cause civil unrest and weaken the global influence of many developed countries.

The impact of changes in weather patterns affects more than just the day-to-day, month-to-month, and year-to-year averages. Studies have shown that extreme weather events are increasing. According to the United Nations, there were 4,212 climate-related disasters between 1980 and 1999, and 7,348 climate disasters between 2000 and 2019 (UN Office for Disaster Risk Reduction, 2020). This puts facilities and infrastructure at risk. In 2018 hurricane Michael destroyed Tyndall Air Force Base in Florida, costing the Air Force $5 Billion, not to mention the additional $20 Billion of non-Government-

owned damages. The intensity and frequency of extreme weather events and climate change in general are national security concerns that require further study.

In 2021, President Joe Biden signed several Executive Orders that focused on climate change. The Executive orders “put the climate crisis at the center of United States Foreign Policy and National Security” (Biden J. , Tackling the Climate Crisis at Home and Abroad, 2021). The United States re-entered the Paris Climate Accord which aims to limit the global temperature increase to 1.5C above pre-industrial levels (Paris Agreement, 2015). To achieve this target; the United States, as a country, must achieve a goal of becoming carbon net-zero by 2050 (The White House, 2021). Furthermore, the SecDef was directed to consider the impacts of climate change on security operations and the potential impacts on the environment of any and all military decisions. SecDef Lloyd Austin subsequently issued direction to the services that they must “elevate climate as a national security priority, integrating climate considerations into the Department's policies, strategies, and partner engagements” (Austin, 2021). Finally, climate change is emphasized in the Interim National Security Strategy. In which, climate change is considered a top-tier threat along with near-peer competition and terrorism; America’s leadership in tackling the climate crisis is a key tenet of the interim strategy (Biden J. R., 2021).

The DoD is the world’s single largest emitter of CO_2 and if it were a country, it would be the 29th largest emitter. The Union of Concerned Scientists estimate that each year the armed forces of the United States consume more than 100 million barrels of oil to power ships, vehicles, aircraft, and ground operations (Union of Concerned Scientists, 2014). If the USA is to reach net-zero carbon/GHG emissions by 2050 the DoD must

contribute to the effort. While the majority of the DoDs carbon emissions will be direct emissions from operations, there will be some amount of carbon emissions from support activities such as construction, maintenance, development, and acquisitions. The focus of this thesis is on how to best estimate the carbon emissions of potential production programs, early in the planning stages before detailed designs are available. Being able to better quantify the carbon emissions early will facilitate decision making that considers the costs, schedule, performance, and climate impacts of a potential program.

Problem Statement

The DoD and the Air Force will need to consider the impact of carbon emissions in future decisions. Currently, in acquisitions decision-making processes carbon emissions are not considered, though environmental impact statements do attempt to capture the potential impacts of programs. The acquisitions community needs a method to estimate and account for the negative externalities caused by climate change and carbon emissions when making programmatic decisions.

Research Objectives/Questions/Hypotheses

The primary objective of this research is to develop a model that can be used to estimate the carbon emissions of an acquisitions product or weapons system in the early stages of development. This model could aid decision-makers to account for the negative externalities caused by greenhouse gas emissions when making programmatic decisions.

A secondary objective is to develop a decision-making framework that can utilize the output from the previous model in order to balance the need to reduce carbon emissions with other programmatic objectives.

The third objective of this research is to establish an acquisition-to-operations carbon emissions ratio. This will help the community to determine where there is potential to reduce carbon emissions in the weapon system lifecycle.

Investigative Questions.

What are the existing frameworks?

When is carbon emitted during the acquisitions process?

What elements can be adjusted to change the carbon emissions?

Can current cost estimation techniques provide a proxy for carbon estimation?

Methodology

This thesis will construct an architectural model that maps the acquisitions (production) process and identify when and where carbon is emitted. The rate of emission will be quantified, and proxies will be identified. This will enable the building of a mathematical model that can be used to estimate carbon emissions of a potential program. Furthermore, this thesis will examine how to incorporate the estimated carbon emissions into acquisitions decision making via the use of multi-objective value functions.

Assumptions/Limitations

There are well-established methods for estimating carbon emissions. However, it generally requires a large team of experts to have unfettered access to an organization to accurately assess its carbon emissions. Access is required because the team needs to be able to analyze all materials and processes to accurately capture the carbon emissions. There is currently a lack of data available to accurately model the full climate impact of acquiring and operating a weapons system.

Implications or Expected Contributions

This thesis will result in the development of a useable mathematical model that can be utilized by both leadership and Integrated Product Teams in Air Force Acquisitions to aid in decision making by enabling them to consider carbon impacts when making programmatic trade-offs between cost-schedule-performance and other factors such as carbon and greenhouse gas emissions.

Preview

The next chapter (two) is the literature review and examines the cost of carbon, how to account for carbon, accounting for carbon in aviation and DoD, model building, and decision making. Chapter 3 is the method. It will describe the unique research that will be undertaken; specifically, the guidelines for building the estimate and decision models. Chapter 4 is the results and discussion. This chapter will go into more detail about the models and discuss the results and implications. Chapter 6 is the conclusion where the results will be discussed further and future recommendations for action and research are recommended.

II. Literature Review

Chapter Overview

The purpose of this chapter is to summarize a sample of the current literature regarding reasons and methods for estimating and accounting for carbon emissions in support of decision-making. The chapter will begin by analyzing literature regarding the cost of carbon, including the expected cost of externalities. Next, it will explore how to account for and estimate carbon emissions. Third, this chapter will explore literature specifically addressing the DoD carbon emissions before examining literature specific to the aviation sector. Forth, this chapter will explore techniques for building models and architecture. The chapter will conclude by reviewing decision-making techniques and how to incorporate carbon emissions into military and government decision-making.

The Cost of Carbon

Social Cost of Carbon

In January 2021, President Joseph Biden signed Executive Order 13990 which established an Interagency Working Group (IWG) on the Social Cost of Greenhouse Gases (Biden J. , Protecting Public Health and the Environment and Restoring Science to Tackle the Climate Crisis, 2021). The Executive Order tasks the IWG with determining appropriate monetized values of the Social Cost of Carbon (SCC), Social Cost of Nitrous Oxide (SCN), and the Social Cost of Methane (SCM). These social costs are to include all negative externalities caused by the release of greenhouse gases. The IWG was directed to provide an interim recommendation within 30 days and a final recommendation by January 2022.

The interim report, published in February 2021, highlighted several knowledge gaps in the current estimates of SCC, SCN, and SCM. First, previous calculations utilized three Integrated Assessment Models (IAM) which utilized the best available data at the time. Since then, the models have had significant updates and the current government estimates do not reflect the best available science. Second, the IWG believes that the use of the social rate of return on capital to discount the future benefits of reducing GHG emissions does not adequately account for the impacts of climate change (Interagency Working Group on Social Cost of Greenhouse Gases, 2021). A larger discount weight emphasizes expected costs in the near term and deemphasizes costs further in the future. Though they have not yet determined a more appropriate discounting method. Despite the limitations of the current knowledge, the IWG recommends re-instating the 2016 estimates using a 3% discount rate until a more robust model can be developed and published in February 2022. Under this guidance the SCC is $51, SCN is $18,000 and SCM is $1,500 per Metric Ton emitted in 2020 and SCC is $56, SCN is $21,000 and SCM is $1,700 per Metric Ton emitted in 2025 (Interagency Working Group on Social Cost of Greenhouse Gases, 2021). The large differences in social cost are because Nitrous Oxide and Methane have a pound-for-pound greater impact on the climate. They have a stronger greenhouse effect but do not remain in the atmosphere for as long as carbon. While other greenhouse gasses have stronger effects, carbon emissions account for the bulk of GHG emissions so have a larger overall impact (NASA, 2021).

The technical report did not mention if the IWG intended to use new IAMs or modify the existing IAMs, though it did recommend using a single model versus three. Furthermore, the IAMs utilized to calculate the SCC in 2016 have some criticism. The

IAMs DICE, FUND, and PAGE are simple IAMs that can calculate the costs and benefits of avoiding certain levels of global warming. However, they do not model the detailed processes, relationships and interactions between the economy, energy, and Earth systems (Evans & Hausfather, 2018). Essentially, the models provide regionalized predictions of social and economic costs based on the expected effects of certain levels of global warming. While they are widely used in calculations of the SCC, they may be oversimplified to adequately assess the true costs of carbon. In fact, Metcalf and Stock (2017) suggest that the simplicity and uncertainty in the three simple IAMs mean that alternate models should be explored. They conclude that for the SCC to be credible it needs to be computed using numerical measures and advanced computer models that include both climate and economic considerations (Metcalf & Stock, 2017). They also suggest that this cannot be based off of IAMs, however, it seems they mean the simple IAMs.

Criticism of SCC and IAMs

In contrast to Metcalf and Stock, Bijgaart et al. argue that even the simple IAMs lack transparency and are a black box (Bijgaart, Gerlagh, & Liski, A Simple Formula for the Social Cost of Carbon, 2016). While they maintain the fidelity of IAMs, they believe that IAMs are inaccessible to policymakers. They propose several mathematical equations using only a handful of inputs including population, discount rate, temperature rise, and others to emulate the SCC that the IAM would predict. The model they developed successfully mimicked the three simple IAMs. However, the authors acknowledge the limitation that it relies heavily on assumptions and “does not present an analysis of policymaking under uncertainty” (Bijgaart, Gerlagh, & Liski, A Simple

Formula for the Social Cost of Carbon, 2016). While the model inputs are fairly quantifiable the resulting predicted SCC is uncertain. This presents a challenge as it creates uncertainty when trying to predict the outcomes of policy choices. Their approach is interesting however, in practice they simply replicated the results of the existing IAMs without reducing the uncertainty. Furthermore, the model is not robust to uncertainty which limits its usefulness in decision making and policy development.

In addition to the challenges of calculating the SCC, there are often barriers to the implementation of the SCC. While the current administration has signaled a commitment to the use of SCC when assessing the cost and benefits of Government policy and action, it is not universally accepted. In fact, in several court cases the judges have failed to enforce the use of SCC by federal agencies in calculating the cost-benefit analysis: creating the CO_2 monetization gap and suboptimal decision making in federal programs (Raduazo, 2018). Often the reasoning involves malleability of the calculations of SCC. For this reason, the Institute for Energy Research believes that the use of SCC in federal decision-making is totally inappropriate and that the practice should be abandoned (Institute for Energy Research, 2014). While they provide valid concerns regarding the use of SCC, they fail to propose an alternative method for assessing the impact on the environment caused by Government actions. Other scholars believe that SCC and the IAMs used to compute them are useful tools but need upgrades. The current models assume a baseline of the 2012 US economy for the entire world and fail to account for subjective preferences such as risk aversion and views towards social equality (Pizer, 2017).

Uses of SCC

Despite some significant flaws in the current estimation of SCC, there is no apparent alternative measure readily available to replace it, though the market rate for carbon may be useful in the private sector. Furthermore, while there is lively debate regarding the exact methods of calculation, there is generally a consensus that SCC can be calculated by the following four steps: projecting the future impact on the climate of a marginal ton of CO_2 using an IAM, identifying the physical consequences of the altered climate on the economy, assess those impacts into monetary terms, and compute the present value of the monetary value of damages (Fleurbaey, et al., 2019). Having an estimate of SCC allows the Government to take action in the form of Pigouvian taxes that force the consumer or producer to pay the monetary cost of the negative externalities (Ploeg, 2016). This is particularly useful because individuals and organizations often fail to consider the long-term implications of choices and actions, or over-value short-term gains; this is known as Hyperbolic Discounting (Haith, Reppert, & Shadmehr, 2012). However, any Pigouvian tax would likely need to be set lower than the actual SCC and have immediate impacts on the taxpayer. Tiezzi and Xiao (2016) found that due to a lack of understanding of the complexities of the climate and a lack of immediate impact results in frustration towards the Pigouvian tax (Tiezzi & Xiao, 2016).

While there is a case for Pigouvian taxes to account for negative externalities of carbon emissions, it may not be the optimal solution when viewed through a wider lens. A 2016 study found that individual provinces in Canada avoid the Pigouvian tax by shifting the production to areas without the tax. They can reduce their tax burden by 20% while not impacting the welfare of the local population (Bohringer, Rivers, & Yonezawa,

2016). This is further corroborated by real-life examples. It has been observed that some developed countries transfer high-polluting industries and processes to developing countries (Hongxia, Zhe, & Kerong, 2018). This suggests that taxation alone would simply shift the emissions to other areas and not result in a countrywide or global reduction in CO_2. Therefore, any tax on emissions should be accompanied by investment in green innovation (Bijgaart, The Unilateral Implementation of Sustainable a Growth Path With Directed Technical Change, 2017). This would require carbon tax revenue to be used to fund activities that reduce the emissions of the country or region. According to Bijgaart (2017), this will lead to increased green innovation both within the boundaries and in external territories. This conclusion is supported by a model built by David Hemous but only when there is physical proximity that facilitates spill-over (Hemous, 2016). While Bijgaart is confident that investment in green innovation would result in additional investment by other entities, it is worth noting that his model only involved two fictitious countries. This is an oversimplification according to the research by Soest et al. (2016), who concluded in their research that models involving only two or three actors were too simplistic to base policy decisions on (Soest, Stoop, & Vyrastekova, 2016).

While Governments can levy taxes based on SCC to increase the cost of goods that emit carbon, the SCC can also be used to determine the true value of a project. Aldy et al. (2021) argue that while the models used to calculate SCC need updating, they are still a useful tool. In fact, SCC is the basis of zero-emission credits (Aldy, Kotchen, Stavins, & Stock, 2021). Which reduces the cost of clean programs by providing tax credits equal to the SCC multiplied by the expected reduction in carbon emissions. This

type of proactive policy would not be possible without a standardized metric that accounts for the effects of carbon and other greenhouse gasses (GHG) on the climate. Some researchers prefer to measure the impacts using a non-monetized metric known as Global Warming Potential (GWP). GWP calculates how much the expected emissions would theoretically increase, or decrease, the temperature on the earth; without regard to the potential economic impact of that warming (DeVynne, et al., 2016). This is certainly useful for calculating the effects of potential emissions, however, has limited use in decision making. Ultimately, carbon emissions cause warming, which causes changes to weather patterns that cause billions of dollars in additional costs worldwide (Schuldt, Nicholson, Adams, & Delorit, 2021).

SCC – Summary

The methods for computing the Social Cost of Carbon and other greenhouse gasses are far from perfect. The models rely on several assumptions that can generate a wide range of results. Some assumptions are within the IAMs that determine the extent of future impacts; with each IAM producing differing regionalized impacts. Furthermore, there are assumptions about the appropriate discount rate which impact the resulting SCC. Therefore, there is ample room for debate on the appropriate rate for SCC. However, presently no metric is a viable alternative to SCC that will allow decision-makers to quantify the effects of Green House Gas emissions in a manner that properly accounts for the negative externalities. The SCC will evolve and change over time and will increase or decrease as the models are refined and as a result of the amount of carbon in the atmosphere. However, in order to apply the SCC in a meaningful way, there must be an accurate estimation or accounting of potential and realized carbon emissions. One

of the aims of this research is to determine how to best utilize the Social Cost of Carbon as a decision-making tool in Air Force acquisitions.

Carbon Estimation

Carbon Footprint Background

Perhaps the most well-known term for examining carbon emissions is the concept of carbon footprint, which evolved during the 1990s out of the concept of ecological footprint. The ecological footprint is a method for measuring the consumption of resources, for example, water, while carbon footprint is a measure of the emission of carbon (Selin, 2020). However, despite carbon footprint being a widely used term, it is surprisingly ill-defined in academic terms. Depending on the specific study, the system boundary changes. Sometimes, the carbon footprint is concerned with only direct emissions. Other times, it is concerned with the direct and indirect emissions. This is likely because carbon footprint appears to be a term that began in marketing and policymaking versus academia. Even then, Wiedmann and Minx (2008) found eight separate definitions of carbon footprint in the grey literature. Grey literature is professionally researched reports from outside academia such as government agencies, corporations, non-profits, and lobbyists. They would go on to propose an overarching definition of Carbon Footprint: “The Carbon Footprint is a measure of the exclusive total amount of carbon dioxide emissions that are directly and indirectly caused by an activity that is accumulated over the life stages of a product” (Wiedmann & Minx, 2008). This definition is useful but is product-centric. However, it is also important to understand the emissions of organizations, individuals, and countries.

Lifecycle Assessment (LCA)

The Wiedmann and Minx definition of carbon footprint is a useful starting point though seems to describe a product-focused lifecycle assessment (LCA). In fact, Carbon Footprint is essentially a truncated and simplified LCA. An LCA involves a cradle to grave analysis of a product and documentation of GHG emissions of each stage (Pandey, Pandey, & Agrawal, 2011). Pandey et al. (2011) discuss two methods for performing an LCA: bottom-up and top-down. The bottom-up method involves examining processes and quantifying emissions based on each process. The top-down method involves using an economic input-output (EIO) model that accounts for all inputs and outputs within a boundary. The bottom-up method is useful when examining smaller entities and products and the top-down method is prefeed when measuring an entire economic region or country as it avoids the issue of double-counting (Pandey, Pandey, & Agrawal, 2011). However, when estimating carbon emissions for a country or zone there is still debate about the best practice; some argue in favor of production-based and others are in favor of consumption-based (Hasegwa, Kagawa, & Tsukui, 2015). If a product is manufactured in Germany and exported to France, then under production-based analysis the carbon emissions are allocated to Germany; under a consumption-based model, the emissions are allocated to France. Some argue that the production-based method leads to undercounting as emissions from the transportation and production of imported goods are ignored. For example, since 2017 the United Kingdom has produced 10% of its electricity through the burning of biomass; much of which is imported from the USA and Canada (Office for National Statistics, 2019). Using production-based accounting the United Kingdom is only considered responsible for the direct carbon emissions from the burning of biomass

and not the production or transportation. This allows the UK to claim a significant reduction in carbon emissions.

Hasegwa et al. (2015) discussed the methods for calculating carbon emissions for an entity such as a country. Meanwhile, Gao et al. (2015) discuss the methods for determining the carbon footprint of organizations and products. When assessing an organization, a boundary is drawn around the organization and the activities of each department are analyzed and summed to determine the organizational Carbon Footprint (Gao, Liu, & Wang, 2014). When assessing inputs such as raw materials and energy consumption are quantified at each stage of the product lifecycle. This includes tracing subcomponents and raw materials through supplier channels. The sum total is the Product Carbon Footprint of the product (Gao, Liu, & Wang, 2014). While it might seem tempting that an organizational or national carbon footprint would be the sum of the product Carbon Footprints this would not be the case as a product Carbon Footprint includes the emissions that would be attributed to separate organizations when conducting an organizational assessment.

Cordero (2013) further discusses the methods for calculating Carbon Footprint at the country, organization, and product level. Generally, carbon or GHG emissions are divided into three categories: Scope 1, Scope 2, and Scope 3. Scope 1 refers to direct emissions such as the on-site burning of hydrocarbons. Scope 2 refers to indirect emissions such as the emissions caused by electricity consumption, when the energy is not created through the on-site burning of fuel. Scope 3 refers to other indirect emissions both upstream and downstream of the product or activity being assessed. Scope 3 is the most difficult to calculate however accounts for approximately 75% of emissions for the

vast majority of businesses (Cordero, 2013). However, industries and projects vary greatly. A study that compared the impacts of the construction and use of road versus railway to move freight found that road construction emits 18 tons of Carbon Dioxide Equivalent per Kilometer (tCO_2e/km) meanwhile, rail construction emits 35 tCO_2e/km (Dimoula, Kehagia, & Tsakalidis, 2016). Meaning that the construction of railway emits almost double the CO_2. However, when examining the operations phase it was found that moving freight by road emitted 380 $grCO_2/tkm$ compared to 17 $grCO_2/tkm$ when transported by rail (Dimoula, Kehagia, & Tsakalidis, 2016). $grCO_2/tkm$ is the annualized grams of carbon emission per ton-kilometer. This means that once operational moving freight by rail is over twenty-two times more efficient from a carbon emissions perspective.

Standards and Protocols

There are several different protocols available to assist in the performance of product, organization, and country Carbon Footprint or LCA. The most common standard is ISO-14067 *Greenhouse Gases – Carbon Footprint of Products – Requirements and Guidelines for Quantification* which is advantageous because it standardizes transparency and methods of communication to ensure the ability to compare apples for apples (Wu, Xia, & Wang, 2015). Another important standard in ISO-14067 is that it does not allow for carbon offsets to be included in the LCA; again, this allows for greater consistency of qualification (International Organization for Standardization, 2018). Carbon Offsets are when an organization purchases a carbon sink, which pulls carbon out of the atmosphere. Examples of carbon offsets include funding for tree planting or investing in renewable energy. ISO recognizes the importance of carbon offsets but does not allow them to be

considered as they can obfuscate the true carbon emissions if they are included. While ISO-14067 provides insight into standardizing aspects of the qualification and communication of an LCA it does not give a detailed guide on how to perform an LCA. This means that the exact methods to quantify Scope 1, 2, and 3 emissions are sometimes inconsistent. For example, often Scope 2 emissions are derived from electricity usage at the site level; other times it is measured by proxy, using the heat fields of individual machines to determine the electricity usage at specific stages of the manufacturing process (Lu, Zhou, & Xiao, 2017).

The issue of standardizing the allocation process has yet to be solved. Likely, no single standard will be applicable across industries and in some cases may not be worth the effort. Even a relatively simple production process, such as T-shirts, involves at least ten processes (Li, Chen, & Ding, 2019) as such, it might be overkilled to determine the Carbon Footprint of each stage. However, Li, Chen and Ding (2019) did gain valuable insight by conducting their analysis. They discovered that around 77% of the carbon emissions were allocated to the processes of ironing and sewing. Meaning efforts to reduce carbon emissions should be focused on these activities. While the impact of Carbon Emissions from a single T-shirt may seem trivial, examining processes in complex systems to reduce emissions is valuable. Especially, when similar products or organizations can be compared. Additionally, high-volume production may be non-trivial. A study found that the US healthcare sector accounted for 8% of the nation's GHG emissions while the NHS only accounted for 3% of the UK's GHG emissions (Chung & Melzer, 2009). While this can be partially explained by the larger size of the US healthcare sector compared to GDP; 4.04% in the USA versus 2.3% in the UK

(Keane, McCormick, & Poplawska, 2020) it is clear that there are other factors causing the increase in carbon emissions. Furthermore, many assessments are conducted as a snapshot in time meaning they fail to account for changes over time and the impact of economic factors such as price variance. This means that the uncertainty in many assessments is high and likely an overestimation of the Carbon Footprint as often the variance is skewed right and single point estimates are artificially high (Jakobs, Schulle, & Pauliuk, 2021).

Other Considerations

Much of the focus of Carbon Footprint and LCA tends to focus on the operational phase. However, it is important to consider the end-of-lifecycle impacts. While currently there are significant gaps in the research regarding Carbon Footprints and LCA concerning the end-of-life phase, research and interest has been increasing. A review of 61 waste electrical and electronic equipment (WEEE) studies found that there was significantly more research in applying LCA methods in WEEE management; particularly in the areas of strategy and systems (Ismail & Hanafiah, 2019). This is an important area to study as assumptions about the end-of-life treatment have a significant impact on product and organizational LCAs. A 2018 study using material flow analysis found that regions with higher ratios of reuse and recycling were able to lower their Carbon Footprints, though different methods of calculation yielded varying results (Ibanescu, Cailean, Teodosiu, & Fiore, 2018).

While the previous study suggests that reuse and recycling result in lower Carbon Footprints, this is only true at the macro level. A study by Boldoczki, Thorenz, and Tuma (2019) found that in many cases, particularly with electronics, new devices were often

more efficient which offsets the potential production Carbon Footprint reduction by reuse or recycling (Boldoczki, Thorenz, & Tuma, 2020). Another study by Iraldo, Facheris and Nucci (2017) found that products with increased durability, a proxy for longer life, had minimal impact on their overall Carbon Footprint because the replacement models yielded greater efficiency. However, the durable product yielded greater economic value unless the cost-of-energy was artificially raised (Iraldo, Facheris, & Nucci, 2017). This suggests that policy regarding how to treat products at the end of life should not be overly prescriptive and allow tailored approaches based on the specific product. However, it is still important to have specific targets as another study found that increasing the recycling rate from 60% to 80.5% at the same facility resulted in the avoidance of an additional 215kg of CO_2e (Unger, Beigl, Hoggerl, & Salhofer, 2017). Which represents an additional 26.5% reduction in CO_2 emissions per ton. These studies highlight the complexity of deciding how to deal with products at the end of their lifecycle.

Inconsistency and Standardization

A common theme in the literature appears to be a lack of consistency in how to conduct Carbon Footprint/LCAs. Generally, it seems accepted that the methodology of Scope 1, 2, 3 is valid. However, according to Vasan, Sood, and Pecht (2014), despite being cited as the largest scope, scope 3 is often left out of these assessments. This is largely because of the complexity in calculating scope 3 emissions. Therefore, it is recommended that there is a move towards Product group-oriented standardization (Vasan, Sood, & Pecht, 2014) where standard frameworks are developed for product types. Vasan, Sood & Pecht (2014) did not recommend what product groups would be appropriate; though they did recommend that each group would have a baseline product

to enable comparisons. This would enable more accurate and standardized assessments and comparisons. Though this may not always be feasible particularly when attempting to assess divergent solutions. A 2014 study attempted to assess the Carbon Footprint of alternate methods of water purification and found that no single tool was equipped to adequately assess all the methods (Cornejo, Santana, Hokanson, Mihelcic, & Zhang, 2014) making an accurate comparison difficult. Though, it can be argued that all that is required in some cases is to find the solution that reduces the energy consumed. Such as the use of grey water in agriculture (Flaming, 2011).

Another area that requires a bespoke standardized method for assessing the Carbon Footprint is in data flow and networks. As the military and civilian domains become increasingly network-centric it is going to become increasingly important to determine the Carbon Emissions of expanding and maintaining these networks. Chan et al. (2016) compared the embodied carbon of a network to the operational carbon. Embodied carbon is the carbon emitted in the building of parts such as modems and antennas. Operational carbon is the energy consumption used by the network. They found that shortened hardware lifecycles increase the embodied carbon but decrease the operation emissions due to efficiency improvements. However, they also found that in the future embodied carbon will account for a greater ratio due to a reduction in projected efficiency improvements (Chan, Gygax, Leckie, Wong, & Nirmalathas, 2016). The concept of embodied carbon is not unique to electronics and networks.

Building and construction are among the top seven major contributors of GHG (Akbarnezhad & Xiao, 2017). In their study, Akbarnezhad and Xiao (2017) found that 20-80% of the lifecycle carbon emissions from buildings were accountable to embodied

emissions. Though this varies depending on the type of building and how long it is in use, the trend is towards embodied carbon accounting for an increasing ratio due to increases in energy-efficient designs (Akbarnezhad & Xiao, 2017). They recommend a number of strategies to minimize the embodied carbon such as using low carbon materials and concrete, optimizing the construction process, reducing the travel distance of materials, and recycling materials were possible. Though as discussed earlier, it is not always optimal to recycle or reuse materials if they are less efficient.

A similar method for accounting for carbon estimation is discussed by Filer et al. (2020). They examine the environmental impact (EI) of remote infrastructure in terms of a portfolio measured in tons of CO_2e. EI is the sum of the initial environmental impact (IEI) and the daily environmental impact (DEI). In this instant, the IEI is synonymous with the embodied carbon concept where it is the Carbon Footprint of building the infrastructure and the DEI is synonymous with operation carbon emissions; measured in tons of CO_2e/day Using this method it is possible to evaluate alternatives for remote communities in terms of upfront emissions, on-going emissions or total emissions (Filer, Delorit, Hoisington, & Schuldt, 2020). This could be extrapolated to calculate a Carbon Breakeven Point, similar to evaluating a financial breakeven point on a potential project. While considering the environmental impact of carbon emissions is important it might not always be adequate and alternative measures may need to be considered.

Many of the methods discussed measure carbon or GHG emissions in terms of tons in an effort to assess the impact on the climate of a specific product. Often, this is translated into a dollar value to conduct a cost-benefit analysis. However, often other constrained resources are overlooked. One of the main efforts in reducing carbon

emissions is to convert to clean energy such as wind and solar for electricity and biofuel for combustion engines. An alternative metric has been proposed known as the Renewable Energy Equivalent Footprint (REEF) that accounts for additional factors beyond just emissions, such as land use and degradation (Ward, Mohr, Costanza, Sutton, & Coscieme, 2020). This method is useful for evaluating if a renewable energy project is viable and efficient based on the topography of the host region.

Thus far, this paper has considered the value/cost of carbon emissions, and several methods for estimating and accounting for carbon emissions through a product lifecycle. However, there has been a wide aperture in order to understand how carbon is assessed across a wide range of industries. The next section will focus on carbon emissions in the defense and aviation sectors.

DoD Carbon Emissions

Background

There is an understanding that Climate Change is a threat to national security and international stability. The 2014 Quadrennial Defense Review (QDR), published by the DoD, describes climate change as a threat multiplier (Werrell & Femia, 2015). This is because climate change can cause or exacerbate other issues by damaging infrastructure, causing mass migration, or by failing crop yields. Dodson et al. (2020) highlight that GHG emissions are increasing, in part due to increased global population, which worsens climate change, which increases the mean temperature and extreme weather events that impact food and water security and human health. However, despite a general understanding of the issue policymakers have yet to fully consider the impacts of

population growth and climate change (Dodson, Derer, Cafaro, & Gotmark, 2020). Additionally, military planners often fail to capture and plan for the multiplier effect of climate change (Werrell & Femia, 2015). Therefore, there is limited available literature on the carbon emissions of military operations and weapon system development. The available literature suggests the military has an extremely high Carbon Footprint and should explore how to reduce it in order to mitigate the threat multiplier of climate change. Though the DoD is not required to report on carbon or GHG emissions from military unique sources some estimates suggest that the DoD emits around 340 million tons of CO_2 per year, which is about 6% of the nation's carbon footprint (Parkinson, 2020). In the fiscal year 2020, the DoD officially reported 51.9 million metric tons of CO_2 emissions (U.S. Department of Energy, 2022). The annual DoD budget is around 3.3% of GDP in 2021 (Peter G. Peterson Foundation, 2021) meaning the DoDs ratio of US GHG emissions is double its ratio to GDP. It should be noted that the Peter G. Peterson Foundation has a stated purpose of raising awareness of America's fiscal challenges and provided this opinion piece to further that agenda.

DoD Carbon Footprint

According to Hastings (2013), the DoD is the organization that emits the most carbon worldwide and the United States Air Force is the world's largest consumer of oil. This is partially due to the size of the organization and the fuel-intensive nature of modern warfare. He also suggests that the DoD is struggling to determine how to conduct war when oil is a constrained resource. Specifically, the Air Force intends to research and develop alternate fuel sources, though it seems unlikely that biofuel will be able to top 25% of the Air Force's needs (Hastings, 2013). However, a significant portion of the

carbon emissions required to support airlift could be reduced by the use of photovoltaic cells at Forward Operating Bases (FOB) (Thomsen, Wagner, Hoisington, & Schuldt, 2019). Due to a lack of reporting, it is impossible to determine the DoD's actual Carbon Footprint. Perhaps the most comprehensive study was conducted by Neta C. Crawford for the Watson Institute and Brown University in 2019.

Crawford (2019) conducted a thorough estimation of the DoD's carbon emissions based on fuel consumption and energy usage. While this study is not a peer-reviewed journal article it provides one of the best estimations of DoD carbon emissions available. It is estimated that 70% of DoD carbon emissions are from operations such as maneuvering tanks, ships, and aircraft, plus the support of those activities, and 30% is attributed to the energy consumption of running installations. By far, the biggest emitter is the Air Force which accounts for over 50% of the operational emissions. The main driver of military carbon emissions is burning fossil fuels. This occurs primarily at the fuel-hungry tooth conducting warfighting and training and through the long logistics tail. Crawford estimates that "From FY1975 to FY2018, total DoD greenhouse gas emissions were more than 3,685 million Metric Tons of CO_2 equivalent" (Crawford, 2019) which is more than the annual emissions of many countries including industrialized countries such as Sweden, Denmark and Portugal. Though it is worth noting that the study only included Scope 1 and Scope 2 emissions and did not include emissions caused by the development and production of weapon systems; therefore, the total Carbon Footprint of the DoD is likely significantly higher.

Crawford (2019) estimates a lower bound carbon footprint of the DoD and gives the impression that there is a path to substantially reduce the carbon emissions of the

military. However, others who have conducted studies posit that militaries are inherently massive emitters of carbon. Jorgenson, Clark, and Kentor (2010) describe the treadmill of destruction where militaries are in perpetual competition and therefore perpetually harm the environment. They describe that this applies both in terms of manpower and technology. Larger militaries are correlated with larger carbon footprints caused by the need to feed, train, shelter, and maneuver the forces. Militaries that have advanced technology cause additional emissions through the development, production, and operation of the technology (Jorgenson, Clark, & Kentor, 2010). This suggests that any military seeking to gain superiority will have a detrimental impact on the environment that is larger because each military is attempting to outgrow the others. General Charles Q. Brown issued direction to the Air Force to prepare for increased competition against near-peer adversaries (Brown C. Q., 2020). Meaning that the Air Force will face tough strategic decisions requiring complex trade-offs between environmental impacts and increased capability and reach.

DoD Climate Policy

The apparent paradox is evident to other scholars. “The US military’s climate policy remains fundamentally contradictory. While the military confronts the effects of climate change, it remains the largest single institutional hydrocarbon consumer in the world” (Nuttal, Samaras, & Bazilian, 2017). Many others believe that, barring any sudden technological breakthrough, the only way to significantly reduce the Carbon Footprint of the military is to significantly scale back operations. This is because in the current paradigm “The logics, logistics, and bureaucratic structures embedded in the overarching modalities of the US war apparatus are inextricably tethered to

hydrocarbons" (Belcher, Bigger, Neimark, & Kennelly, 2019). In their analysis, Belcher et al. (2019) found that a significant driver of the DoD's Carbon Footprint is the logical supply chain and the need to fight around the world. The impact of logistics on the military's Carbon Footprint is an important consideration, especially as the Air Force is considering lots of 75 fighter aircraft every 8 years (Roper, 2020) which will presumably complicate the logistics tail. To adequately assess the carbon emissions for the Air Force a better understanding is required of the carbon emissions of the aviation sector.

Aviation Sector Carbon Emissions

Industry Carbon Footprint

In contrast to the defense sector, there are numerous articles pertaining to the Carbon Footprint of the aviation industry, though much of the research remains in the grey literature. Given that the vast majority of the carbon emissions of the aviation sector come from the direct emissions in the operational stage it is logical that efforts to minimize fuel consumption will reduce carbon emissions and costs. Many algorithms exist to optimize routes and flying patterns but are necessarily constrained. For example, the Non-dominated Sorting Genetic Algorithm II (NDGA-II) has been utilized by Alliance to optimize flying routes and assist in outsourcing decisions (Yan, Zhang, & Tang, 2020). Based on the expected distance, the fuel use, and therefore Carbon Footprint can be analyzed for the airline. Other studies have focused on the Carbon Footprint of the operation of the airport itself. This is done by counting the number of arrivals and departures of each aircraft type to determine the number of Landing-Take-Off cycles (LTO). The distance the aircraft travels is irrelevant as the emissions for each LTO are

attributed to the airport. The LTO cycles are multiplied by the emission factor to calculate the Carbon Footprint of the airport (Kumas, Aksu, Inan, Akyuz, & Gungor, 2019). The simplicity and practicality of this method is appealing. Though, it is limited in that it does not account for the Scope 2 and Scope 3 emissions. Furthermore, it uses average emissions and does not account for variations caused by weather, weight, and other factors, therefore the estimates are of limited use.

Many of the studies are concerned with industry at a macro level. These studies lack the detail to make trade-off decisions but highlight the impact of the industry as a whole. An interesting finding in a study of 88 aviation companies found that the ratio of carbon emissions for manufacturing is between 1 and 2% for a 30-year lifespan depending on the exact calculation (Pierrat, Rupcic, Hauschild, & Laurent, 2021). While this appears to suggest that aviation manufacturing is not a significant source of carbon emissions the study did not include Scope 3 emissions which could alter the outcome. Although it is unlikely to have a major impact as the scope 3 emissions are ignored in studies of operations and production, meaning each would be increased if scope 3 was included. Furthermore, the carbon emissions for manufacturing were estimated to be between 13.2 and 27.6 $MtCO_2e$ for 2213 produced aircraft (Pierrat, Rupcic, Hauschild, & Laurent, 2021). The low ratio is because of the high fuel use in operations versus an inherently clean production process. This suggests that to reduce carbon emissions attention should be focused on reducing operational emissions; perhaps through the use of alternate fuels, or carbon capture technology (Krishnan, 2021).

Product Carbon Footprints

While most studies are focused on the industry as a whole, the handful of assessments that have been conducted on individual products seem to confirm that manufacturing only accounts for about 1% of carbon emissions. A 2013 LCA of the Airbus A320 found that the operational phase of the lifecycle accounted for 99.9% of the environmental impact and 99% of the carbon emissions (Howe, Kolios, & Brennan, 2013). This study calculated the Carbon Footprint of the manufacturing stage by determining the weight of each major subcomponent, the composition of materials used in each subcomponent, and the transportation of each subcomponent.

The study did not account for Scope 3 emissions. This suggests that the study is underreporting the Carbon Footprint and that the focus on reducing Carbon Footprint should be on the operational phase. However, the Carbon Footprint of manufacturing could be reduced further by changing the ratio of renewable energy used and increasing the use of recycled metals versus virgin metals. Recycled metals used in aviation have been shown to emit significantly less carbon than extracting new materials (Eckelman, Ciacci, Kavlak, Nuss, & Reck, 2014).

Operational Carbon Emissions

Calculating the Carbon Footprint of air travel in the operational phase is relatively simple. LTO cycles are assigned a specific footprint and that is added to the distance multiplied by a cruising factor unique to each configuration of aircraft (Simone, Stettler, & Barrett, 2013). Though when using the constant factors, it is unclear if they are fully burdened i.e., include an estimate for the ground support and maintenance that would be required to enable the flight. While most estimation techniques follow the basic premise

of LTO cycles and cruise, others break it down further. By defining the LTO cycle as the sum of the emissions from the 5 LTO phases a more accurate estimate can be achieved. The 5 sub-phases are taxi-out, take-off, climb, approach-landing, and taxi-in. The emissions of each phase are calculated using bespoke fuel burn rates and travel distances (Chao, 2014). Typically, LTO consists of activities below 3,000 feet and cruise rates are utilized above 3,000 feet. It is likely that this model is useful for estimation purposes but could be refined further.

Another method for calculating the Carbon Footprint is available that provides a more accurate estimate but requires more information. The algorithm requires the departure and arrival airport, the flight schedule (to provide the aircraft type), fuel burn tables (which provide information on how much fuel each aircraft burns in different configurations), airline load factor (combination of cargo weight and passenger occupancy), and the average passenger weigh including luggage. Then the distance, fuel burn, and payload can be calculated resulting in a more accurate Carbon Footprint estimate (Yin, Dargusch, & Halog, 2015). This method is useful for making comparisons between types of aircraft to determine which would be most efficient for a specific journey based on occupancy and cargo weight. However, it is limited in that it uses averages and does not account for differing routes between airports or weather conditions.

Alternative Fuels

The aviation sector is a huge emitter of carbon and many question whether it can truly become sustainable. Some governing bodies are even considering banning short-haul flights to reduce the aviation sector’s impact (Macola, 2021). Even best-case

projections for the use of biofuel in aviation limit its use to about 60% while ground-based transportation could be fully electrified and powered by renewables (Robertson, 2018). The use of biofuel as a solution is dubious; while some estimates suggest it could reduce emissions by 78% (United States Department of Energy) others argue that estimates do not fully account for the effects of deforestation and farming (Erikson, 2016). If the best-case scenario is reached that results in a significant reduction in carbon emissions, however, does not result in an elimination of carbon emissions. Other engineering solutions will need to be explored to reduce the Carbon Footprint further. Other than fuel these innovations will need to come in the form of more efficient engines and improvements in the Airframe (Williams, 2007). As these innovations will result in reduced fuel use, they simultaneously reduce costs and carbon emissions. Therefore, most design teams already aim to innovate in these areas.

There are several options for estimating Carbon Footprints. The method chosen will depend greatly on what is being examined, who the audience is, the intended use of the information, and the available data. Despite being recognized as a major source of carbon emissions Scope 3 emissions are often left out of analysis due to the complexity of obtaining the relevant information. This is especially true regarding the aviation and defense sectors. The following section is going to focus on methods of systems modeling and architecting that could be useful in building a Carbon Footprint model specific to Air Force weapon systems.

System Modeling/Architecting

Designing a system typically begins by defining requirements, refining those requirements into system requirements, and then specification. From the specifications, components are designed to meet the specifications and are integrated back into the system design and validated and verified. This is known as the Systems Engineering Vee (Buede & Miller, 2016). However, often to understand how the components interact and if they will meet the specification a model is used. A model is any incomplete or simplified representation of reality (Buede & Miller, 2016). Models are currently used to calculate the cost, schedule, and performance across DoD programs and potentially could be expanded to include carbon estimations. Given that the carbon emissions of a system are driven by other factors such as weight, energy usage, and material it would be well suited to be represented in a language such as SysML. A Practical Guide to SysML describes a parametric diagram that is used to analyze factors such as performance, reliability, and mass (Fiedenthal, Moore, & Steiner, 2015). Using these methods would result in a model unique to a specific platform.

In the future, there may be detailed models of each weapons system with enough data to calculate the expected Carbon Footprint, but they do not exist today. Therefore, any Carbon Footprint analysis will be conducted separately from the system modeling and design. For this reason, a Carbon Footprint architecture that is platform agnostic could be useful, though there would likely need to be categorical groupings such as fixed-wing and rotary-wing aircraft. An architecture describes a system to a certain level of abstraction in terms of form and function, it can identify activity and item flows that may otherwise be obscured (Crawley, Cameron, & Selva, 2016). Analyzing, weapons systems

using systems architecting techniques and a focus on drivers of Carbon Emissions may enable to Air Force to better estimate the Carbon Footprint of platforms and programs.

To develop an architecture the existing models and systems must be examined in their non-specific forms. The general functions and behaviors must be identified, and the relationships understood. This will allow for a universal architecture to be developed (Kornuta, Zielinski, & Winiarski, 2020). Once the architecture is established it can be used to evaluate potential future systems. Using design structured matrix (DSM) and a clustering algorithm and design constraints researchers were able to optimize the choice of a static inverter of an electric train to reduce maintenance (Sinha, Han, & Suh, 2020). Utilizing a similar method may prove useful in optimizing future designs to minimize carbon emissions. This technique has been useful to optimize for other factors such as maintainability and sustainability but not for emission reduction. Finally, the emergent fields of Artificial Intelligence and Machine Learning may provide tools to reduce the Carbon Footprint of DoD activities. Cui et al. (2016) utilized an Artificial Neural Network and a meta-learning model to combine various data-driven modeling techniques. Using this ANN, they could model the potential energy use of buildings with increased accuracy (Cui, Wu, Hu, Weir, & Li, 2016). If this technique could be refined to operate on more complex systems it could prove useful in the optimization of many factors, including carbon emissions, for DoD systems. Though, it would need to be utilized in combination with more traditional systems engineering approaches as a tool rather than a whole-cloth replacement for the current systems engineering process.

Decision Making

The procedures for estimating carbon emissions given little information are somewhat hazy. However, given detailed engineering data of products or of material usage of organizations the methods of accounting for carbon and greenhouse gasses are well documented; though they are difficult and complicated to execute. The questions remain as to how to factor carbon emissions into decision making particularly for DoD systems. DoD Directive 5000.01 requires that Systems Engineers consider environmental factors when designing systems (Department of Defense, 2021). This requirement is further refined in DoDI 5000.02 which directs the use of Environmental Safety and Health analysis that includes chemicals and emissions (Department of Defense, 2020). However, the instructions lack clarity on how to execute this analysis and what pollutants are counted. The Defense Acquisition Guidebook provides a little more clarity. It recommends that the Systems Engineering team perform a sustainability analysis using a Lifecycle Assessment (LCA) method (Defense Acquisition University, 2020). Though this guidance is non-binding and most major programs would likely not have the required information to perform an LCA. Therefore, the majority of programs have not conducted this analysis.

DoD Decision Making

The Department of Defense has issued more detailed guidance on integrating sustainability into acquisitions. The guidance provides details about synergies between conducting a Life Cycle Cost Assessment and a Life Cycle Assessment. It provides guidance on how to capture the external and contingent costs that are revealed through the LCA, which can be monetized and included in the LCC (Department of Defense,

SAG, 2020). However, the methods it described using would only be of use to programs in later stages of development that have detailed engineering designs. Furthermore, there is no requirement to conduct this analysis or report the results in any official capacity. Finally, it does not give any guidance on how to properly value the assessed impacts or how to incorporate the results into decision-making. While the guidance on integrating sustainability into acquisitions does not provide details on how to make decisions based on the findings of an LCC, the document does reference the DoD guidebook for Business Case analysis. When conducting a business case analysis, environmental factors including carbon and greenhouse emissions are to be treated as risks in the risk section of the report (Department of Defense, 2014). Though the risk may be hard to quantify without a detailed understanding of the carbon impact of the product and the long-term effects of the emissions.

In a traditional business, the goal is to maximize shareholder value (Rothaermel, 2019). Therefore, project selection often relies on business case analysis that identifies the potential investment and potential future cash flows to determine if the project will return value to shareholders. This means projects are generally undertaken if the positive change in future cash flows is larger than the investment or if it is required due to legal or regulatory pressures (Brown & Hyer, 2010). The process and analysis can be quite complex as there can be uncertainty regarding the future cash flows and certain projects may be performed at a loss in order to enter a new market and unlock future revenue sources (Rothaermel, 2019). However, in the DoD, the decision-making process is not motivated by profit. While the DoD measures program performance against the criteria of cost-schedule-performance; there is no standard decision support mechanism leading to

mishmash, often ad hoc and contradictory set of decision criteria (Miller, 2010). Often decisions and project approvals appear to be based on the lowest price technically acceptable (LPTA) which does not take into account external costs or other important factors such as performance.

Multi-Objective Value Functions

One method that has been suggested for improving the programmatic decision-making in the DoD has been presented by the Mitchell Institute of Aerospace Studies. They recommend a new metric: cost-per-effect (CPE). CPE would be a ratio of the cost compared to the desired effect that is tied to a specific mission objective (Deptula & Birkey, 2020). Considering the mission effects versus cost rather than bottom-line costs has challenges. Most notably, the ability to estimate mission effectiveness, which is likely to be some combination of the performance characteristics of the system. Perhaps a more robust option would be to utilize a multi-objective value function that would include the values or utilities of each criterion. A multi-objective value function is an equation that provides an overall value score to a set of combined single-value functions, based on the scores and relative importance (Kirkwood, 1997). The advantage of this method is that it provides an adaptable framework that can be adjected to add, remove or change the importance of criteria. This would provide an opportunity to develop a weighted function that included cost, schedule, performance, and environmental impact. Though, determining the exact elements of performance and environmental impact could prove challenging. Each program or category of program would likely need to set differing performance and environmental criteria and goals.

When developing the multi-objective value function, cost and schedule are relatively straightforward. Cheaper and faster is better however, quantifying the trade-off between the two is a challenge. A challenge which is amplified by adding the third dimension of performance, and a fourth of carbon emissions. Kirkwood (1997) suggests ranking the criteria from most to least important, then determining the relative importance of each criterion to the lowest ranked. Once the ranking and relative importance is determined simple algebra enables the determination of the weights. This method should always be subject to sensitivity analysis because it is relatively subjective. In more complex problems, particularly when a criterion in the function is a measure of sub-criteria, tools such as influence diagrams can be beneficial. Influence diagrams can be used to determine how the criteria and bub-criteria interact with each other. Usually, they are not quantified, rather they are used to understand the interactions and relationships (Clemen & Reilly, 2004). Once, these interactions are understood decision-makers can more adequately determine the relative importance of each criterion. The method discussed earlier involved determining the relative importance based on a stated preference. However, it is often valuable to determine the revealed preferences of the decision-maker. Revealed preferences are not explicitly stated, rather they are inferred based on statements and actions by the decision-maker (Slovic, 1987). After determining the relationships and relative values of decision criteria using revealed and expressed preferences, it is important to conduct a sensitivity analysis. The sensitivity analysis will highlight if any of the assumptions will alter the ultimate outcome of the decision (Kirkwood, 1997).

Summary

The preceding literature review examined how the cost of carbon is determined. Specifically, the methods used to attempt to account for the future damage and impact that result from the carbon emissions. Then, it examined the techniques for estimating and accounting for carbon emissions. This is usually referred to as a Carbon Footprint or a carbon LCA. When applied to the DoD and aviation sectors there are inconsistencies and gaps. Mainly, that reporting by DoD is limited and while it is possible to estimate the total DoD Carbon Footprint, at least the direct emissions, it is opaque and lacks details regarding specific programs. Furthermore, it is understood that Scope 3, indirect emissions of the activity, account for a sizeable percentage of carbon emissions however, scope 3 emissions are often left out of studies due to the difficulty of accounting for them. The neglect of scope 3 emissions is prevalent across studies examining DoD and aviation. Then, this literature reviewed a sample of techniques that can be utilized to develop systems models or architecture. A DoD weapon system architecture or model that specifically focuses on carbon emissions could be a useful tool in reducing the DoDs Carbon Footprint. Finally, decision-making processes were discussed. A review of decision-making directly related to the DoD and carbon emissions found that there is guidance directing the consideration of climate impacts; however, it is not clear on how to perform that analysis or how to make programmatic decisions based on it.

III. Methodology

Chapter Overview

This research effort will consist of two parts. Part one will establish a model that will be utilized to estimate the carbon emissions of a weapon system in the early design phases; before detailed engineering data is available. Part two will examine how decision-makers can utilize the results when making programmatic decisions while making tradeoffs among cost, schedule, performance, and carbon emissions.

Overview of Research Methodology

The following sections will provide and overview of the two parts of the research.

Part 1: Carbon Emissions Estimate

Decisions made early in the Acquisition process will have an increased impact on the potential costs and carbon emissions of a program. However, early in the lifecycle of a program detailed engineering plans are likely unavailable. This framework intends to allow for early estimations based on the best information available. As the program progresses the estimate can be refined to develop a more complete Lifecycle Assessment. Another goal is to create a model that would require minimal additional effort to integrate into the Acquisition decision-making process.

First, the basic structure of the model will be established using existing frameworks. MIL-STD-881E is the latest guidance on work breakdown structures for the DoD. This guidance defines the WBS down to level 3, though during the program the WBS is usually defined to lower levels. for the purposes of this research, the standard WBS for a fixed-wing aircraft will be used. Appendix A illustrates the standard WBS

from MIL-STD-881E for a weapons system. For each element in the WBS key drivers of carbon dioxide and greenhouse gas emissions will be identified. The carbon footprint of each WBS element will be the product of the quantity or value of the driver multiplied by the carbon emission factor. The estimated carbon emissions of the aircraft will be the sum of the carbon emissions of the individual elements. The model will display both the acquisition carbon footprint and the operational carbon footprint and total carbon footprint.

Material Input Model

In this model, to determine the acquisition carbon footprint the primary drivers of each element have been selected as a combination of manhours, material, transport distance, and fuel burn. These elements were chosen because they represent large contributors of carbon emissions. Fuel burn is a direct contributor of carbon. Material use accounts for the carbon that is emitted from material extraction to the manufacturer. Distance accounts for the fuel use in transporting sub-assemblies to the integration point. Finally, manhours are a proxy for energy use. The combination is unique to each WBS element based on the type of activity. The following equations are the mathematical representation of the model. Equation 1 is the calculation for the embodied carbon of each element. And Equation 2 is the total carbon footprint of the embodied carbon of the system.

Equation 1: Carbon Footprint of Element

$$CF_{Element} = M1_{Weight} * M1_{Factor} + M2_{Weight} * M2_{Factor} + M3_{Weight} * M3_{Factor} + Labor_{Cost} * Labor_{Factor} + Distance * Method_{Factor} + Fuel_{Weight} * Fuel_{Factor}$$

Equation 2: Total Carbon Footprint

$$CF_{Total} = \sum CF_{Element\ 1} \ldots CF_{Element\ n}$$

Distance to assembly is how far a component travels to the next higher assembly location. The tCO_2e output is a function of the weight of the component, the travel distance, and the emissions factor based on the method of transport. Scope 1 emissions, which is direct fuel burn, are simply the weight of fuel multiplied by the emission factor. The outputs are summed to determine the tCO_2e for each WBS element and then summed to the entire Aircraft. The factors for travel and direct fuel burn were retrieved from the EPA. The overall output of the model provides an estimate on a per aircraft and per-program basis. The per aircraft basis spreads the cost of oversight and support, buildings, testing across all aircraft evenly.

Each materiel and labor category has a conversion factor that is retrieved from one of several databases on LCA Commons (LCA Commons, 2021). The most common database that was used was the EPA database. The factor is then used to produce an estimate of the tons of CO_2 equivalent (tCO_2e) based on the weight of material used in pounds. tCO_2e in this model is the result of multiplying the CO_2, Methane, and Nitrous

Oxide emissions by their respective Global Warming Potentials (GWP). The equation to convert the three greenhouses into CO_2e is as follows.

Equation 3: CO_2e Conversion Using GWP

$$CO_2e = CO_2 + CH_4 * 25 + N_2O * 298$$

Economic Input-Output Model (EIO)

The secondary method involves utilizing the EIO-LCA (Carnagie Mellon University, 2021) from Carnegie Mellon University which provides a point estimate of carbon emissions based on the type of activity, economic sector, and cost. This is used to get a rough estimate when other data is unavailable. For the operational carbon footprint, the expected fuel use per flight hour will be used. This information is readily available as part of the standard LCC estimates. The equation for the model is similar to the Material Input model except the input parameters are in monetary terms.

Equation 4: EIO Model Equation

$$CF_{Element} = Cost\ Estimate_{Element} * Emission\ Factor$$

Upon completion of the model, it will be validated using dummy data of three similar platforms. The validation will provide a proof of concept that the model can be used as a viable estimate of carbon emissions. This will enable an exploration of how to further integrate the outputs of the model into the decision-making process. It will also enable the verification that the production of aircraft is only responsible for 1-5% of emissions compared to operations.

Distributions

For both the Material Input Model and EIO model only a point estimate is produced. This is due to the nature of the source data. LCA commons provides adequate access to point estimates for emission factors; however, the true distributions of the factors are not provided. The EIO-LCA model only provides a point estimate based on the average emissions in a specified category. To increase the robustness of the results a post-hoc distribution will be applied to each output. The EIO model provides an estimate based on the average emissions in a category and the background calculations and distributions are unavailable. Therefore, the output provided is the only data point available. Given the single data point and lack of further insights, a uniform distribution was chosen. In a uniform distribution the mean is equal to the low and high divided by two. Since the model predicts the mean carbon emissions, this is multiplied by 0.5 to determine the lower bounds of the distribution. The high is calculated by adding the low to the mean. The material input model distribution will be created using a triangular distribution. A triangular distribution was chosen due to the lack of available data points. The low, most likely and high estimates are calculated by adjusting the travel method between, rail, road, and air. Rail has the smallest emission factor and will be the low, air has the highest emissions factor and will be the high, and road has the middle emission factor and will be the most likely. For both the material and EIO models a Monte Carlo simulation with 2,000 iterations will be conducted to build a distribution of the possible outputs.

Assumptions

The following assumptions are built into the model:

- At this stage there is no complete LCA on a military weapons system that can be utilized as analogy or as inputs into a parametric estimate.
- The acquisition carbon footprint is the embodied carbon that would be emitted in the production of a weapon system. This includes emissions that would be emitted by the program for support facilities, testing, support equipment, oversight, and management activities.
- The equations that form the basis of the models are generic and can be applied over different stages of the product lifecycle. However, in this case they are applied to post milestone B activities.
- The estimates will provide and estimate of the overall embodied carbon footprint of producing a weapon system. The estimate will consist of:
    - Scope 1 and 2 emissions.
    - Scope 3 emissions will be partially accounted for
        - In the primary model scope 3 emissions are accounted for in the materials; however, the estimate is based on average emissions over the lifecycle.
        - The secondary model also accounts for the average lifecycle scope 3 emissions based on activity type.

Data

The data was created based on a cost estimate retrieved from the Office of the Secretary of Defense (OSD) Cost Assessment Data Enterprise (CADE) system. It was

expected that CADE would provide a dataset that would be able to populate the model. This was an incorrect assumption. First, the cost estimates only report the expected cost to WBS level 2. The model was built to level 3 meaning the dollar amount needed to be spread across the lower levels for the EIO model. However, this had little impact as many of the factors remained constant at the lower levels of an element. Second, the cost estimates were developed under an older standard so there was an imperfect alignment of WBS elements that required adjustment for the secondary model. The third issue affected only the primary model. The data in CADE is based primarily on analogy estimates and does not include details like labor hours and materials that are required for the model. While some of the elements such as labor could be estimated as a factor of the cost of a specific element the material could not. The data for the materials was based on the weight of a Boeing 767, which is the basis of the KC-46 airframe, and an estimation of the percentage of materials used in its construction.

Three sets of data were developed. Program A, based on the data from the KC-46 cost estimate in CADE. Program B is built off of the Program A data and added extra activities such as testing and additional construction. Program C removed the testing and construction requirement, changed the ratio of carbon fiber to aluminum in the fuselage, and reduced the program size from 175 aircraft to 160. The ratio was changed in line with other commercial aircraft designs. 175 was chosen as that was the size of the KC-46 program. The changes in program C were chosen to explore the impact of design choices related to materials. Aluminum and carbon fiber are currently the materials used in the greatest amount for the airframe. The change in quantity is to explore how quantity decisions affect the decision criteria and the decision-making models.

Part 2: Decision Making

Once a method for estimating a carbon footprint is established and validated with dummy data the research will begin to examine how to use the output when making decisions. Three methods for including carbon emissions in decision-making will be explored. The Federal Government is now required to consider SCC in decision making. However, it is not mandated how. Therefore, the first model will include SCC in the overall cost of the program. This means that the SCC is weighted the same as cost and is in effect treated as a cost increase for the program. The second model splits the SCC into its own factor. This allows for the SCC and cost to be weighted differently if desired. The third model forgoes the SCC in favor of raw carbon emissions to explore if this impacts the outcome of the decision model.

The models in part 1 of this paper provide a method for estimating the carbon emissions of a potential program. However, when selecting a program or project to pursue there are competing priorities that need to be balanced. Often, this boils down to trade-offs between cost, schedule, and performance. The aim of these decision models is to explore methods of incorporating the carbon impacts of a potential program into the decision-making process. All models utilize a multi-objective value function as described by Craig Kirkwood (Kirkwood, 1997).

One of the first steps in decision-making is to determine the objectives. A Value Hierarchy can assist in identifying measurable objectives, goals, and evaluation measures. The following value hierarchy was developed to aid in the decision-making process. The objective is to purchase a weapon system. The first tier of values is populated with the traditional project management metrics or cost, schedule, and

performance. The schedule is ultimately about ensuring the system is designed and produced to align with force structure goals and budgetary cycles. Performance is more subjective, and the specific criterion will change depending on the specific mission of a weapon system. For the purposes of this thesis performance measures have been kept generic; in application lethality and survivability would be further refined to characteristics that suit the system of concern. The cost element is where the value hierarch diverges from the traditional project management measures. Cost is divided into external costs and internal costs. Internal costs are the costs that the Air Force/DoD incur to develop, produce, operate, sustain, and dispose of the system over its life cycle. The external costs, or negative externalities, are costs that are borne by individuals, agencies, and organizations outside of the Air Force/DoD. These include the climate impacts, economic costs, infrastructure damage, security problems, and social impacts caused by the program. These impacts are what the Social Cost of Carbon aims to account for.

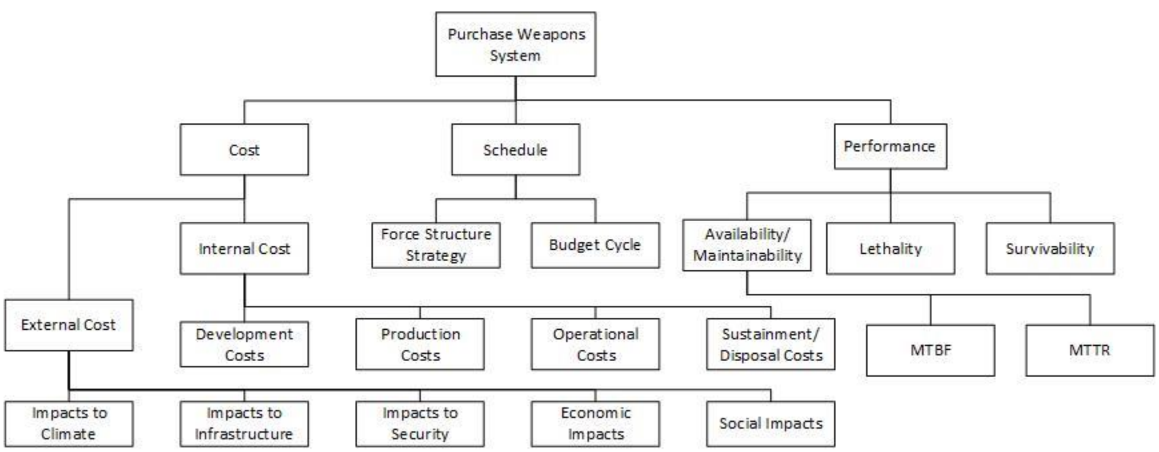

Figure 1: Value Hierarchy

In all three models a value function for cost, schedule, and performance are calculated. The single-dimensional value functions are combined to form a multi-

objective value function that provides a value score for the program. The elements of schedule and performance are common to all three models. The value function for the schedule is a linear function with the objective targets and threshold values representing the high and low parameters. A linear function was chosen based on the assumption that value decreases at a constant rate as the schedule increases. For the purposes of this research, the objective and threshold values of 36 and 16 were used. This was based on a KC-46 lead-time of 24 months and historical delivery times of the KC-46. The equation for the schedule single dimensional value function is as follows.

Equation 5: Schedule Value Function

$$Value_{Schedule} = \frac{36 - Schedule_{Estimate}}{36 - 16}$$

The value function for performance is a multi-dimensional value function consisting of three criteria equally weighted. The criteria are range, mission effectiveness, and maintainability. The value of range is a linear function with a low of 3,000 and a high of 7,000 based off of KC-46 characteristics. Both mission effectiveness and maintainability are linear functions based on a subjective score of 1 through 10. Linear functions were chosen because it was assumed that each unit of increase represented an equal increase in value. The factors are combined to determine the performance value using the following equations. The elements unique to the individual models will be discussed and displayed separately. The subjective values for mission effectiveness and maintainability were kept vague for this research. In practice they would be rated on a set of criteria specific to mission requirements. The purpose of this research is to evaluate the

overall model in a generic form. Similarly, the weights were kept uniform but would be customized to the specific mission needs if used in practice.

Equation 6: Performance Value Functions

$$Value_{Range} = \frac{Range_{Estimate} - 3{,}000}{7{,}000 - 3{,}000}$$

$$Value_{ME} = \frac{ME_{Estimate} - 0}{10 - 0}$$

$$Value_{Maint} = \frac{Maint_{Estimate} - 0}{10 - 0}$$

$$Value_{Performance} = 0.33 * Value_{Range} + 0.33 * Value_{ME} + 0.33 * Value_{Maint}$$

Decision Model 1: Multi-Objective Value Function with the Social Cost of Carbon Included as a Cost

In this method the calculated Social Cost of Carbon will be included as a cost to the potential program. Under this method the cost of the program will consist of the internal costs based off of the program office estimate and the external costs, which include the monetized damages of the carbon emissions from the program. The Social Cost of Carbon will be set at $52 per ton of CO_2. This amount will be added to the cost of the program to determine the value of the cost. This function is exponential with a low of $150,000,000, mid of $180,000,000 and a high of $200,000,000. An exponential function was chosen because there is no upper bound to potential cost overruns. In theory, the perceived increase or decrease in value as costs decrease or increase does not change uniformly. The high and low values are based off of the KC-46 estimate with an additional amount added for the cost of carbon. The following equation represents the

value function where ρ is found through look-up tables in Kirkwood based on a normalized mid-value of 0.40. The normalized mid-value represents the point at which 50% of value is achieved. In this case the mid-value indicates that there is a preference to avoid the threshold and less preference for meeting the objective.

Equation 7:Cost+SCC Value Function

$$Value_{Cost} = \frac{1 - \exp\,[-(200{,}000{,}000 - (Cost_{Estimate} + SCC_{Estimate}))/\rho}{1 - \exp\,[-(200{,}000{,}000 - 150{,}000{,}000)/\rho]}$$

Equation 8: Decision Model 1

$$V_{Program} = W_{Cost} * V_{Cost} + W_{Schedule} * V_{Schedule} + W_{Performance} * V_{Performance}$$

Decision Model 2: Multi-Objective Value Function of Cost, Schedule, Performance, Social Cost of Carbon

The second decision model will use a Multi-Objective Value Function using the traditional metrics of cost, schedule, and performance plus the SCC that is emitted by the potential program. The SCC will be a dollar value that is equal to emissions multiplied by the SCC which is currently \$52 per ton of CO_2 equivalent. Both the cost and SCC functions are exponential functions. Cost has a high of \$160,000,000, low of \$112,500,000 and a midpoint of \$150,000,000. The SCC has a high of \$40,000,000, low of \$15,000,000 and a midpoint \$30,000,000. The values are based on the original estimate of the KC-46 unit price and an estimate of the expected carbon footprint. The expected carbon footprint was estimated by the using the worst-case scenario as a benchmark. The equations are as follows.

Equation 9: Cost Value

$$Value_{Cost} = \frac{1 - \exp\left[-(160{,}000{,}000 - (Cost_{Estimate})/\rho\right.}{1 - \exp\left[-(160{,}000{,}000 - 112{,}500{,}000)/\rho\right]}$$

Equation 10: SCC Value

$$Value_{SCC} = \frac{1 - \exp\left[-(40{,}000{,}000 - SCC_{Estimate})/\rho\right.}{1 - \exp\left[-(40{,}000{,}000 - 15{,}000{,}000)/\rho\right]}$$

Equation 11: Decision Model 2

$$V_{Program} = W_{Cost} * V_{Cost} + W_{Schedule} * V_{Schedule} + W_{Performance} * V_{Performance} + W_{SCC} * V_{SCC}$$

Decision Model 3: Multi-Objective Value Function of Cost, Schedule, Performance, Carbon Emissions

The third method will also utilize a Multi-Objective Value Function. However, rather than provide a dollar value to the carbon emissions just the raw carbon emissions will be utilized as a factor. The value functions for cost, schedule and performance will be consistent with the formulas used in the previous models. The value function for carbon emissions will be an exponential function with a high of 384,615, a low of 9,615 and a midpoint of 144,230. The values were derived by converting the objective and threshold values for the SCC to raw carbon.

Equation 12: Value of Carbon

$$Value_{Carbon} = \frac{1 - \exp\left[-(384{,}615 - SCC_{Estimate})/\rho\right.}{1 - \exp\left[-(144{,}230 - 9{,}615)/\rho\right]}$$

Equation 13: Decision Model 3

$$V_{Program} = W_{Cost} * V_{Cost} + W_{Schedule} * V_{Schedule} + W_{Performance} * V_{Performance} + W_{Carbon} * V_{Carbon}$$

All three models will be used to calculate the value of a program on both a per-aircraft and programmatic basis. Table 1 provides a comparison of the three models. As programs have differing quantities they must be examined on a per aircraft and per program basis. Furthermore, the different models assist in determining the effects of factors such as additional testing, construction, and quantity differences. Finally, as each program is unique and has differing priorities the weights for the models will initially be set to equal. Sensitivity analysis will be conducted on the weight of each element to determine the effects of differing weights. For the sensitivity analysis, the target factors weight will be set to 0 and incrementally increased to highlight changes in the overall value based on the weighting. For example, to explore the effect of the weighting of cost on the overall value the weight of cost will initially be set to 0. The weight of cost will be incrementally increased, eventually reaching a weight of 1. The weights of the other factors will be adjusted in proportion to the weight of cost. The result will be a visual representation of the effects of weighting on the specific factors.

	Model 1	Model 2	Model 3
Cost	Dollar Cost + SCC ($)	Dollar Cost ($)	Dollar Cost ($)
Schedule	Delivery time (months)	Delivery time (months)	Delivery time (months)
Performance	Range*MX*ME (value)	Range*MX*ME (value)	Range*MX*ME (value)
Carbon	NA (included in cost)	SCC ($)	Carbon emissions (tCO_0e)

Table 1: Comparison of Models

Summary

In order to consider carbon emissions in acquisition decision making there must first be a method of estimating the emissions early in the process. The aim of this thesis is to develop a model that can estimate the embodied carbon of a weapon system before detailed engineering data is available. This will be accomplished by building two models. First, a model that estimates the carbon emissions associated with producing a weapon system based on major material inputs, labor, fuel use, and travel/shipping. The second model estimates a carbon footprint based off of a cost estimate and activity type. These can then be used as inputs into a decision-making model. This thesis presents three decision-making models utilizing multi-objective value functions. The first treats the SCC as part of the cost element. The second separates SCC from cost and considers it as a separate factor in the value function. The third is to consider the carbon emissions in their raw form, not as a monetary value.

IV. Analysis and Results

Chapter Overview

The following chapter will discuss and analyze the results of the two carbon estimation models. The output of the models will be discussed and compared. A post hoc distribution will be applied to each model to further explore the possible true carbon emissions. Then there will be a discussion regarding the results of the three decision models. Finally, the results of the sensitivity analysis will be discussed to determine the effects of weights and assumptions on the results.

Overall Results and Analysis

This research yielded results from two carbon estimation models and three decision-making models on a per aircraft and per-program basis. Each model was run using dummy data, based on the KC-46 estimate from CADE (KC-46 System Program Office, 2020), resulting in four carbon estimates: material input per aircraft, material input per program, EIO per aircraft, and EIO per program. Post-hoc distributions were applied for further analysis. The initial point-estimate output of each model was used to run the three decision models: social cost of carbon included in the cost, the social cost of carbon as a separate element, and raw carbon emissions as an element. While the decision models show little difference in the ranked outcome, the two carbon estimation models yielded vastly differing results. These results will be discussed in the following paragraphs.

Part 1: The Models and Data

Material Input Model

The primary model is the material input model and was created using the elements of a standard WBS to level three. Each level three element can receive up to six inputs: three materials, labor in dollars, travel mileage, and direct fuel burn. An example is shown in the following figure. Note: due to rounding of very small values may display as 0.

1.2.2 Air Frame																		
	Material 1			**Material 2**			**Material 3**			**Labor**			**Distance to assembly**			**Scope 1 (direct fuel burn)**		
	Weight	Type	tCO2e	Weight	Type	tCO2e	Weight	Type	tCO2e	Dollars	Type	tCO2e	Distanc	Method	tCO2e	Fuel Burn	Type	tCO2e	tCO2e Est.
Fuselage	47,034	Aluminum	5,177	10,142	Carbon Fil	0	8,379	Titanium	42	61,698	Industrial	32	0	NA	0	0	NA	0	5,251
Wing	29,751	Aluminum	3,274	7,649	Carbon Fil	0	6,126	Titanium	31	61,698	Industrial	32	3,755	Rail	4,126	0	NA	0	7,463
Empennage	12,423	Aluminum	1,367	7,794	Carbon Fil	0	4,331	Titanium	22	61,698	Industrial	32	1,847	Rail	1,145	0	NA	0	2,566
Nacelle	11,105	Aluminum	1,222	1,559	Carbon Fil	0	1,228	Titanium	6	61,698	Industrial	32	1,847	Rail	648	0	NA	0	1,908
Other		NA	0		NA	0		NA	0		NA	0	0	NA	0	0	NA	0	0
Integration		NA	0		NA	0		NA	0		NA	0	0	NA	0	0	NA	0	0
Air Frame			11,041			0			100			129			5,918			0	17,188

Figure 2: Air Frame WBS Estimate (Primary)

Figure 4 displays the Air Frame WBS element. A material is selected, and its weight is entered for each sub-element. The carbon estimate is produced by multiplying its weight by the emissions factor. A similar process determines the labor carbon emissions and fuel burn. The factors for travel are based on ton-miles. The weight of each element is multiplied by the transportation's methods factor to determine the footprint. The CO_2 emissions are then added together for each sub-element to determine the total CO_2 for the WBS element. Then each WBS element is summed to provide an overall estimate as shown in Figure five.

Primary Method	tCO2e	
	Per AC	Program
1.1 Aircraft Sys Int	82.88	13,261.58
1.2 Air Vehicle	464,434.41	74,309,506.08
1.3 Payload	0.00	0.00
1.4 Ground Host	0.00	0.00
1.5 AC Software	0.00	0.00
1.6 SE	0.03	4.33
1.7 PM	0.03	4.33
1.8 Test	0.00	0.00
1.9 Training	31.36	5,017.19
1.10 Data	0.30	47.81
1.11 PSE	5.88	941.18
1.12 CSE	5.88	941.18
1.13 Site Activation	2.19	350.21
1.14 CLS	0.27	42.72
1.15 Industrial Facilities	1.50	240.35
1.16 Initial Spare	376.86	60,297.90
Total	464,941.59	74,390,654.84

Figure 3: Primary Method Results

EIO Model

The secondary model is the EIO model. This model simply requires a cost estimate of each WBS element to provide an estimate of the carbon emissions. Each sub-element, for example, fuselage, has a factor assigned based on the type of work being performed. The cost estimate is multiplied by this factor to determine the carbon emissions. Again, the summation is the embodied carbon emissions estimate.

Secondary Method Estimate			
	Cost ($M)	Rate per M$	tCO2e
Fuselage	3.5	204	714
Wing	3.5	204	714
Empennage	3.5	204	714
Nacelle	3.5	204	714
Other	3.5	204	714
Integration	3.5	204	714
Air Frame	[redacted]		4,284

Figure 4: Secondary Method Air Frame

Secondary (EIO)	tCO2e	
	Per AC	Program
1.1 Aircraft Sys Int	597.72	95,635.20
1.2 Air Vehicle	28,673.40	4,587,743.20
1.3 Payload	0.00	0.00
1.4 Ground Host	0.00	0.00
1.5 AC Software	0.00	0.00
1.6 SE	3.27	523.26
1.7 PM	2.22	354.96
1.8 Test	2.42	387.27
1.9 Training	11.72	1,875.02
1.10 Data	1.92	307.58
1.11 PSE	2.23	357.48
1.12 CSE	2.23	357.48
1.13 Site Activation	4.34	694.40
1.14 CLS	1.09	175.16
1.15 Industrial Facilities	5.83	932.37
1.16 Initial Spare	16.19	2,590.80
Total	29,324.59	4,691,934.18

Figure 5: Secondary Method Results

The final output each time the model is run is a comparison of the models on a per aircraft and per-program basis. The example in figure 8 has certain elements removed to better fit the available space.

Prgm A												
	1.1 Aircraft	1.2 Air Vehicle	1.6 SE	1.7 PM	1.9 Trainin	1.10 Data	1.11 PSE	1.13 Site A	1.14 CLS	1.15 Indus	1.16 Initial	Total
Prime Per AC	82.88	464,434.41	0.02	0.02	28.67	0.27	5.38	0.19	0.24	1.37	344.56	464,898.04
Prime Per Program	14,504.85	81,276,022.28	4.33	4.33	5,017.19	47.81	941.18	34.05	42.72	240.35	60,297.90	81,357,156.97
Secondary Per AC	597.72	30,325.80	2.99	2.03	10.71	1.76	2.04	0.62	1.00	5.33	14.80	30,964.80
Secondary Per Progra	104,601.00	5,307,014.13	523.26	354.96	1,875.02	307.58	357.48	108.80	175.16	932.37	2,590.80	5,418,840.55

Figure 6: Program A Comparison

Part 1: The Results

Material Input Method – Results

The data was input into the Material Input model and the three datasets produced an estimate of the embodied carbon broken down by WBS element then summed for the total. The results are summarized in the following table.

Program	**Number of AC**	**tCO2e (Aircraft)**	**tCO2e (Program)**
Program A	175	464,898	81,357,157
Program B	175	464,905.2	81,358,414
Program C	160	507,518.7	81,202,991

Table 2: Material Input Method Results

Program A has the lowest carbon emissions per aircraft while Program C has the lowest per program. In Program A 50% of the airframe weight was attributed to Carbon Fiber, whereas in Program C approximately 50% of the weight was attributed to Aluminum. This resulted in higher embodied carbon per-aircraft. However, because the program was producing fewer aircraft the overall carbon footprint is lower. While the materials used in Program B were identical to Program A, the addition of testing and increased construction requirements resulted in a higher carbon footprint both per aircraft and for the program. However, difference between the estimate for Program A and B is relatively small. Neither output should be considered in isolation as the program’s carbon

footprint represents the amount of carbon expected to be released into the atmosphere based on current numbers. While the per aircraft number allows for scaling based on changes to program structure. The following charts show the results compared on a per aircraft and per-program basis.

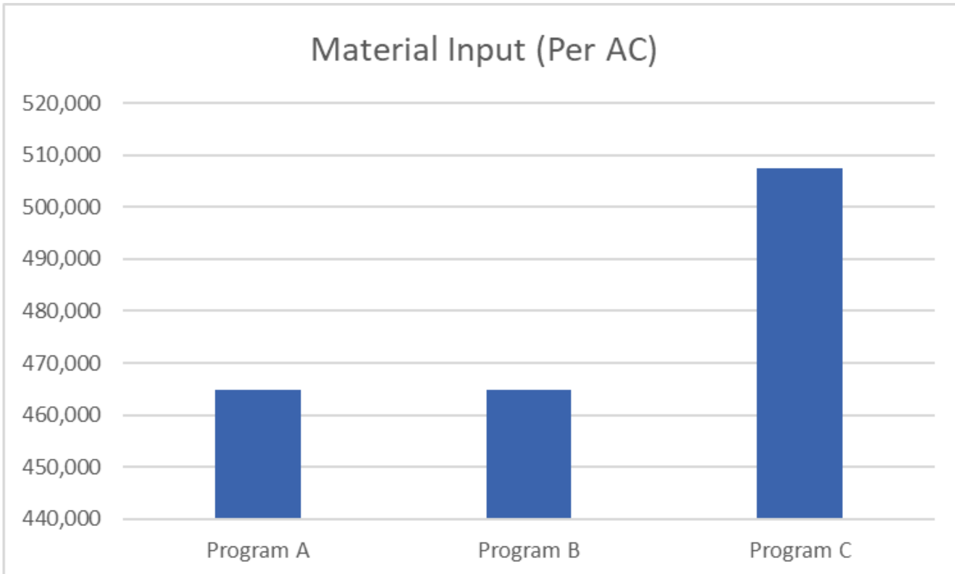

Figure 7: Material Model Results (Per AC)

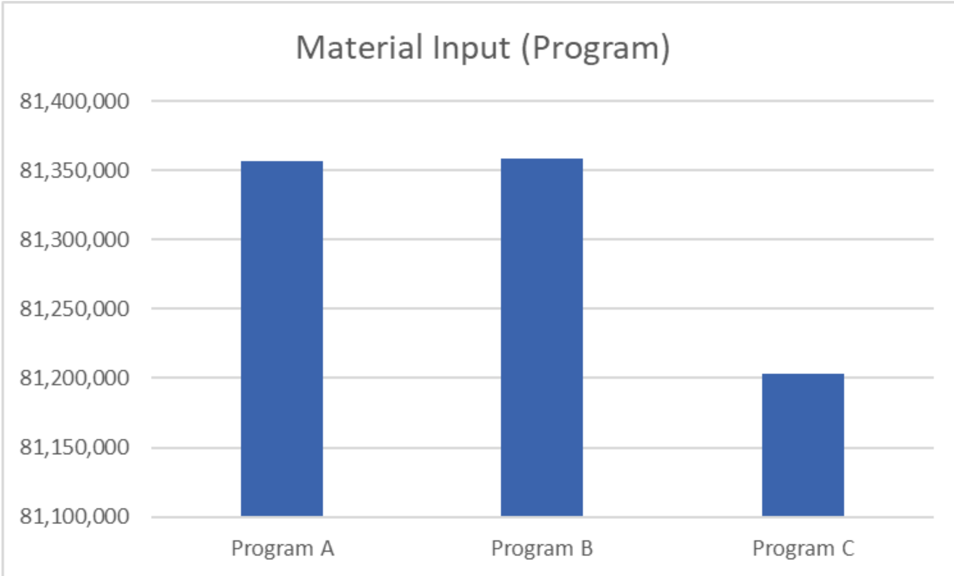

Figure 8: Material Model Results (Program)

Material Input – Limitations

There are several limitations to this estimate. First, it is a point estimate based on the expected structure of the aircraft. Therefore, it fails to account for the full range of possible true values of the carbon footprint. Second, the materials and factors used in the model were standard metals such as titanium, aluminum, and standard composites such as carbon fiber. In practice, there are several alloys based off of the materials used and many different carbon fiber composites; each with a specific emission factor that is ignored in this model. The emissions factors for most alloys and carbon fiber composites were unavailable in the open-source databases.

EIO Model – Results

The secondary method, which produces an estimate based on the dollar value of each WBS element the summed for the total footprint is summarized in the following table.

Program	Number of AC	Cost Estimate ($M)	tCO_2e (Aircraft)	tCO_2e (Program)
Program A	175	149.25	30,964.8	5,418,841
Program B	175	153.05	30,972.41	5,420,171
Program C	160	143.86	29,324.59	4,691,934

Table 3: EIO Method Results

Using this model Program C produces the lowest carbon footprint both on a per aircraft and per-program basis. This suggests that even if Program C was scaled up to 175 aircraft it would still have less embodied carbon for production. This is because the per aircraft cost is lower due to cheaper materials (aluminum) being more extensively used. Again, Program B has a higher level of carbon due to increased spending on testing and facilities. The following charts show the results graphically.

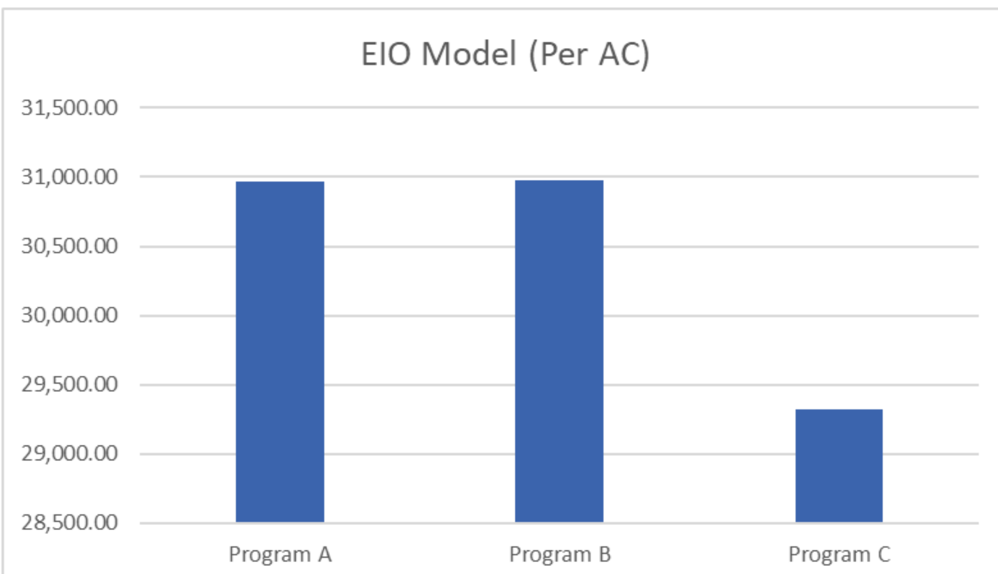

Figure 9: EIO Results (Per AC)

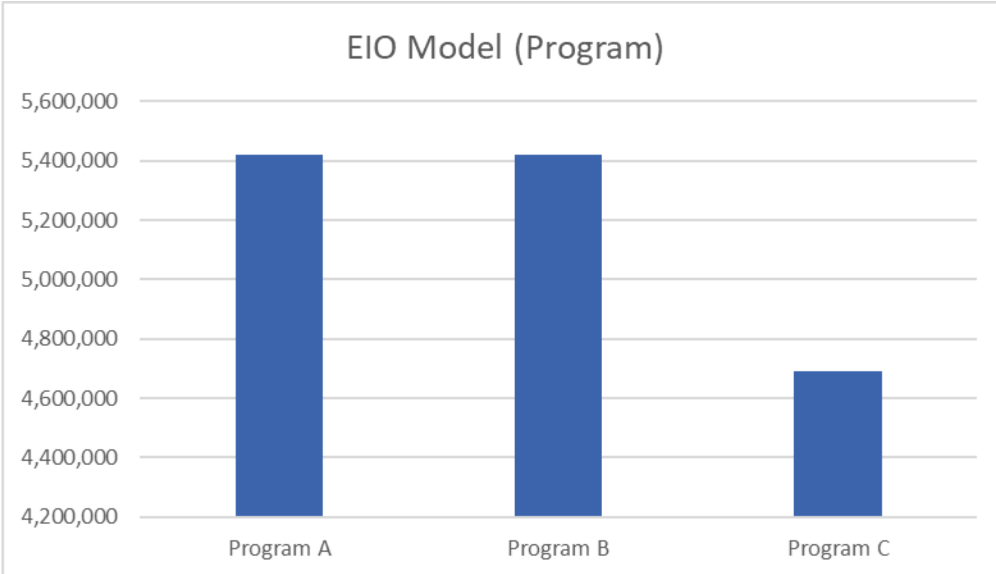

Figure 10: EIO Results (Program)

Secondary Method – Limitations

As with the primary method, there are some limitations. First, it is also a point estimate that fails to capture the true range of possible outcomes. Second, it does not distinguish between dollars spent on green materials and heavy emitting materials or activities. The output is based on the average emissions for dollars spent in the particular categories. Finally, while it provides a useful estimate of the potential impacts of a program it does not aid in decision making as the carbon footprint rises and falls in line with the cost.

Comparison

The following table highlights the rank order of each program on a per-aircraft and per-program basis depending on the method used.

Method/Program	Program A	Program B	Program C
Primary (Aircraft)	1	2	3
Primary (Program)	2	3	1
Secondary (Aircraft)	2	3	1
Secondary (Program)	2	3	1

Table 4: Method/Program Rank Order

Program C is ranked first under 3 methods. This is in part due to producing fewer aircraft. Though it is also due to the secondary method not distinguishing between the materials used. The relative rank of the programs changes in the primary method only because of the differing quantity. The relative rank differs between primary and secondary methods due to the price difference.

Of particular concern is the vastly differing estimates the two methods provide. This difference is highlighted in the following chart.

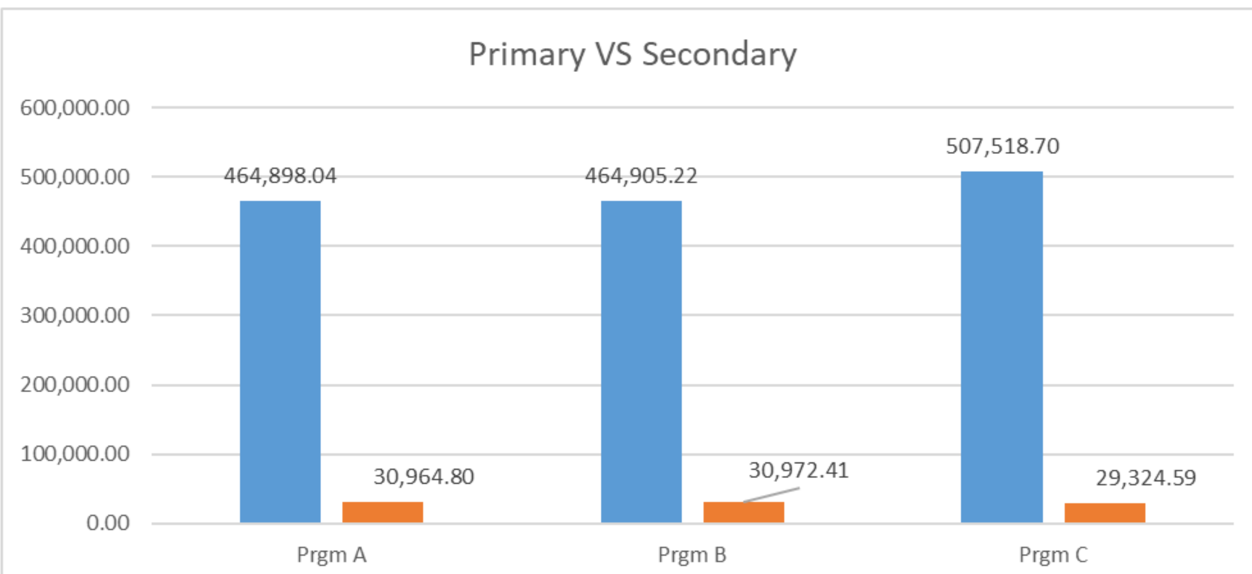

Figure 11: Primary vs Secondary Estimate

While it was expected that each model would provide differing results, this is a much larger difference than anticipated. While all of the WBS elements have differences in the estimate the bulk of the difference is driven by element 1.2 Air Vehicle. The difference between the primary and secondary estimates for element 1.2 is 434,108.6, 434,108.6, and 478,338.1 while the total difference is 433,933.2, 433,932.8, 478,194.1. A closer examination reveals that a significant driver of the additional carbon cost is the travel element. Which accounts for 459,080 tCO_2e for programs A and B, and 493,650 tCO_2e for program C. If the difference were to be removed, then the EIO method would have a higher estimate than the materials method. The difference may be explained either by double counting of carbon emissions as average travel is included in the materials or if the EIO model does not adequately account for travel. Furthermore, the assumption that most of the materials would have been transported by air has contributed to the difference in the estimates.

Distributions

The differences in the point estimates of the models are quite extreme. However, there are many unknowns and uncertainty in the models. Therefore, each model has a range of possible outcomes should these be accounted for in some degree. The models are limited by the available data regarding the emission factors. In order to provide a more complete picture of the possible carbon footprints a post-hoc distribution has been applied to each model.

One of the drivers of the divergent estimates appears to be the carbon emissions associated with shipping sub-assemblies in the Air Vehicle element. This is partially explained by the use of the initial worst-case assumption. The assumption was that the

majority of shipping would occur by air. After discussions with SMEs, it appears that shipping would most likely be by road. To better understand the range of possible outcomes a triangular distribution was chosen. The low estimate assumed all transport was conducted by rail, the most likely assumed road and the high assumed air. The EIO model only had a single datapoint, the mean, so a uniform distribution was chosen. In a uniform distribution the mean is equal to the sum of the low and high divided by two. Therefore, the low was calculated to be half of the mean and the high was calculated to be the mean plus the low. The following table summarized the distributions.

Program	**Per AC (Thousand $)**	**Program (Million $)**
A – Material Model	Triangle(13.6 , 63.5, 469.7)	Triangle(2.4, 11.1, 82.2)
B – Material Model	Triangle(13.7, 63.5, 470.1)	Triangle(2.4, 11.1, 82.3)
C – Material Model	Triangle(22.5, 77.3, 513)	Triangle(3.6, 12.4, 82)
A – EIO Model	Uniform(15.4, 46.4)	Uniform(2.7, 8.1)
B – EIO Model	Uniform(15.5, 46.5)	Uniform(2.7, 8,1)
C – EIO Model	Uniform(14.7, 43.9)	Uniform(2.3, 7)

Table 5: Distributions

Using the distributions in the table above a Monty Carlo simulation was run for 2,000 iterations. On each run, a random number generator was used in conjunction with the distribution to provide an estimate and build a distribution of the estimate. The following charts depict the material model distributions. The program level distributions and the EIO model distributions are available in the appendix.

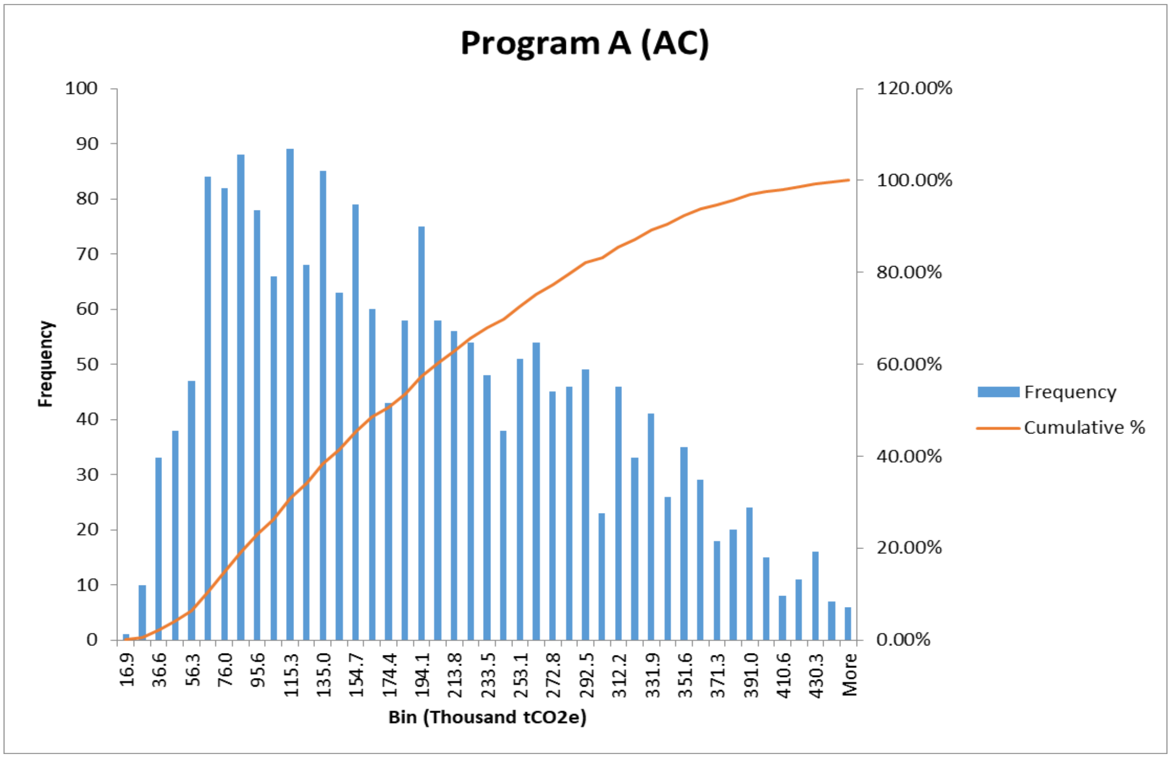

Figure 12: Material Model A Distribution

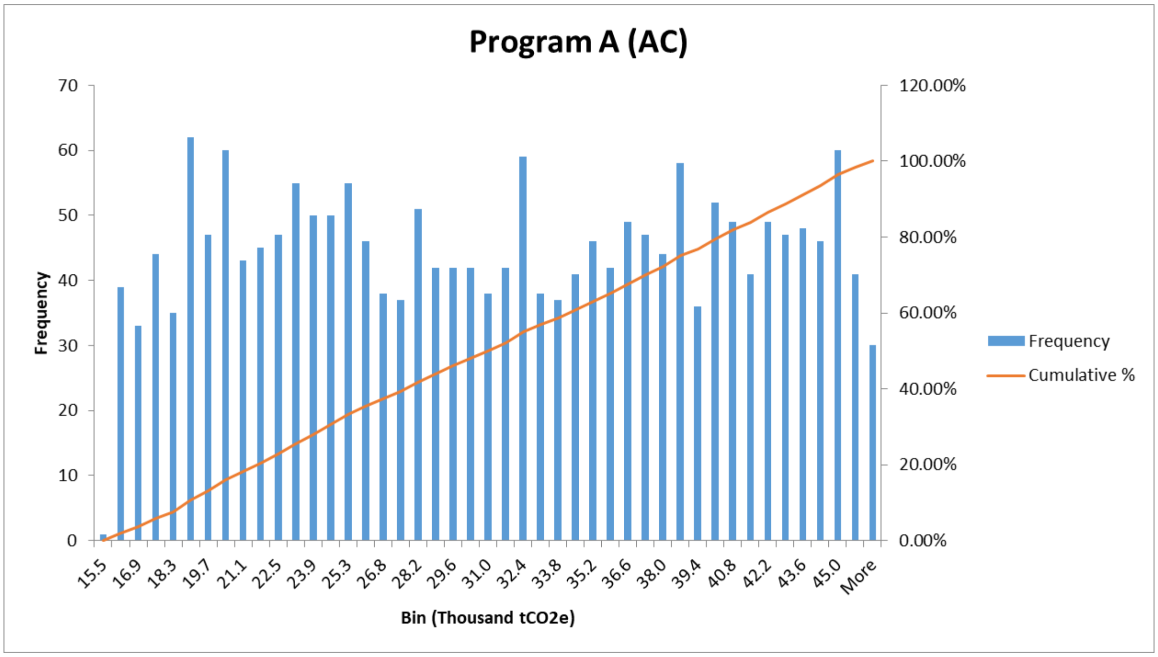

Figure 13: EIO Model A Distribution

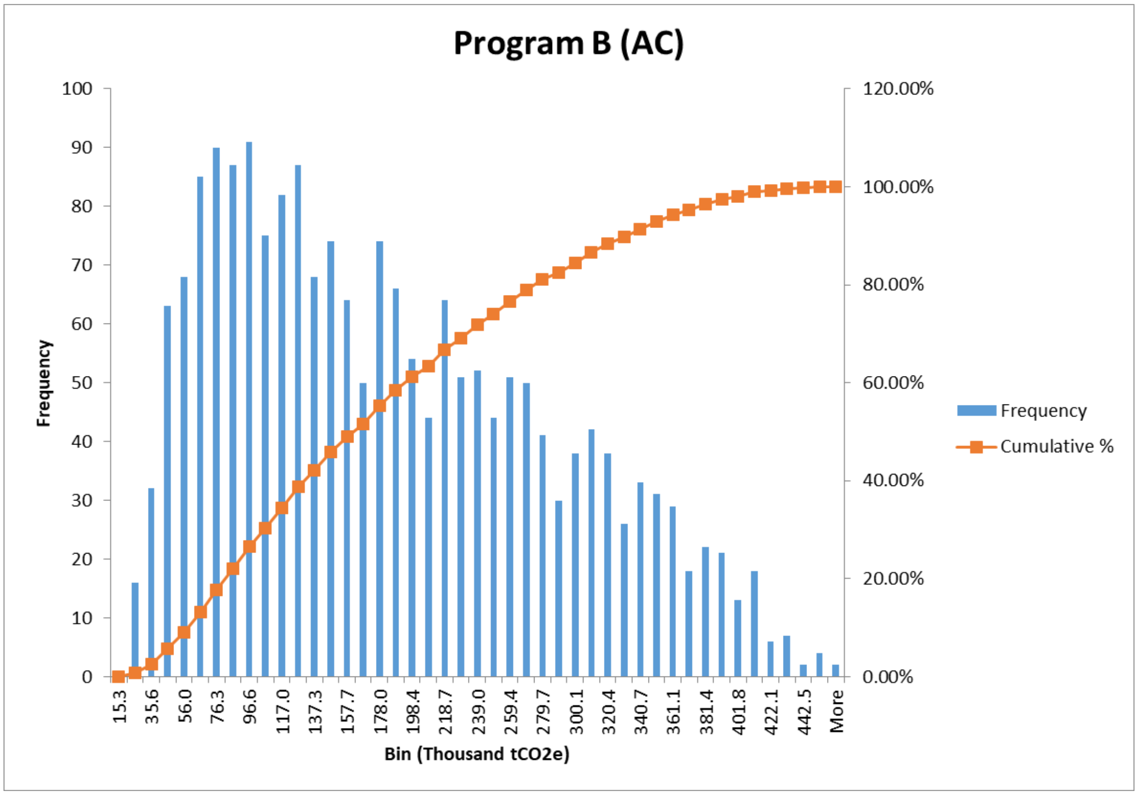

Figure 14: Material Model B Distribution

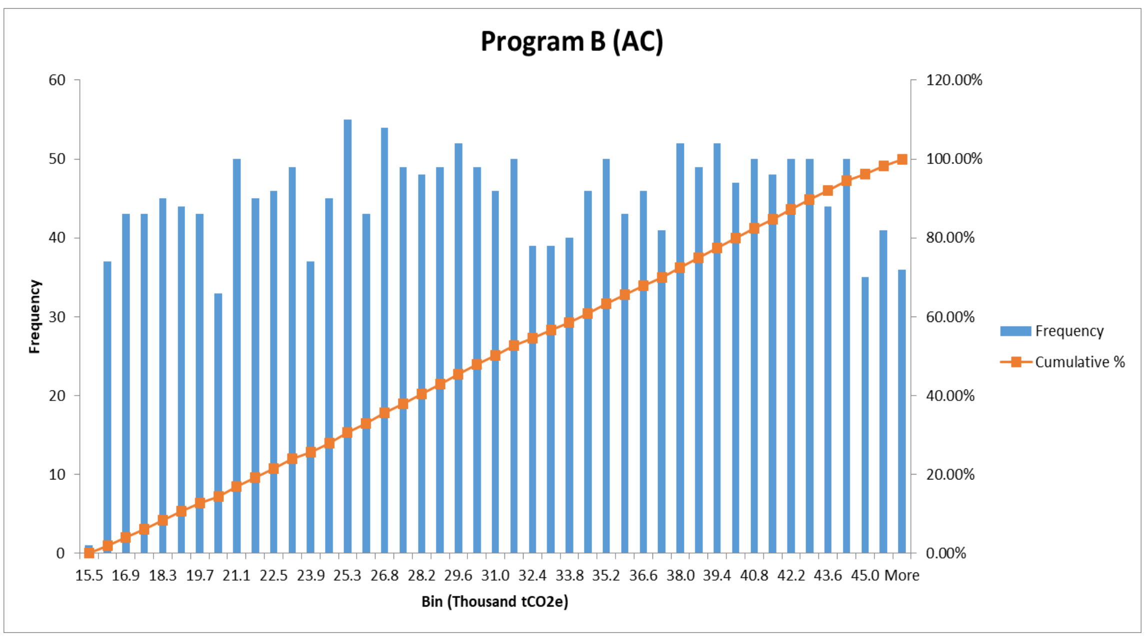

Figure 15: EIO Model B Distribution

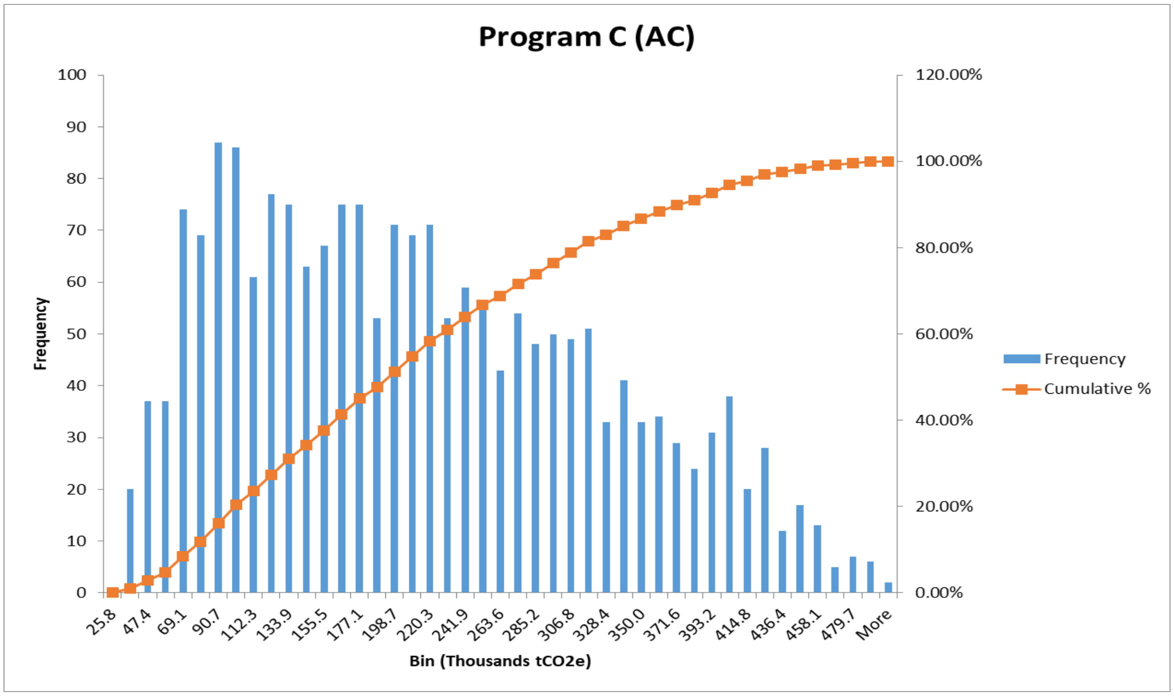

Figure 16: Material Model C Distribution

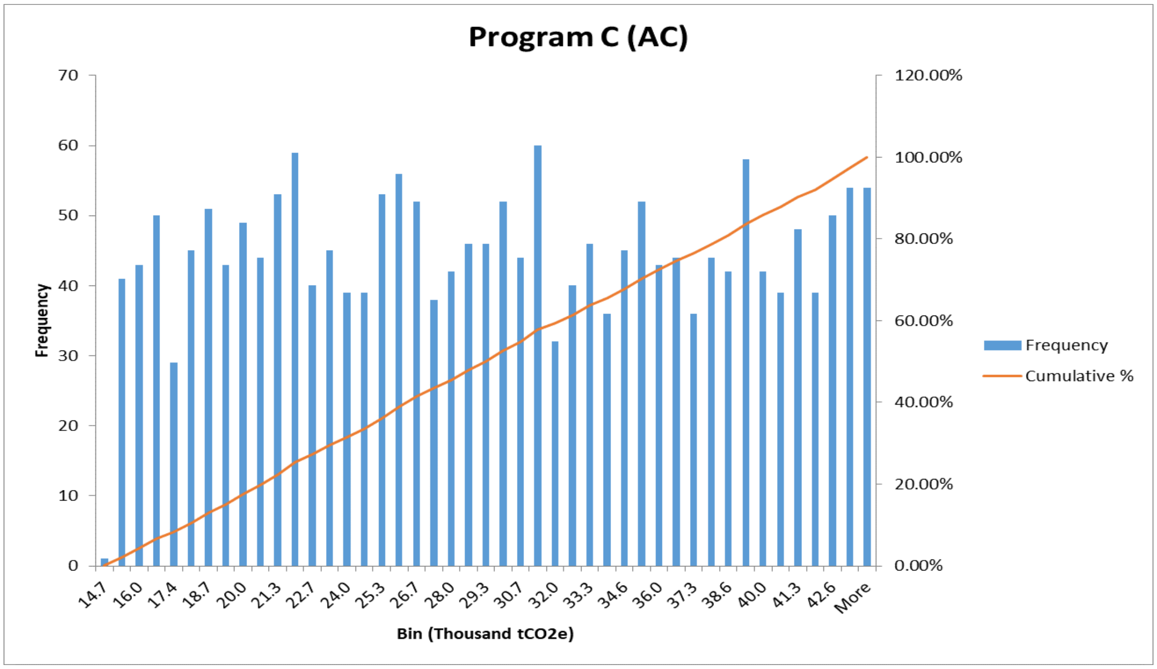

Figure 17: EIO Model C Distribution

The distributions depicted in the preceding charts highlight that even though the point estimates appear vastly different there is some overlap in the ranges of outcomes. This suggests that the models might be less different than first appear. Although, there is not enough consistency between the two models to determine a consensus of the true range. One of the issues is that the emissions factor for both short and long-haul air travel are significantly higher than the other factors. This skews the range of distribution on the material input model. A better understanding of proportions of travel methods would improve the model. However, the two model's differences are not fully reconciled even with the air travel ignored.

Part 2: The Decision Models

The following sections examine the results of the decision models. The sections are grouped based on the model used to estimate the carbon emission; primary or secondary. This is to enable a clearer comparison between the decision models. In each case, the weight of each element was initially set to equal then adjusted to determine the effects of different weights on the results.

Part 2: Material Model Results

Per Aircraft Results

The initial per aircraft results are summarized in the following table. The initial worst case carbon estimate was used in the decision models.

		Model 1	Model 2	Model 3
Program A	Value	0.66	0.65	0.71
	Rank	2	2	2
Program B	Value	0.56	0.55	0.61
	Rank	3	3	3
Program C	Value	0.72	0.70	0.78
	Rank	1	1	1

Table 6: Material Model Per Aircraft Results

Under all three models with equal weighting the elements Program C is the optimal choice. This is to be expected due to the lower cost and lower carbon emissions. Sensitivity analysis reveals that the ranking remains constant for the first model regardless of weighting except when performance is weighted at 0.80 or above at which point Program B becomes the top choice. The reason that Program B becomes the top choice when the weight reaches 0.8 is because it has a higher single-dimension value function for performance. Therefore, in a situation where performance is considered to be the most important factor by a significant amount even a small advantage in performance increases the overall value of the program.

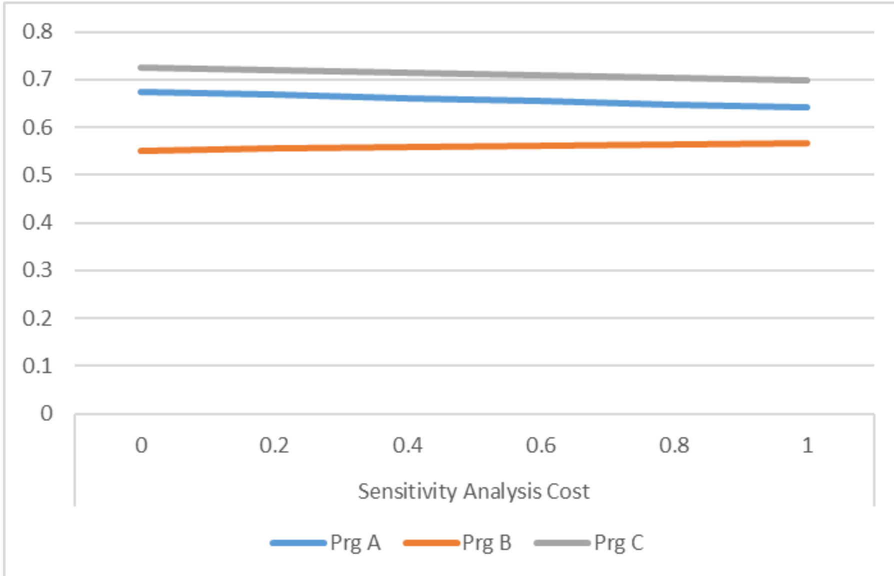

Figure 18: SA Cost: Model 1 (Per AC)

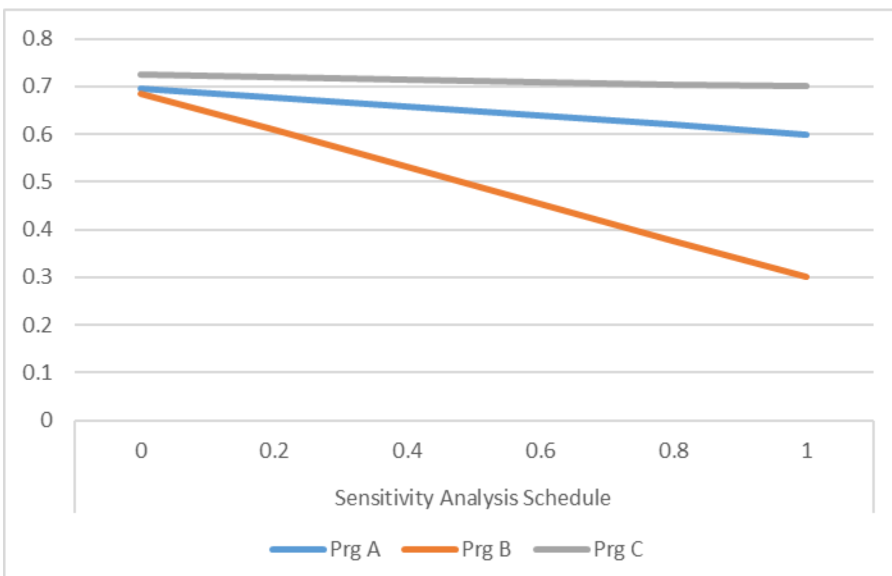

Figure 19: SA Schedule: Model 1 (Per AC)

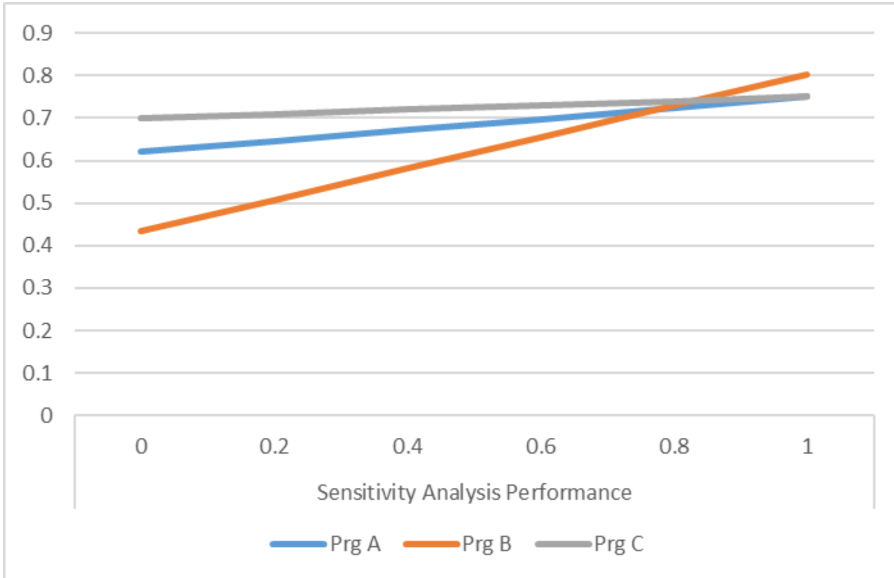

Figure 20: SA Performance: Model 1 (Per AC)

The second decision model was more sensitive to changes in weights. As shown below, Program C remains the top choice under most weightings. However, it is often not the top choice, particularly when the social cost of carbon and performance are weighted higher. This suggests that if this decision model is utilized additional care must be taken to ensure the chosen weights are representative of the true relative importance of each element. As discussed in the previous paragraph, small advantages in performance can result in shifting program preferences when performance is highly weighted. This affect is amplified somewhat for the SCC and cost factors. This is because it is a lower dollar value than the cost factor. Therefore, the effects of relatively small increased or decreases in the value of SCC are amplified when it is given a particularly high weight.

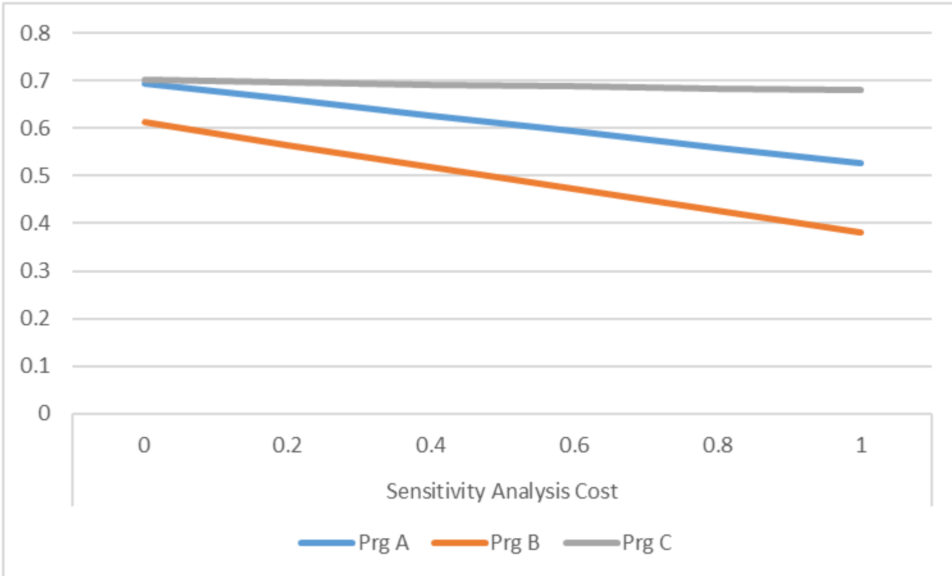

Figure 21: SA Cost: Model 2 (Per AC)

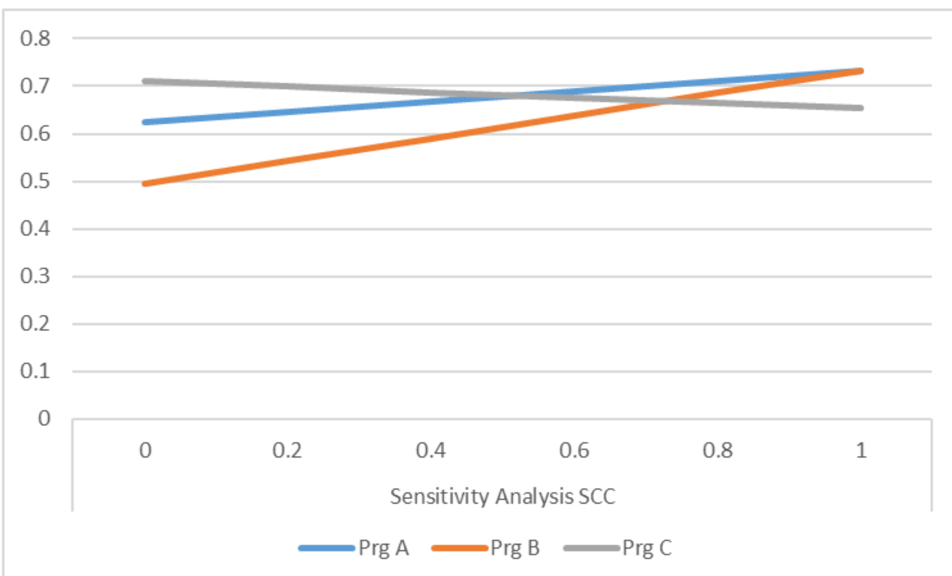

Figure 22: SA SCC: Model 2 (Per AC)

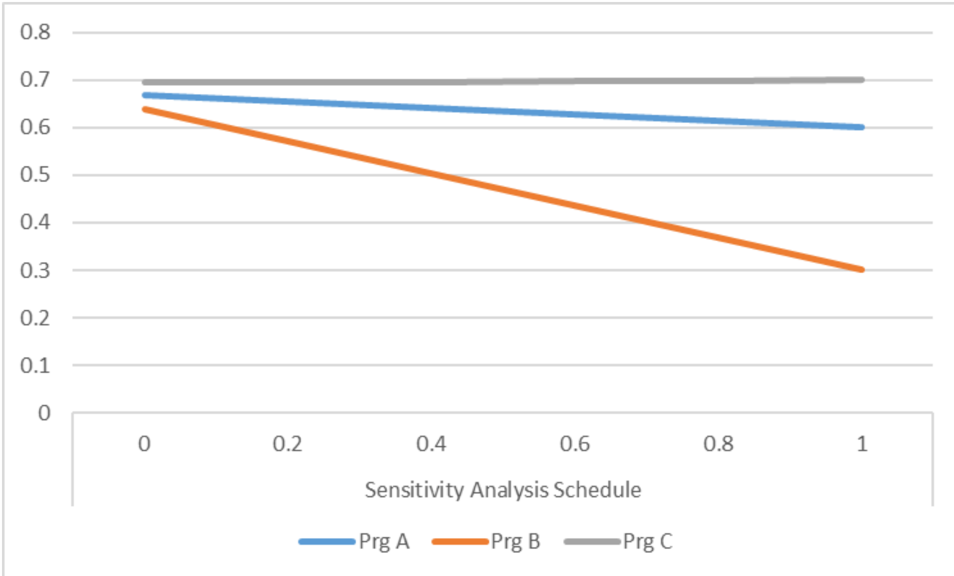

Figure 23: SA Schedule: Model 2 (Per AC)

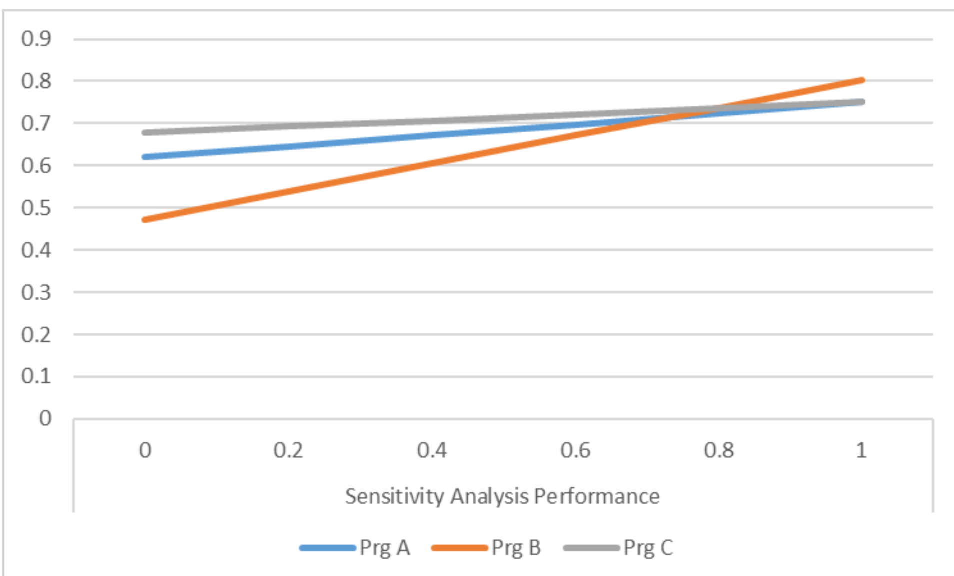

Figure 24: SA Performance: Model 2 (Per AC)

This sensitivity did not carry over into the third model. When utilizing a value function with raw carbon emissions Program C again dominates regardless of weighting; except when performance is weighted above 0.80.

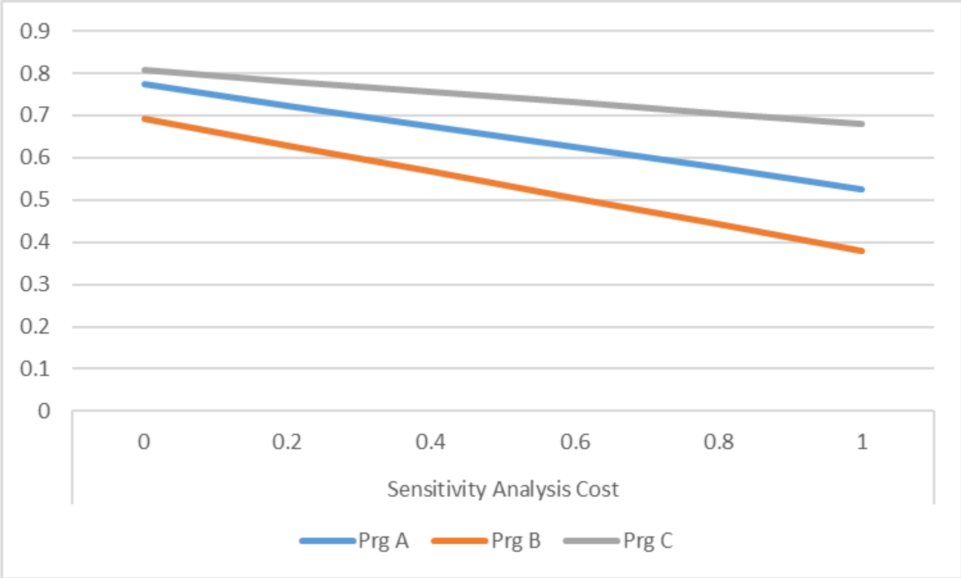

Figure 25: SA Cost: Model 3 (Per AC)

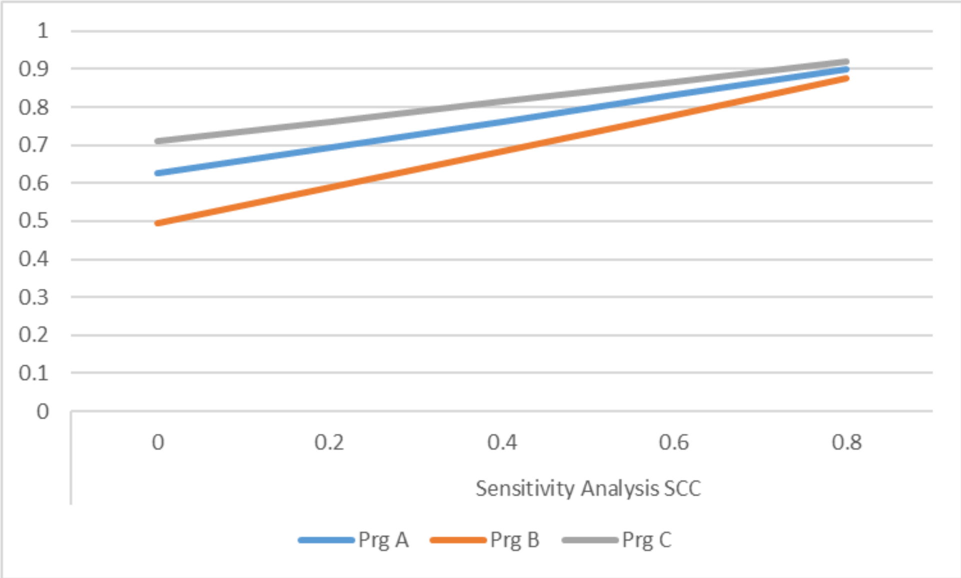

Figure 26: SA Carbon: Model 3 (Per AC)

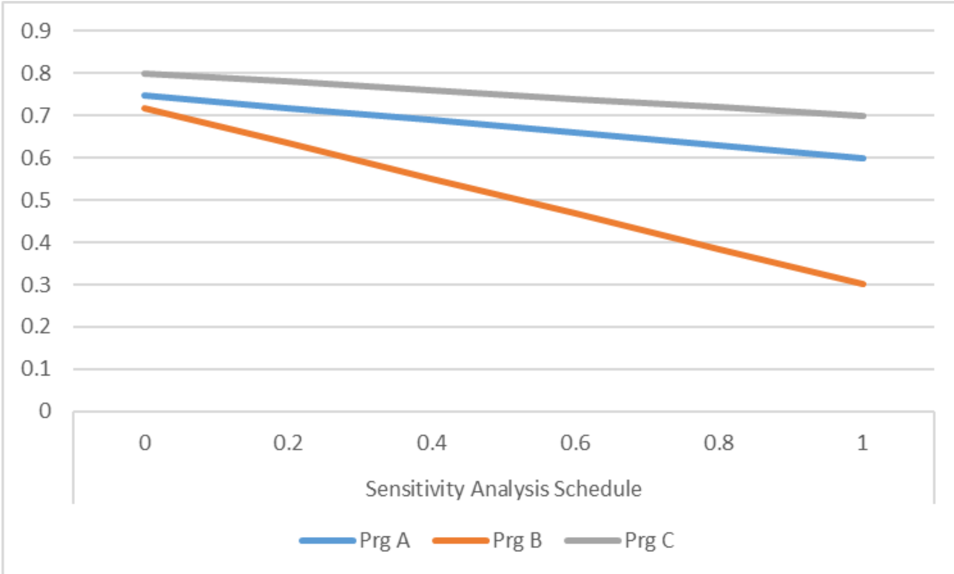

Figure 27: SA Schedule: Model 3 (Per AC)

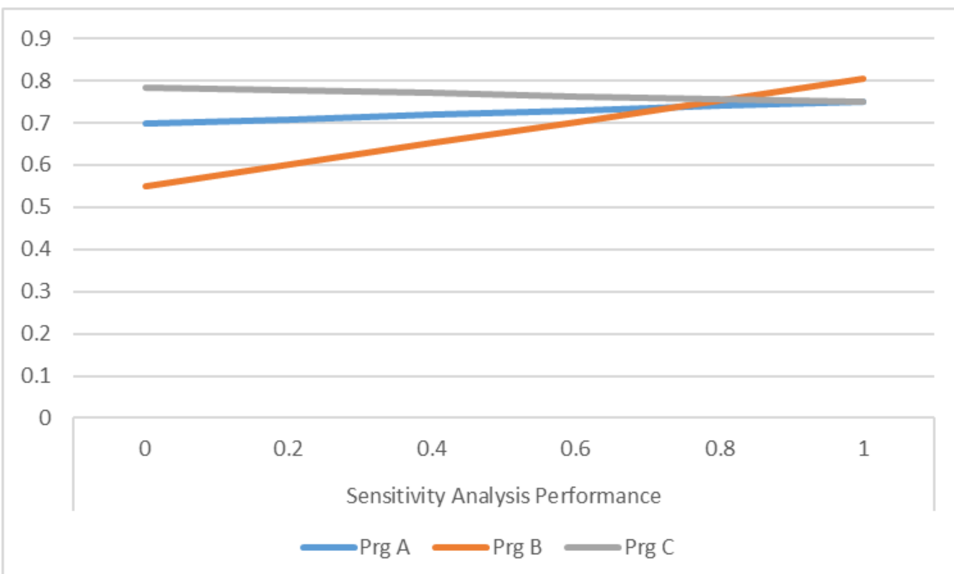

Figure 28: SA Performance: Model 3 (Per AC)

Per Program Results

When examined at the program level the overall results in terms of ranking remain consistent. Though the relative distance between the programs increases. This is

largely due to the different quantity of Program C. When conducting the sensitivity analysis, it was noted that Program C now dominated all three models regardless of weighting except when performance was rated at 0.80 or above. The following table summarizes the results of the models, and the chart shows the sensitivity analysis for all three models of the performance element.

		Model 1	**Model 2**	**Model 3**
Program A	Value	0.59	0.51	0.50
	Rank	2	2	2
Program B	Value	0.47	0.41	0.40
	Rank	3	3	3
Program C	Value	0.78	0.68	0.67
	Rank	1	1	1

Table 7: Material Per Program Results

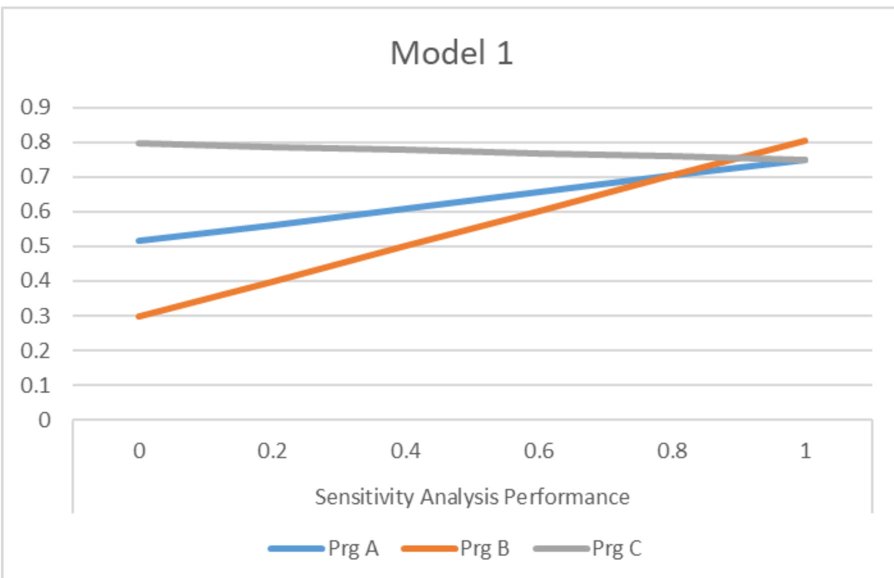

Figure 29: SA Performance: Model 1 (Program)

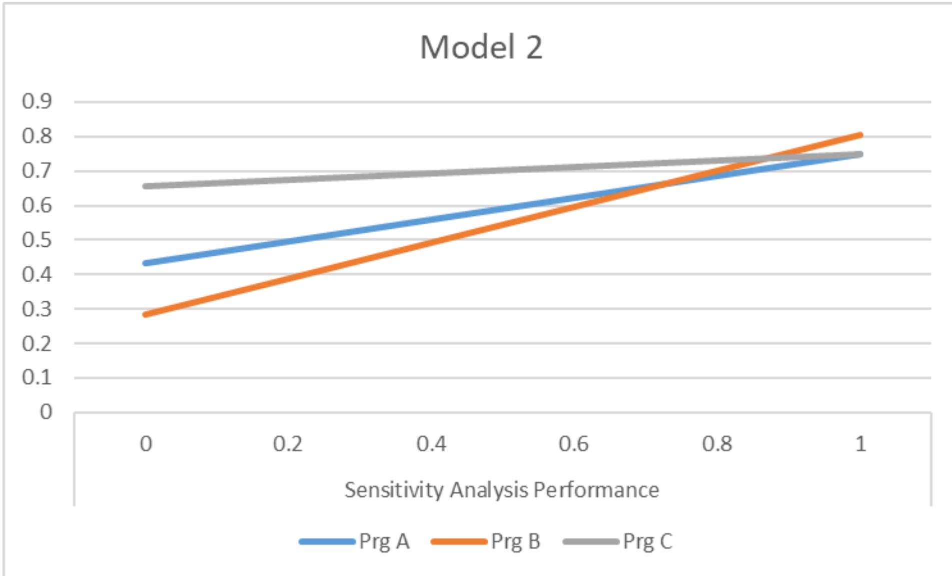

Figure 30: SA Performance: Model 2 (Program)

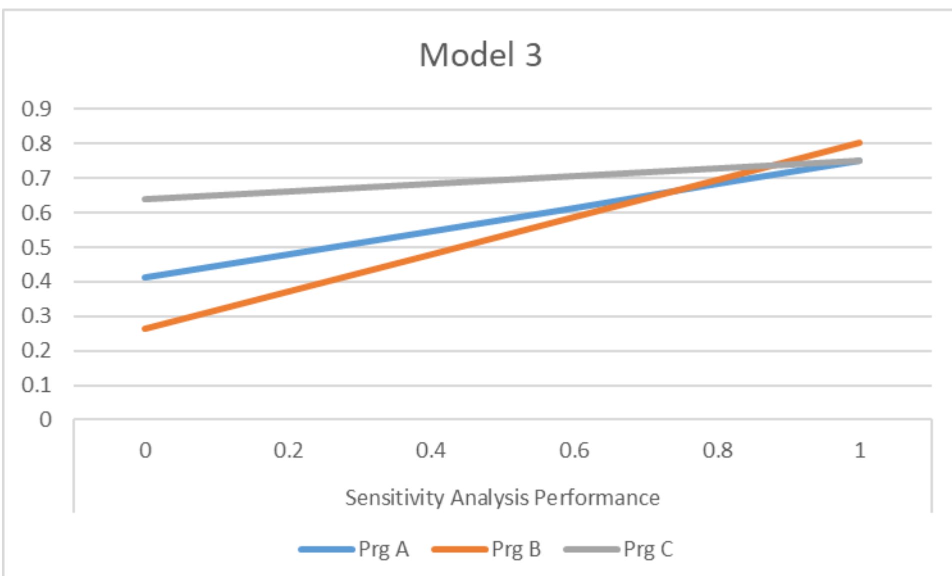

Figure 31: SA Performance: Model 3 (Program)

Part 2: EIO Model Results

Per Aircraft Results

The decision model results are very similar when the models use the secondary method as the carbon input. In all three models when each element is equally weighted Program C is the toped rank choice. The overall results are summarized in the following table.

		Model 1	Model 2	Model 3
Program A	Value	0.75	0.71	0.65
	Rank	2	2	2
Program B	Value	0.65	0.62	0.55
	Rank	3	3	3
Program C	Value	0.80	0.77	0.70
	Rank	1	1	1

Table 8: EIO Per Aircraft Results

The sensitivity analysis reveals the same outcomes as when the models were populated with the primary estimate. Program C tends to dominate except when the weight of performance is above 0.80 and when the raw carbon is weighted higher than 0.60. In these situations, Program B and Program A become the optimal choice. The following charts display the instances when the rank order is affected by the adjustment of the weights.

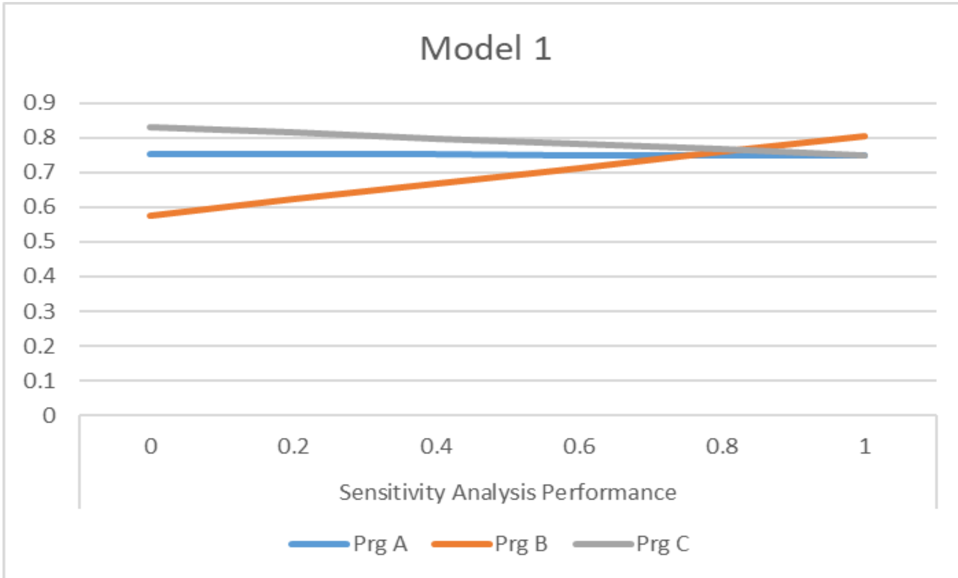

Figure 32: SA EIO Performance: Model 1 (Per AC)

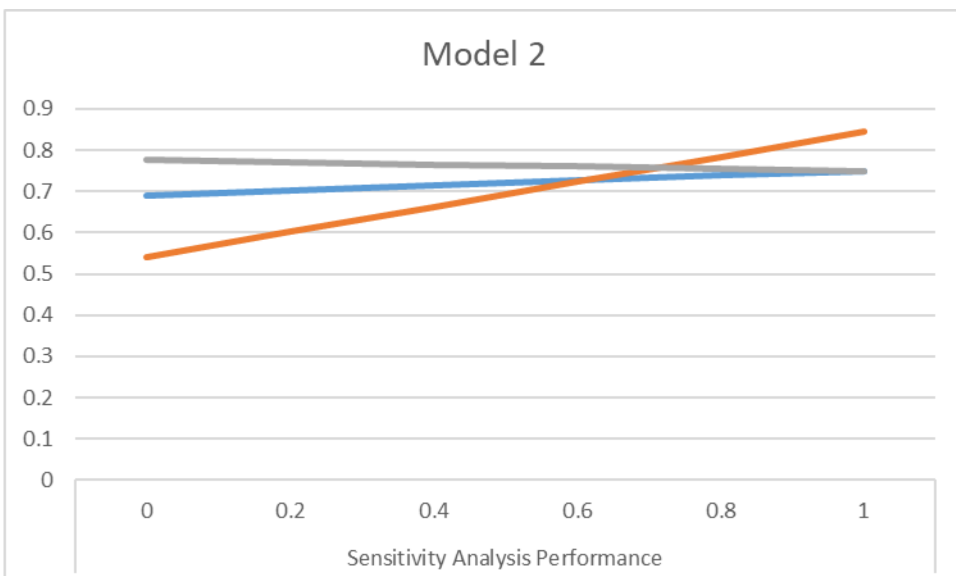

Figure 33: SA EIO Performance: Model 2 (Per AC)

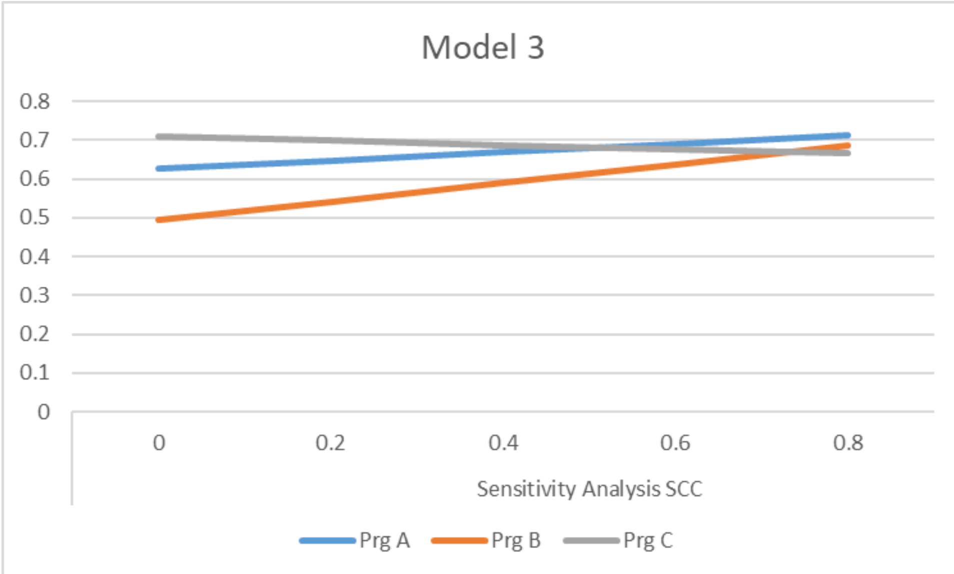

Figure 34: SA EIO Carbon: Model 3 (Per AC)

Per program Results

When utilizing the secondary method of carbon estimation to populate the decision models on a programmatic basis the results remain consistent with the per aircraft model and the primary estimation method. As with the primary estimation technique, the ranks of the programs remain consistent however, the distance between the values increases. The results are summarized in the following table.

		Model 1	**Model 2**	**Model 3**
Program A	Value	0.71	0.56	0.56
	Rank	2	2	2
Program B	Value	0.59	0.46	0.46
	Rank	3	3	3
Program C	Value	0.87	0.73	0.73
	Rank	1	1	1

Table 9: EIO Per Program Results

The results of the sensitivity analysis remain consistent. Program C dominates regardless of weighting except when performance is rated above 0.80; at which point Program B becomes the preferred choice. The following charts display the instances where there is a change in rank preference.

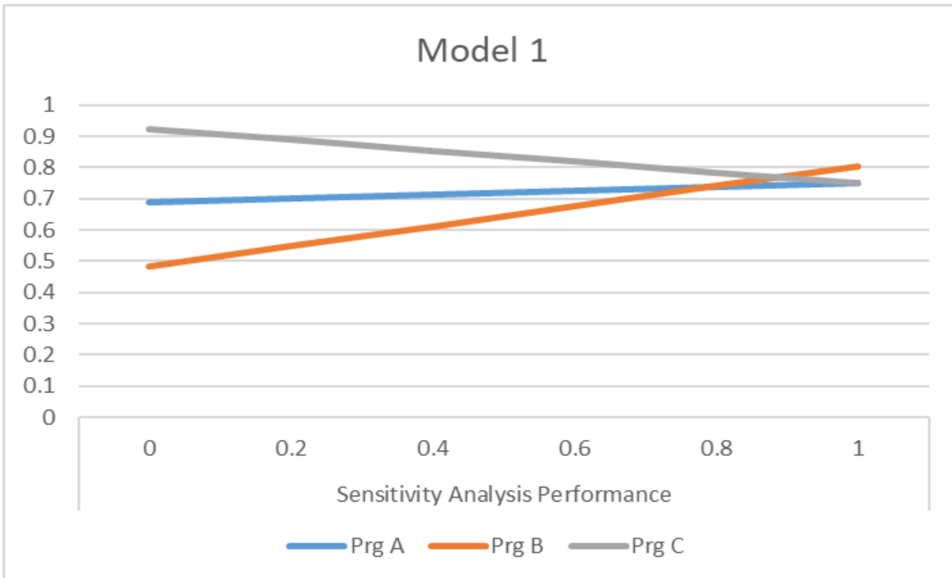

Figure 35: SA EIO Performance: Model 1 (Program)

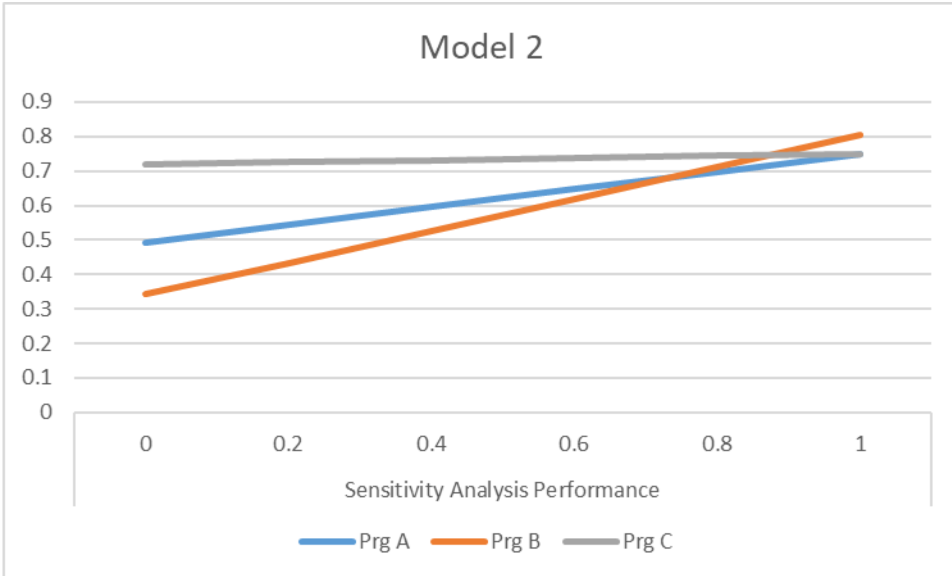

Figure 36: SA EIO Performance: Model 2 (Program)

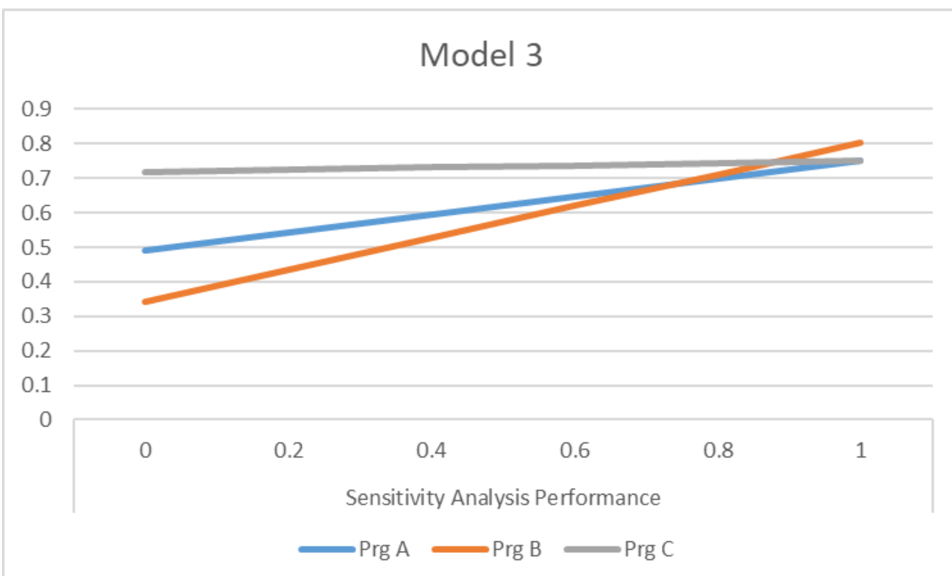

Figure 37: SA EIO Performance: Model 3 (Program)

Summary

This chapter examined in greater detail the development of the estimation models, the data to feed the models, and the decision models. It analyzed the discrepancy between

the primary and secondary model outputs, which is largely driven by the assumptions regarding material transport. Upon applying an output distribution to each model there is significantly less difference between the two models. Ultimately, the models each provide an estimate that could prove useful in quantifying the external costs of a production program. The decision models show that carbon dioxide emissions in either raw form or as a cost can be incorporated into effective decision models. Furthermore, it showed that the method chosen does not affect the outcome of the decision models in this limited setting. Though, it is not clear if there would be a subjective difference in the interpretation of the results based on decision-maker preference. The following chapter will further consider the implications of these results and suggest future research.

V. Conclusions and Recommendations

Introduction *of Research*

Over the course of several decades, the impacts of climate change and the impact humanity is having on the climate have become increasingly clear. There is growing international consensus that countries, particularly rich industrialized countries, need to take action to reduce carbon emissions and slow the effects of global warming. Thus far, international agreements such as the Paris Climate Accords have exempted military unique emissions from reporting and reduction requirements. However, if the USA is to meet its goal of net-zero by 2050 then the military must reduce its carbon footprint. This sentiment is echoed in executive orders signed by President Biden directing the Department of Defense to consider climate impacts and carbon emissions in all planning and decision-making processes.

There are well-established methods for conducting Lifecycle Assessments; these include climate impacts such as carbon footprint. However, these assessments are time-consuming and require detailed engineering breakdowns of a product or service to yield results. Furthermore, often early in lifecycles the designs are uncertain. In defense acquisition, by the time such details are available, it is often too late to influence the design choice or decision. While the DoD has in-house guidance on conducting LCAs it would be impractical to conduct such analysis in time to support key decisions in the acquisition process. Therefore, the aim of this research was to develop a model that could estimate the carbon emissions of a potential program early in its lifecycle without the need for detailed designs. This will enable decision-makers to truly weigh the internal

and external costs of a program and make decisions and design choices based on criteria beyond cost, schedule, and performance.

Specifically, this research aimed to determine if it is possible to build a model that can provide an acceptable estimation of the carbon footprint of producing a weapon system before detailed designs are complete? This research showed that simple models based on the standard WBS can be used to produce a carbon estimate of producing a weapons system. The EIO model provides a Rough Order of Magnitude (ROM) estimate based on only cost estimates of each element. As additional information becomes available the material model can provide additional insights into the carbon impacts of shipping methods and production choices such as materials and fuel use. It should be noted that these models have not been compared to a bone fide LCA that would provide a more accurate and verified estimate of the CO_2. In the absence of a verified LCA on a military system it may be possible use commercial platforms to verify the models. However, this would require examining the commercial product and converting its cost and materials into the military style WBS.

The second question was how can this estimate best be used in conjunction with cost, schedule, and performance as a factor in acquisition decision making? This research presented three decision models that utilize multi-objective value functions. Overall, based on this researche’s assumptions and limited scenarios there appears to be little impact on the outcomes based on the specific model chosen. However, as the SCC is likely to be increased in 2022 that could impact the results. The models developed in this research were kept generic to enable use and customization to the specific needs of a program. As such, the choices of value functions need to be adapted and targeted for

individual programs. In general, exponential functions were chosen for factors that could increase or decrease indefinitely and linear functions were chosen for subjective measures. From a technical standpoint changing the specific value functions and parameters to meet the specific needs of the program and decision maker would not be a difficult problem to solve. However, it could prove time-consuming and challenging to collect the information and establish the priorities of the decision maker.

A third question was also considered which was answered during the literature review. What is the ratio of carbon from production to operations? Multiple sources in the literature review estimate that production accounts for between one and five percent of the lifecycle emissions, based on a 30-year lifecycle. There appears to be some level of consensus on this ratio. However, no study reviewed in this research had included scope 3. It is possible that the inclusion of scope 3 emissions would alter this outcome, but this is unlikely as the other stages of the lifecycle should have similar levels of scope 3 emissions.

Contribution

This research has produced two models for estimating embodied carbon of producing a weapons system. The EIO model provides a useful tool when determining an initial estimate based on early cost estimates. This information can be used to better account for and understand the climate impacts of a program and its external costs (when combined with the SCC). The material model provides a more detailed estimate as more information becomes available. Though this model requires additional refinement before it is ready to be used in practice. The combination of the two models will provide

additional insight to decision-makers. The decision models provide a more objective framework for choosing between alternative proposals or programs by considering tradeoffs among cost, schedule, performance, and carbon. The basic model is platform agnostic and could easily be customized to meet the needs and objectives of a specific program.

Study Limitations

This study has some limitations, some of which have already been discussed.

Estimation Techniques

The estimation techniques are limited in that the database of emissions factors was limited to open-source databases. This means that many of the specific alloys and composite materials were not listed and had to be approximated. Second, the data was not a perfect fit for the design of the model and assumptions had to be made when converting the costs from the old WBS to the new. Third, the two methods disagree on the final estimate by a considerable amount. Though much of this is explained by the effect of the emissions from travel; it is not yet clear if it is a double count or undercount of emissions. Which should be further investigated in future research. Furthermore, once distribution ranges are applied to the outputs of the models the estimates are closer than the point estimates would indicate. Finally, while the models generate an estimate of the embodied carbon footprint there has yet to be a comprehensive LCC conducted on a military aircraft. This presents challenges for validating the results.

Decision Models

The decision models have limitations in that they do not adequately highlight the effects of quantity on the final output. Furthermore, as designed it does not appear there is an impact on the overall outcome based on the carbon estimates. This could be because the emissions are closely related to cost or because the data used in the decision model was not diverse enough to highlight the difference between internal and external costs.

Recommendations for Action

At this stage, it would not be recommended to include these models as a part of the decision-making process in acquisition. However, it is recommended that in the absence of a more robust estimation model that the EIO model (or an improved version) be used to develop a carbon estimate based on the cost estimate that every program requires. This carbon estimate should be multiplied by the current SCC rate and reported as external program costs as part of normal acquisition reporting. This would comply with and meet the intent of President Bidens EO 14008. As the estimation models are improved then the external costs should be further included in the decision-making process.

Recommendations for Future Research

When conducting this research, it became clear there are many areas that warrant further investigation. First, one of the issues facing the estimation models is the lack of a fully quantified Lifecycle Assessment or even carbon footprint calculation on Air Force weapons systems. A detailed LCA should be conducted to provide a measuring stick with which estimation models can be compared. It would also indicate which estimate from this research is more accurate.

Second, the models contained in this research could be combined and refined. Once a detailed LCA has been completed, this model could be built upon and refined to give a more robust estimate. The material input model and the EIO model should be compared to the LCA to determine if discrepancy in travel truly accounts for the differences in the model. The models could then be combined and refined to provide a better ROM based on limited information. Though a thorough LCA would need to be conducted first to provide a robust estimation of the lifecycle carbon impacts of a military aircraft.

Third, the model should be expanded to be able to account for phases beyond production. Again, this would require the full LCA to be accomplished before validating the estimate.

Finally, research should be conducted into how to incorporate LCA into Model Based System Engineering. There appears to be overlap in the techniques and if successful this could provide estimations of the carbon footprint of system designs that increase fidelity as the engineering process unfolds.

Summary

The goal of this research was to build a model that could provide an adequate estimate of the carbon emissions generated in the production phases of building a weapon system. This estimate would then be used to aid in the decision-making process and ensure acquisition leaders were considering the negative externalities of production decisions. While this research did not conclude with a final model ready for deployment, it did create the basic framework of a model which could lead to a more definitive model.

Furthermore, the literature review revealed that only a small percentage of the lifecycle emissions are produced in the production phase of an aircraft. This provides guidance that the preponderance of effort should be directed at reducing emissions in the operational phase, though many of the decisions will need to be made early in the lifecycle. Finally, while the model is not ready for widespread use as-is the concept was proved to be viable and can aid in increasing decision-makers' awareness of the negative external costs associated with their programs.

Appendix A: Standard WBS of Aircraft System

CWBS Code	CWBS Element Name
1.0	Aircraft System
1.1	Aircraft System, Integration, Assembly, Test, and Checkout
1.2	Air Vehicle
1.2.1	Air Vehicle Integration, Assembly, Test, and Checkout
1.2.1.1	Integration and Assembly
1.2.1.2	Test and Checkout
1.2.1.3	Rate Tooling
1.2.2	Airframe
1.2.2.1	Airframe Integration, Assembly, Test, and Checkout
1.2.2.2	Fuselage
1.2.2.2.1	Forward Fuselage
1.2.2.2.2	Center Fuselage
1.2.2.2.3	Aft Fuselage
1.2.2.2.4	Other Fuselage (specify)
1.2.2.3	Wing
1.2.2.4	Empennage
1.2.2.5	Nacelle
1.2.2.6	Other Airframe Components 1..n (Specify)
1.2.3	Propulsion
1.2.3.1	Propulsion Integration, Assembly, Test, and Checkout
1.2.3.2	Propulsion Hardware
1.2.3.3	Propulsion Software Release 1..n (Specify)
1.2.3.3.1	Propulsion Software CSCI 1..n (Specify)
1.2.4	Vehicle Subsystems
1.2.4.1	Vehicle Subsystem Integration, Assembly, Test, and Checkout
1.2.4.2	Flight Control Subsystem
1.2.4.2.1	Flight Control Hardware Integration, Assembly, Test and Checkout
1.2.4.2.2	Flight Control Hardware 1..n (Specify)
1.2.4.2.3	Flight Control Software Release 1..n (Specify)
1.2.4.2.3.1	Flight Control Software CSCI 1..n (Specify)
1.2.4.3	Auxiliary Power Subsystem
1.2.4.3.1	Auxiliary Power Hardware Integration, Assembly, Test, and Checkout
1.2.4.3.2	Auxiliary Power Hardware 1..n (Specify)
1.2.4.3.3	Auxiliary Power Software Release 1..n (Specify)
1.2.4.3.3.1	Auxiliary Power Software CSCI 1..n (Specify)
1.2.4.4	Hydraulic Subsystem
1.2.4.4.1	Hydraulic Hardware Integration, Assembly, Test, and Checkout

1.2.4.4.2	Hydraulic Hardware 1..n (Specify)
1.2.4.4.3	Hydraulic Software Release 1..n (Specify)
1.2.4.4.3.1	Hydraulic Software CSCI 1..n (Specify)
1.2.4.5	Electrical Subsystem
1.2.4.5.1	Electrical Hardware Integration, Assembly, Test, and Checkout
1.2.4.5.2	Electrical Hardware 1..n (Specify)
1.2.4.5.3	Electrical Software Release 1..n (Specify)
1.2.4.5.3.1	Electrical Software CSCI 1..n (Specify)
1.2.4.6	Crew Station Subsystem
1.2.4.6.1	Crew Station Hardware Integration, Assembly, Test, and Checkout
1.2.4.6.2	Canopy /Cockpit System
1.2.4.6.3	Mechanical System
1.2.4.6.4	Fire Protection System
1.2.4.6.5	Crew Station Software Release 1..n (Specify)
1.2.4.6.5.1	Crew Station Software CSCI 1..n (Specify)
1.2.4.7	Environmental Control Subsystem
1.2.4.7.1	Environmental Control Hardware Integration, Assembly, Test, and Checkout
1.2.4.7.2	Environmental Hardware 1..n (Specify)
1.2.4.7.3	Environmental Software Release 1..n (Specify)
1.2.4.7.3.1	Environmental Control Software CSCI 1..n (Specify)
1.2.4.8	Fuel Subsystem
1.2.4.8.1	Fuel Hardware Integration, Assembly, Test, and Checkout
1.2.4.8.2	Fuel Subsystem Hardware 1..n (Specify)
1.2.4.8.3	Fuel Subsystem Software Release 1..n (Specify)
1.2.4.8.3.1	Fuel Subsystem Software CSCI 1..n (Specify)
1.2.4.9	Landing Gear
1.2.4.9.1	Landing Gear Hardware Integration, Assembly, Test, and Checkout
1.2.4.9.2	Landing Gear Hardware 1..n (Specify)
1.2.4.9.3	Landing Gear Software Release 1..n (Specify)
1.2.4.9.3.1	Landing Gear Software CSCI 1..n (Specify)
1.2.4.10	Rotor Group
1.2.4.10.1	Rotor Group Hardware Integration, Assembly, Test, and Checkout
1.2.4.10.2	Rotor Group Hardware 1..n (Specify)
1.2.4.10.3	Rotor Group Software Release 1..n (Specify)
1.2.4.10.3.1	Rotor Group Software CSCI 1..n (Specify)
1.2.4.11	Drive Group
1.2.4.11.1	Drive Group Hardware Integration, Assembly, Test, and Checkout
1.2.4.11.2	Drive Group Subsystem Hardware 1..n (Specify)
1.2.4.11.3	Drive Group Subsystem Software Release 1..n (Specify)
1.2.4.11.3.1	Drive Group Subsystem Software CSCI 1..n (Specify)
1.2.4.12	Vehicle Subsystem Software Release 1..n (Specify)
1.2.4.12.1	Vehicle Subsystems Software CSCI 1..n (Specify)

1.2.4.13	Other Subsystems 1...n (Specify)
1.2.4.13.1	Other Vehicle Subsystem Hardware Integration, Assembly, Test, and Checkout
1.2.4.13.2	Other Vehicle Subsystem Hardware 1..n (Specify)
1.2.4.13.3	Other Vehicle Subsystems Software Release 1..n (Specify)
1.2.4.13.3.1	Other Vehicle Subsystem Software CSCI 1..n (Specify)
1.2.5	Avionics
1.2.5.1	Avionics Integration, Assembly, Test And Checkout
1.2.5.2	Communication/Identification
1.2.5.2.1	Communication/Identification Hardware Integration, Assembly, Test, and Checkout
1.2.5.2.2	Communication/Identification Hardware 1..n (Specify)
1.2.5.2.3	Communication/Identification Software Release 1..n (Specify)
1.2.5.2.3.1	Communication/Identification Software CSCI 1..n (Specify)
1.2.5.3	Navigation/Guidance
1.2.5.3.1	Navigation/Guidance Hardware Integration, Assembly, Test, and Checkout
1.2.5.3.2	Navigation/Guidance Hardware 1..n (Specify)
1.2.5.3.3	Navigation/Guidance Software Release 1..n (Specify)
1.2.5.3.3.1	Navigation/Guidance Software CSCI 1..n (Specify)
1.2.5.4	Mission Computer/Processing
1.2.5.4.1	Mission Computer/Processing Hardware Integration, Assembly, Test, and Checkout
1.2.5.4.2	Mission Computer/Processing Hardware 1..n (Specify)
1.2.5.4.3	Mission Computer/Processing Software Release 1..n (Specify)
1.2.5.4.3.1	Mission Computer/Processing Software CSCI 1..n (Specify)
1.2.5.5	Fire Control
1.2.5.5.1	Fire Control Hardware Integration, Assembly, Test, and Checkout
1.2.5.5.2	Radar
1.2.5.5.3	Fire Control Hardware 1..n (Specify)
1.2.5.5.4	Fire Control Software Release 1..n (Specify)
1.2.5.5.4.1	Fire Control Software CSCI 1..n (Specify)
1.2.5.6	Data Display & Control
1.2.5.6.1	Data Display and Control Hardware Integration, Assembly, Test And Checkout
1.2.5.6.2	Data Display & Control Hardware 1..n (Specify)
1.2.5.6.3	Data Display & Control Software Release 1..n (Specify)
1.2.5.6.3.1	Data Display & Control Software CSCI 1..n (Specify)
1.2.5.7	Survivability
1.2.5.7.1	Survivability Hardware Integration, Assembly, Test, and Checkout
1.2.5.7.2	Survivability Hardware 1..n (Specify)
1.2.5.7.3	Survivability Software Release 1..n (Specify)
1.2.5.7.3.1	Survivability Software CSCI 1..n (Specify)
1.2.5.8	Reconnaissance
1.2.5.8.1	Reconnaissance Hardware Integration, Assembly, Test, and Checkout
1.2.5.8.2	Reconnaissance Hardware 1..n (Specify)
1.2.5.8.3	Reconnaissance Software Release 1..n (Specify)

1.2.5.8.3.1	Reconnaissance Software CSCI 1..n (Specify)
1.2.5.9	Electronic Warfare
1.2.5.9.1	Electronic Warfare Hardware Integration, Assembly, Test, and Checkout
1.2.5.9.2	Electronic Warfare Hardware 1..n (Specify)
1.2.5.9.3	Electronic Warfare Software Release 1..n (Specify)
1.2.5.9.3.1	Electronic Warfare Software CSCI 1..n (Specify)
1.2.5.10	Automatic Flight Control
1.2.5.10.1	Automatic Flight Control Hardware Integration, Assembly, Test, and Checkout
1.2.5.10.2	Automatic Flight Control Hardware 1..n (Specify)
1.2.5.10.3	Automatic Flight Control Software Release 1..n (Specify)
1.2.5.10.3.1	Automatic Flight Control Software CSCI 1..n (Specify)
1.2.5.11	Health Monitoring System
1.2.5.11.1	Health Monitoring Hardware Integration, Assembly, Test, and Checkout
1.2.5.11.2	Health Monitoring System Hardware 1..n (Specify)
1.2.5.11.3	Health Monitoring System Software Release 1..n (Specify)
1.2.5.11.3.1	Health Monitoring System Software CSCI 1..n (Specify)
1.2.5.12	Stores Management
1.2.5.12.1	Stores Management Hardware Integration, Assembly, Test, and Checkout
1.2.5.12.2	Stores Management Hardware 1..n (Specify)
1.2.5.12.3	Stores Management Software Release 1..n (Specify)
1.2.5.12.3.1	Stores Management Software CSCI 1..n (Specify)
1.2.5.13	Avionics Software Release 1..n (Specify)
1.2.5.13.1	Avionics Software CSCI 1..n (Specify)
1.2.5.14	Other Avionics Subsystems 1...n (Specify)
1.2.5.14.1	Other Avionics Subsystem Hardware Integration, Assembly, Test, and Checkout
1.2.5.14.2	Other Avionics Subsystem Hardware 1..n (Specify)
1.2.5.14.3	Other Avionics Subsystem Software Release 1..n (Specify)
1.2.5.14.3.1	Other Avionics Subsystem Software CSCI 1..n (Specify)
1.2.6	Armament/Weapons Delivery
1.2.6.1	Armament Installation, Assembly, Test, and Checkout
1.2.6.2	Armament/Weapons Delivery System 1..n (Specify)
1.2.6.3	Armament/Weapons Delivery Software Release 1..n (Specify)
1.2.6.3.1	Armament/Weapons Delivery Software CSCI 1..n (Specify)
1.2.7	Auxiliary Equipment
1.2.8	Furnishings and Equipment
1.2.9	Air Vehicle Software Release 1..n (Specify)
1.2.9.1	Air Vehicle Software CSCI 1..n (Specify)
1.2.10	Other Air Vehicle 1...n (Specify)
1.3	Payload/Mission System
1.3.1	Payload Integration, Assembly, Test, and Checkout
1.3.1.1	Integration and Assembly
1.3.1.2	Test and Checkout

1.3.1.3	Rate Tooling
1.3.2	Survivability Payload 1...n (Specify)
1.3.3	Reconnaissance Payload 1...n (Specify)
1.3.4	Electronic Warfare Payload 1...n (Specify)
1.3.5	Armament/Weapons Delivery Payload 1...n (Specify)
1.3.6	Payload Software Release 1...n (Specify)
1.3.6.1	Payload Software CSCI 1..n (Specify)
1.3.7	Other Payload 1...n (Specify)
1.4	Ground/Host Segment
1.4.1	Ground Segment Integration, Assembly, Test, and Checkout
1.4.1.1	Integration and Assembly
1.4.1.2	Test and Checkout
1.4.1.3	Rate Tooling
1.4.2	Ground Control Systems
1.4.3	Command and Control Subsystem
1.4.4	Launch Equipment
1.4.5	Recovery Equipment
1.4.6	Transport Vehicles
1.4.7	Ground Segment Software Release 1...n (Specify)
1.4.7.1	Ground Segment Software CSCI 1..n (Specify)
1.4.8	Other Ground/Host Segment 1...n (Specify)
1.5	Aircraft System Software Release 1...n (Specify)
1.5.1	Aircraft System Software CSCI 1...n (Specify)
1.6	Systems Engineering
1.6.1	Software Systems Engineering
1.6.2	Integrated Logistics Support (ILS) Systems Engineering
1.6.3	Cybersecurity Systems Engineering
1.6.4	Core Systems Engineering
1.6.5	Other Systems Engineering 1...n (Specify)
1.7	Program Management
1.7.1	Software Program Management
1.7.2	Integrated Logistics Support (ILS) Program Management
1.7.3	Cybersecurity Management
1.7.4	Core Program Management
1.7.5	Other Program Management 1...n (Specify)
1.8	System Test and Evaluation
1.8.1	Development Test and Evaluation
1.8.1.1	System Acceptance Test (SAT)
1.8.1.2	Wind Tunnel
1.8.1.3	Structural Test
1.8.1.4	Flight Test
1.8.1.5	Ground Test

1.8.1.6	Cybersecurity Test and Evaluation
1.8.1.6.1	Cybersecurity Development Test
1.8.1.6.2	Cybersecurity Operational Test
1.8.1.6.3	Cybersecurity Other (1...n)
1.8.1.7	Service/Agency DT&E 1...n (Specify) (GOV ONLY)
1.8.1.8	Other DT&E Tests 1...n (Specify)
1.8.2	Operational Test and Evaluation
1.8.2.1	Limited User Evaluation (LUE/M-LUT/FUE)
1.8.2.2	Interoperability Testing (IOP with IA/OT&E)
1.8.2.3	Flight Test
1.8.2.4	Ground Test
1.8.2.5	Cybersecurity Test and Evaluation
1.8.2.5.1	Cybersecurity Development Test
1.8.2.5.2	Cybersecurity Operational Test
1.8.2.5.3	Cybersecurity Other (1...n)
1.8.2.6	Other OT&E Tests 1...n (Specify)
1.8.3	Live Fire Test and Evaluation
1.8.3.1	Cybersecurity Development Test
1.8.3.2	Cybersecurity Operational Test
1.8.3.3	Cybersecurity Other (1…n)
1.8.4	Mock-ups/System Integration Labs (SILs)
1.8.5	Test and Evaluation Support
1.8.6	Test Facilities
1.8.6.1	Commercial (GOV ONLY)
1.8.6.2	Government (Pay-as-You-Go) (GOV ONLY)
1.9	Training
1.9.1	Equipment
1.9.1.1	Operator Instructional Equipment
1.9.1.2	Maintainer Instructional Equipment
1.9.2	Services
1.9.2.1	Operator Instructional Services
1.9.2.1.1	Development of Training Materials
1.9.2.1.2	Provide Training
1.9.2.2	Maintainer Instructional Services
1.9.2.2.1	Development of Training Materials
1.9.2.2.2	Provide Training
1.9.3	Facilities
1.9.4	Training Software 1...n (Specify)
1.9.4.1	Training Software CSCI 1...n (Specify)
1.10	Data
1.10.1	Data Deliverables 1...n (Specify)
1.10.2	Data Repository

1.10.3	Data Rights 1...n (Specify)
1.11	Peculiar Support Equipment
1.11.1	Test and Measurement Equipment
1.11.1.1	Test and Measurement Equipment (Airframe/Hull/Vehicle)
1.11.1.2	Test and Measurement Equipment (Propulsion)
1.11.1.3	Test and Measurement Equipment (Electronics/Avionics)
1.11.1.4	Test and Measurement Equipment (Other Major Subsystems 1...n (Specify))
1.11.2	Support and Handling Equipment
1.11.2.1	Support and Handling Equipment (Airframe/Hull/Vehicle)
1.11.2.2	Support and Handling Equipment (Propulsion)
1.11.2.3	Support and Handling Equipment (Electronics/Avionics)
1.11.2.4	Support and Handling Equipment (Other Major Subsystems 1...n (Specify))
1.12	Common Support Equipment
1.12.1	Test and Measurement Equipment
1.12.1.1	Test and Measurement Equipment (Airframe/Hull/Vehicle)
1.12.1.2	Test and Measurement Equipment (Propulsion)
1.12.1.3	Test and Measurement Equipment (Electronics/Avionics)
1.12.1.4	Test and Measurement Equipment (Other Major Subsystems 1...n (Specify))
1.12.2	Support and Handling Equipment
1.12.2.1	Support and Handling Equipment (Airframe/Hull/Vehicle)
1.12.2.2	Support and Handling Equipment (Propulsion)
1.12.2.3	Support and Handling Equipment (Electronics/Avionics)
1.12.2.4	Support and Handling Equipment (Other Major Subsystems 1...n (Specify))
1.13	Operational/Site Activation by Site 1...n (Specify)
1.13.1	System Assembly, Installation and Checkout on Site
1.13.1.1	Deployment HW and SW
1.13.1.2	Site Activation
1.13.2	Contractor Technical Support
1.13.3	Site Construction
1.13.4	Site/Ship/Vehicle Conversion
1.13.5	Interim Contractor Support (ICS)
1.14	Contractor Logistics Support (CLS)
1.15	Industrial Facilities
1.15.1	Construction/Conversion/Expansion
1.15.2	Equipment Acquisition or Modernization
1.15.3	Maintenance (Industrial Facilities)
1.16	Initial Spares and Repair Parts
1.16.1	PMP Spare and Repair 1...n (Specify)
1.16.2	Support Equipment Spare and Repair Parts
1.16.3	Training Equipment Spare and Repair Parts
1.16.4	Packaging, Handling, Storage, and Transportation (PHS&T)
1.16.4.1	Containers

1.16.4.2 Transportation

Appendix B: Distributions

Program	Per AC	Program
A – Material Model	Triangle(13,665, 63,496, 46,9715)	Triangle(2,391,356, 11,111,886, 82,200,134)
B – Material Model	Triangle(13,699, 63,534, 470,107)	Triangle(2,397,293, 11,118,528, 82,268,812)
C – Material Model	Triangle(22,492, 77,289, 512,661)	Triangle(3,598,705, 12,366,175, 82,025,769)
A – EIO Model	Uniform(15,483, 46,448)	Uniform(2,709,421, 8,128,262)
B – EIO Model	Uniform(15,486, 46,458)	Uniform(2,710,086, 8,130,257)
C – EIO Model	Uniform(14,663, 43,988)	Uniform(2,345,967, 7,037,901)

Table 10: Distributions (Exact)

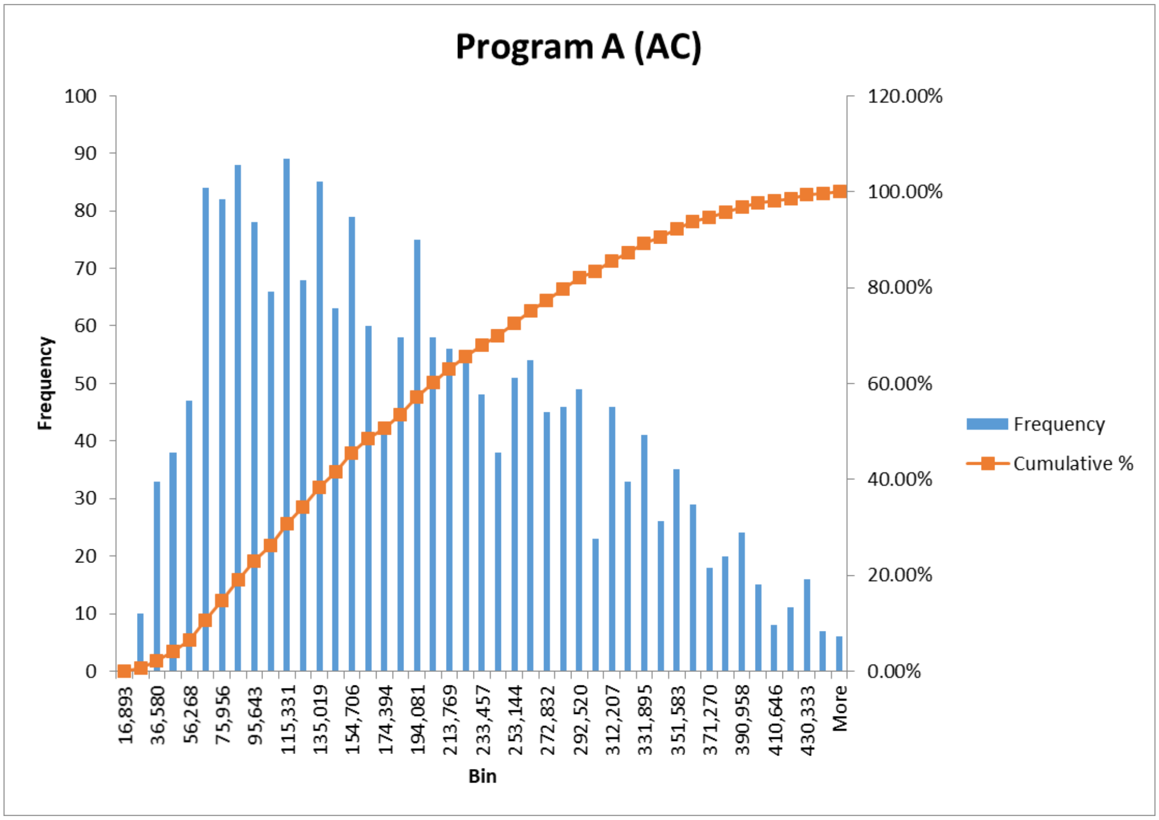

Figure 38: Program A (AC) Material

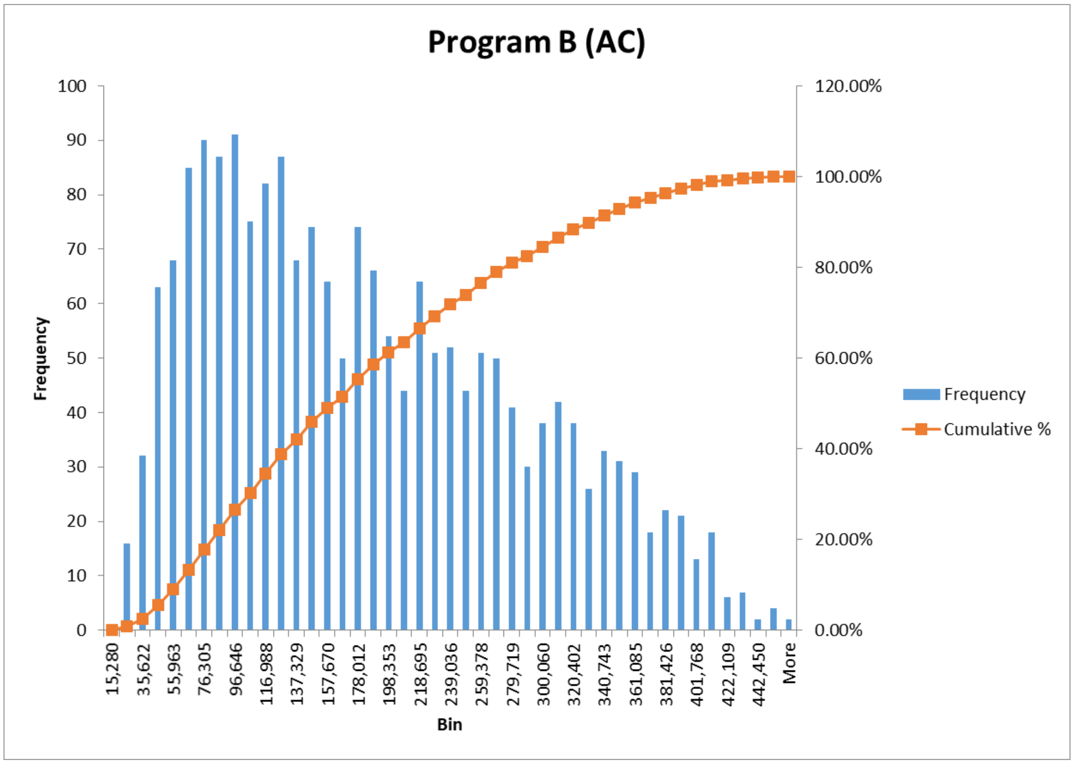

Figure 39: Program B (AC) Material

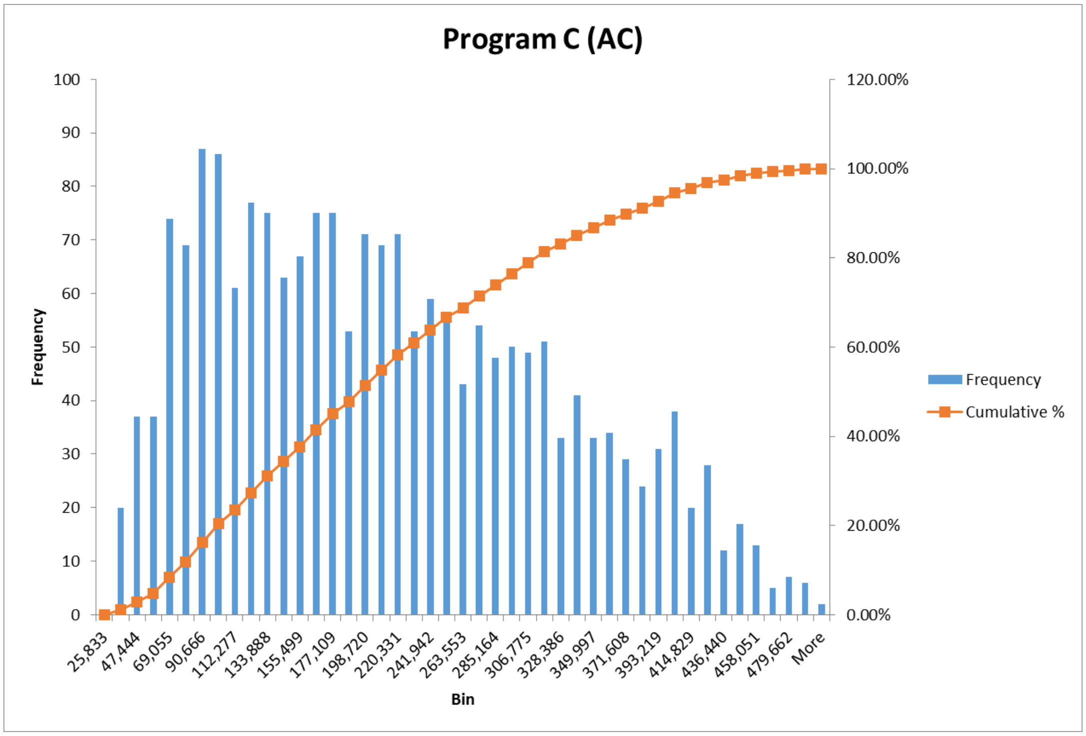

Figure 40: Program C (AC) Material

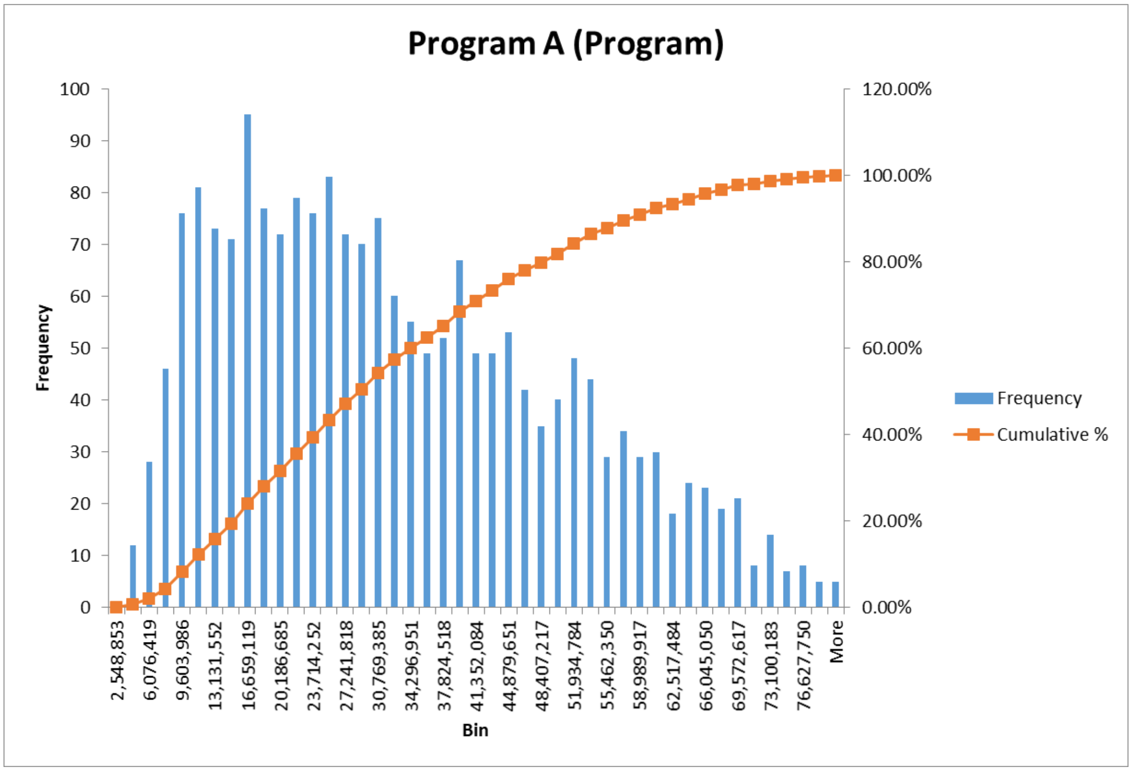

Figure 41: Program A (Program) Material

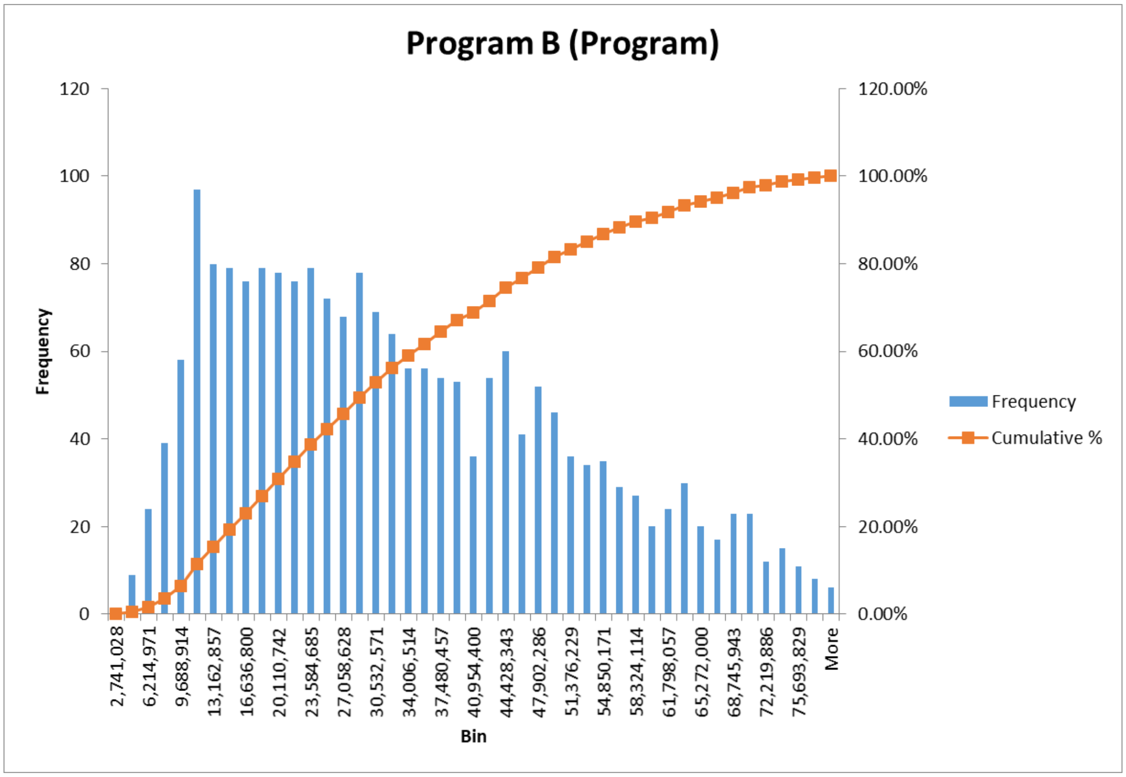

Figure 42: Program B (Program) Material

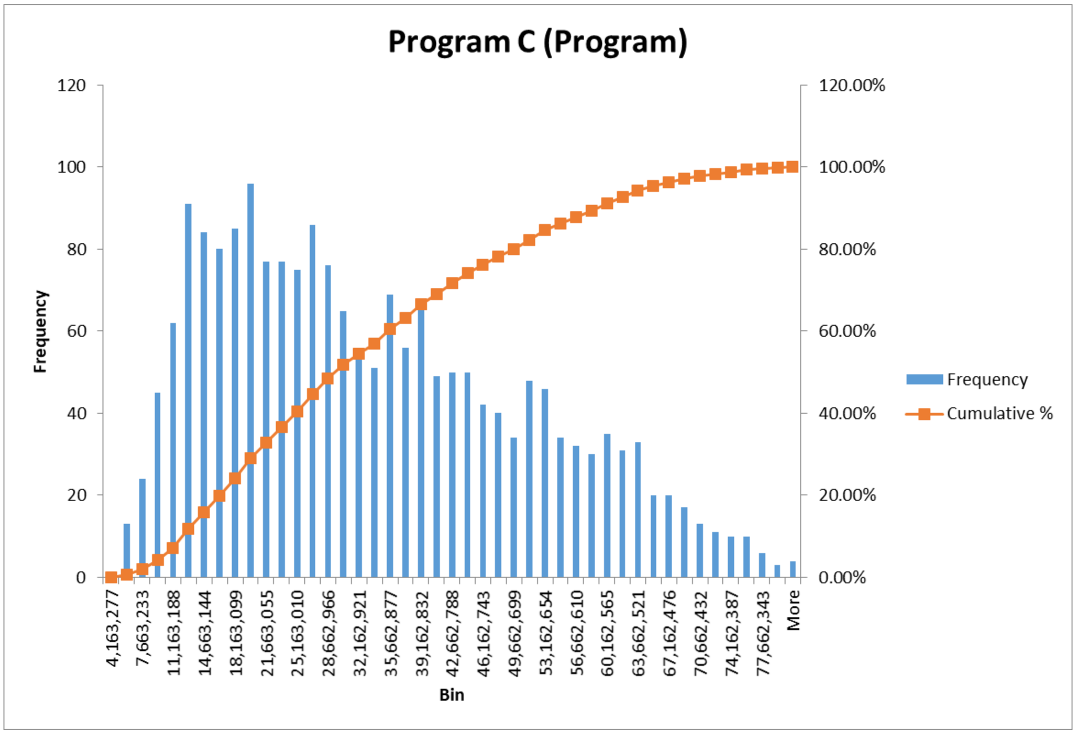

Figure 43: Program C (Program) Material

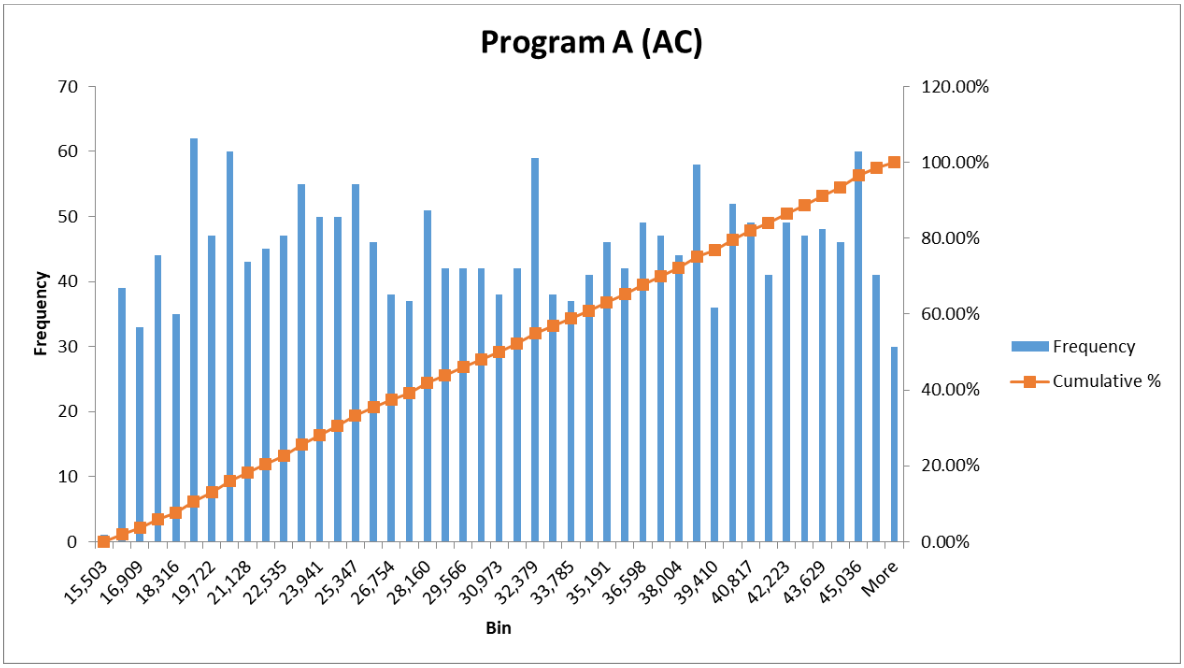

Figure 44: Program A (AC) EIO

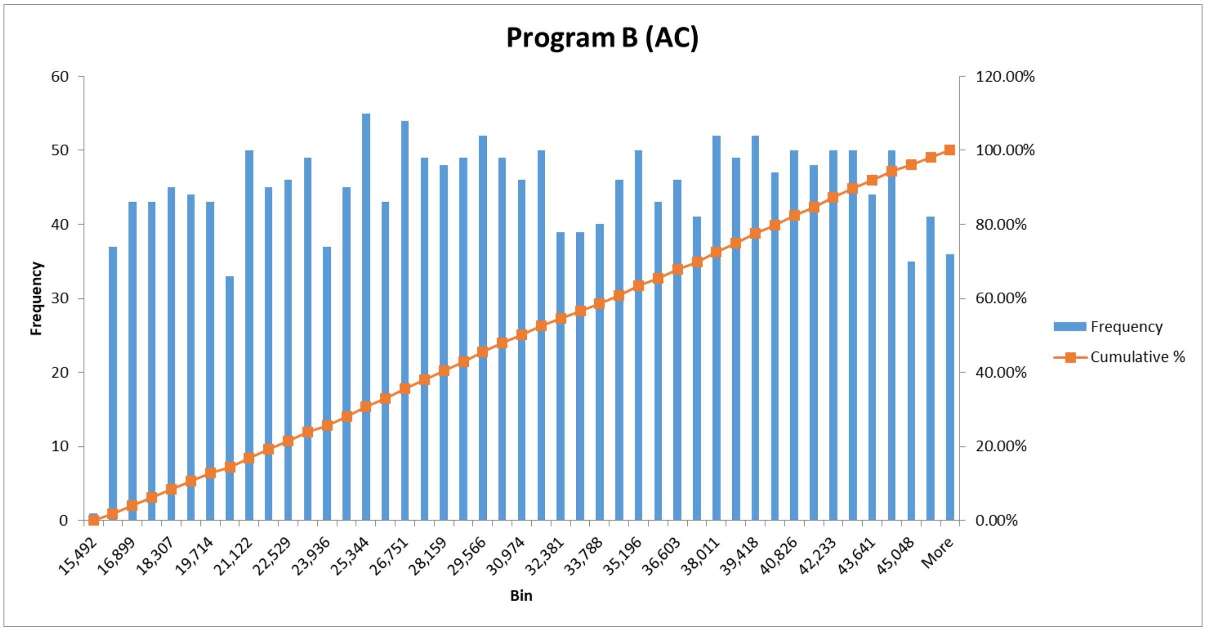

Figure 45: Program B (AC) EIO

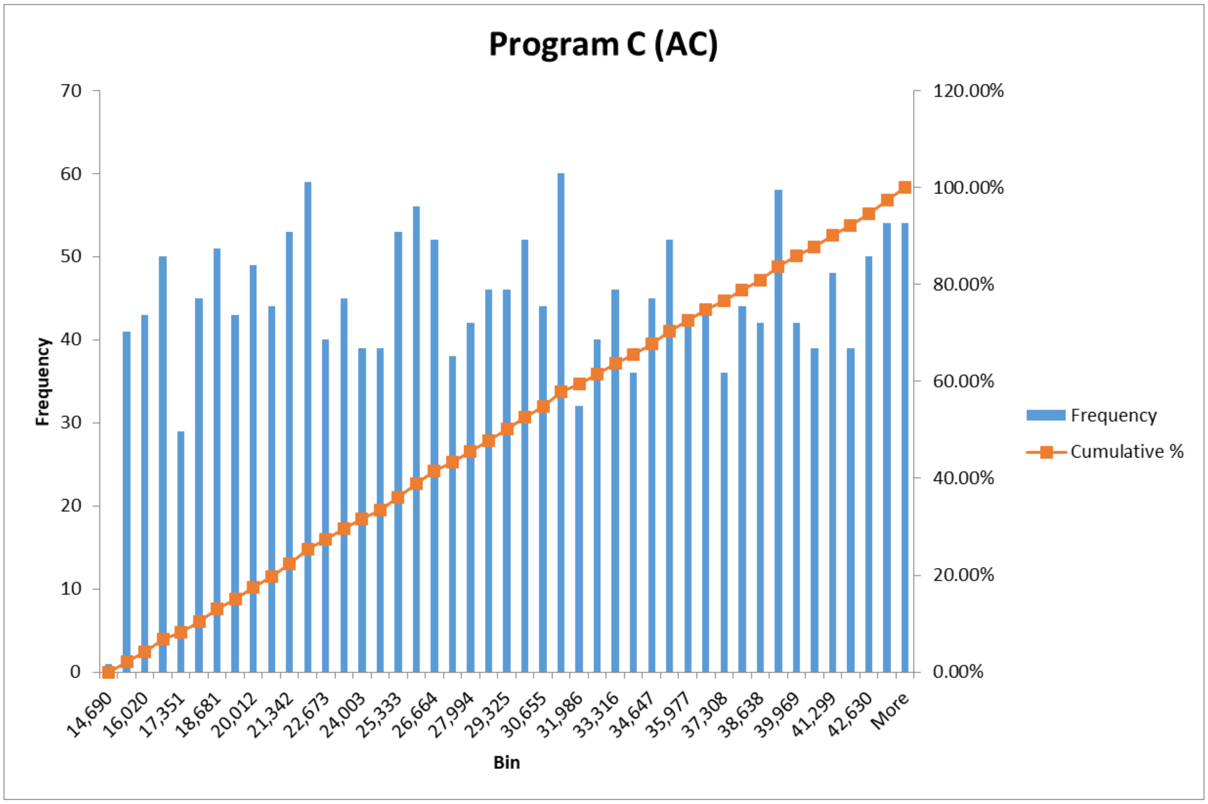

Figure 46: Program C (AC) EIO

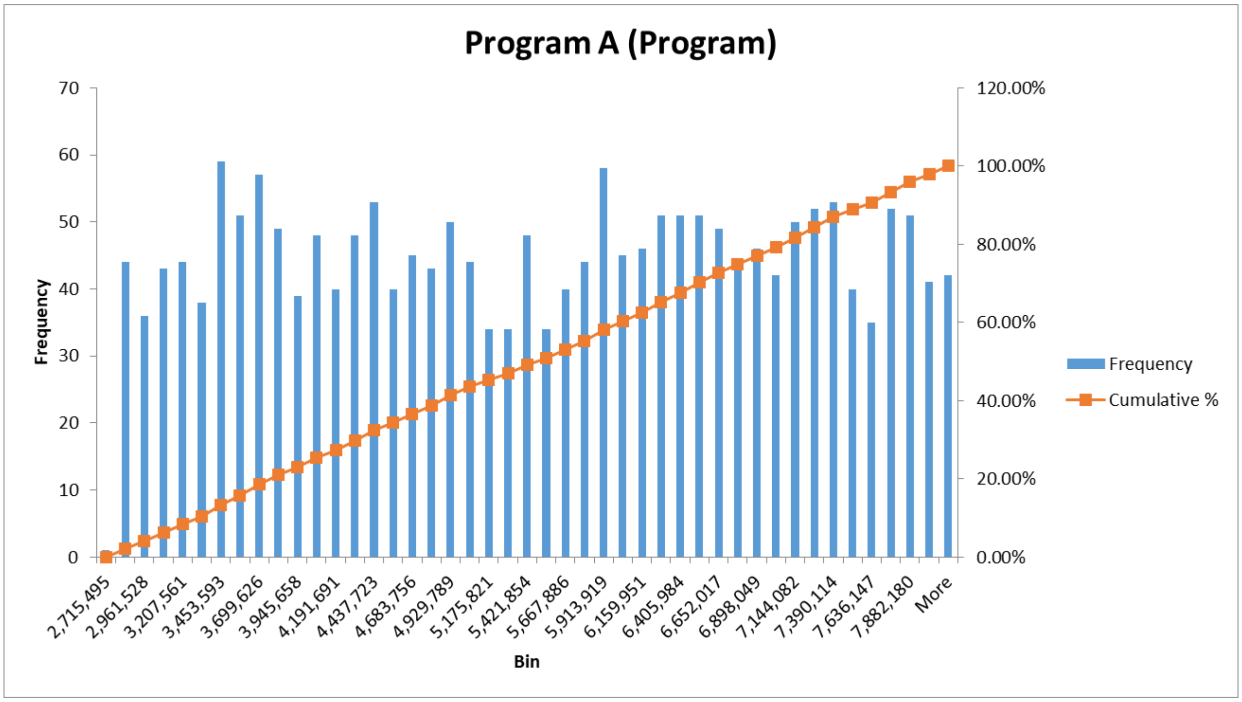

Figure 47: Program A (Program) EIO

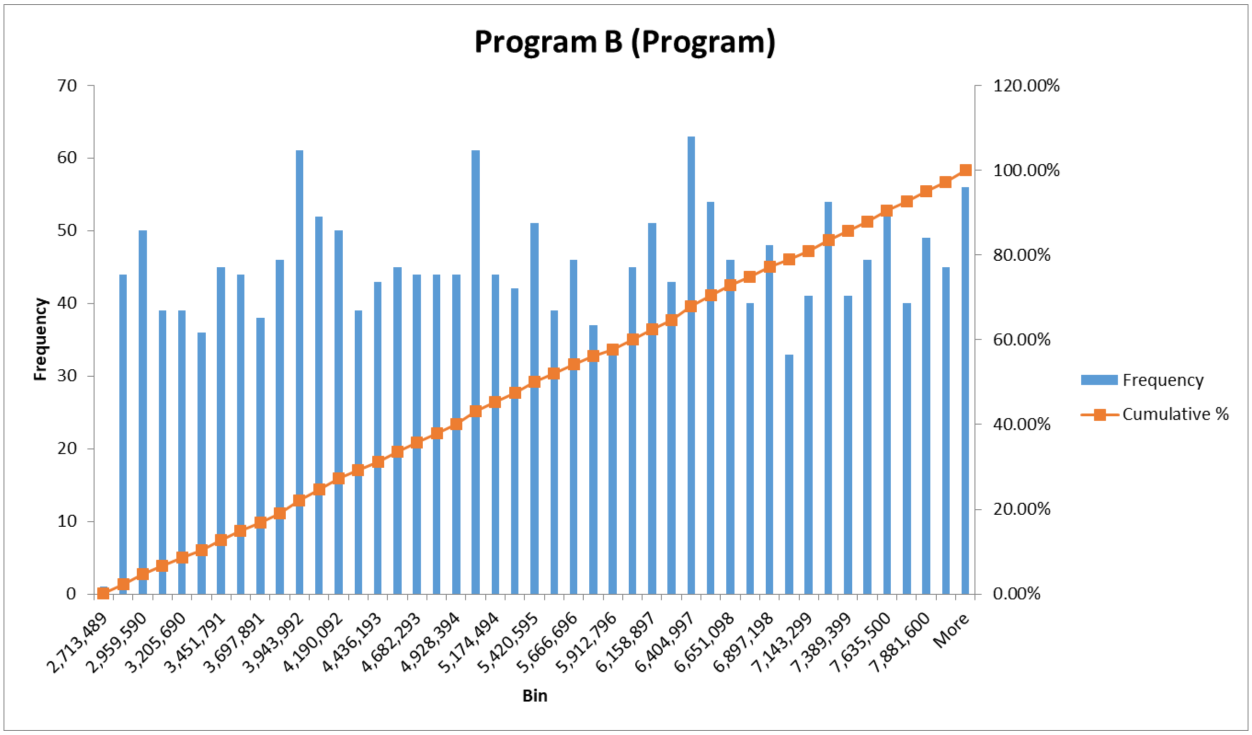

Figure 48: Program B (Program) EIO

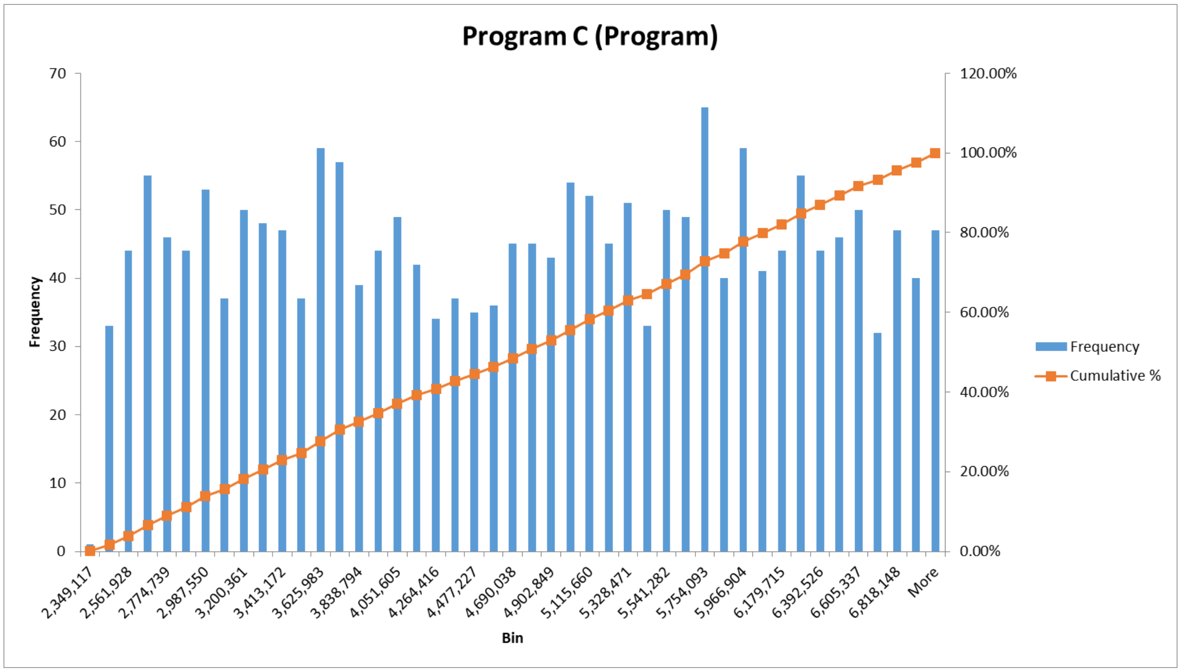

Figure 49: Program C (Program) EIO

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Education

2020	Master of Business Administration, Troy University
2016	Bachelor of Science in Technical Management (Project Management), Embry Riddle Aeronautical University
2014	Associates in Aerospace Maintenance Technology, Community College of the Air Force

Certification and PME

2021	Systems Engineering Certificate – AFIT, WPAFB, OH
2019	Level 2 Certificate – Program Management
2017	Officer Training School, Distinguished Graduate, Maxwell AFB, AL
2016	Airman Leadership School, Distinguished Graduate, Dyess AFB, TX
2012	Basic Military Training, Lackland AFB, TX

Professional History

2020-Pres	Government Acquisitions: System Management Graduate Student Air Force Institute of Technology, Wright-Patterson AFB, OH Acquisitions focused degree to develop project management and systems engineering skills. This program prepares Officers to lead Air Force acquisitions in the digital age.
2019-2020	Executive Officer, KC-46 System Program Office Air Force Life Cycle Management Center, Wright-Patterson AFB, OH Led the front office team through transition to COVID-19 operations. Ensured smooth information flow between SPM, PEO, SAF-AQ and AMC/CC during critical stages of KC-46 production.
2017-2019	Avionics Program Manager, F-15 System Program Office Deputy PM on ACAT II program; ADCP II and lead PM on ACAT III SATCOM UON. Led the team in modifying 218 F-15E aircraft in less than 2 years.
2012-2017	US Air Force Enlisted Member As a Crew Chief on C-130 aircraft I was responsible for inspection, troubleshooting and heavy repair actions on 24 assigned aircraft. My experience culminated in a deployment to Djibouti and the award of my 7-level.

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14. ABSTRACT

Recent executive orders and international agreements require the United States to significantly reduce its carbon and greenhouse gas emissions. The DoD is a significant contributor to the carbon emissions of the USA and will be required to reduce the emissions. Therefore, in order to make appropriate programmatic decisions the DoD needs to develop an appropriate method for estimating carbon and making programmatic decisions; trading-off carbon emissions with the traditional cost-schedule-performance metrics. This thesis examines the possibility of developing a model that can be used to estimate the carbon footprint of producing a system before detailed engineering designed have been complete. Furthermore, it examines the viability of using such an estimate in the decision-making process. While the model produced requires refinement before being used to inform quantitative and objective decisions. The output of the EIO model can certainly be used to increase awareness of the negative impacts and external costs caused by carbon emissions in acquisitions.

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