On the impact of direct digital manufacturing on supply chain operations, cost and environmental performance in an aerospace application

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Abstract

The impact of direct digital manufacturing on supply chain operations, cost and environmental performance in an aerospace application.

Matthias Heppa

Industry 4.0 concepts, such as direct digital manufacturing (DDM), are expected to change the world, the society and the industry within the coming decades. This study explores the potential implications of DDM on supply chain operations by performing a case study. It assesses the impact of distributed production capabilities enabled by additive manufacturing (AM) on the life cycle cost and environmental impact in an aerospace application. It builds on a previous life cycle assessment (LCA) conducted by GE to compare the environmental impacts of using fuels nozzles produced via additive and conventional manufacturing over a future period of 30 years. Here, simulation models are developed to represent the aftermarket of the LEAP engine based on current and forecasted airline fleets for US and Canadian airline operators. Three supply chain operation scenarios are considered: (1) conventional manufactured at a central GE manufacturing plant at a high volume; (2) additive manufactured, high-volume at the same plant; and (3) de-centralized, low-volume, additive manufactured at 7 identified demand locations. 648 experiments were run to capture all relevant combinations of service levels, electricity mix, carbon pricing, and electric truck adoption. Production, distribution, and energy consumption were simulated based on information from publicly available sources. Environmental impacts on resource availability, climate change, human health and ecosystem quality were assessed using an integrated hybrid LCA model developed by the United States (US) Department of Defense (DOD). Data-envelopment analysis was used to benchmark the supply chain operation systems based on their cost, environmental and supply chain performance.

Both additive production systems show stronger efficiencies than the traditional manufacturing system. The de-centralized system benefits from its flexibility and locations that already contain high amounts of renewable energy highlighting the significance of the site selection process. The centralized system requires inventory to be competitive but shows benefits due to economies of scale and strategic investments that would not be justified for smaller facilities.

The applied methodology has shown plausible results over all experiments and can therefore be recommended for decision makers from private and public sectors for benchmarking their alternatives when considering cost and environmental criteria.

Keywords: Additive Manufacturing; Benchmarking; Data Envelopment Analysis; De-Centralized Manufacturing; Direct Digital Manufacturing; Life-Cycle Assessment; Performance Analysis; Simulation; Supply Chain

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Dedicating yourself to a project like this after several years in the industry demands a kind of skillset that has been neglected for a while. Quick decision making is replaced by thorough research, the work is build up step by step from the broad to the specific and rather than being pushed to meet deadlines, patience and persistence bring progress.

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Table of Contents

List of Abbreviations

3DP	3D Printing, see AM
737NG	Boeing 737 Next Generation
A319LR	A319 long range, the extended range version of the A319, equipment with additional center tanks (ACT)
Autofab	Automated Fabrication, see AM
AM	Additive manufacturing (AM) is the formalized term that can also be referred to as Automated Fabrication (Autofab), Freeform Fabrication or Solid Freeform Fabrication, Layer-Based Manufacturing, Stereolithography, 3D Printing or Rapid Prototyping.
bbl	Oil barrel, a volume unit used for fuel. 1 bbl equals 42 US gallons or about 159 litres
CAD	Computer aided design
	Canadian Dollar, Exchange rate has been set to 1.30 CAD = 1 USD
CMS	Centralized manufacturing systems
CO2	Carbon dioxide
DDM	Direct digital manufacturing (DDM) is a term that describes the usage of additive manufacturing technologies for production or manufacturing of end-use components. Some literature refers to it as "rapid tooling".
DIY	Do It Yourself
DMLM	Direct Metal Laser Melting
DMS	Distributed manufacturing systems
DoD	US Department of Defence
EBM	Electron Beam Melting

EFC	Engine flight cycles
EFH	Engine flight hours
EGT	Exhaust gas temperature
EIA	US Energy Information Administration
EOQ	Efficient Order Quantity
EPA	US Environmental Protection Agency
FOG	Foreign object damage
IATA	International Air Transport Association
ICT	Information and Communication Technology (ICT)
ISO	International Organization for Standardization
KG	One kilogram is the base unit of mass in the International System of Units (SI)
lb, lbs	Pound, a unit of mass. It is equivalent to 0.45359237 kg
LDT	Light duty trucks
LMCS	Lockheed Martin Commercial Solutions
MRO	Maintenance, repair, overhaul industry
OEM	Original Equipment Manufacturer
®	Registered trademark symbol
RP	Rapid prototyping, see AM
Tonne	Equals one metric ton or 1,000 kg
UNIDO	United Nations Industrial Development Organization
UPS	United Parcel Service of America, Inc.
USA	United States of America
USD	United States Dollar

List of Figures

List of Tables

1. Introduction

1.1 Background

This thesis addresses two major trends observed in today's industry. Driven by the increasing awareness of customers and governments for the finiteness of natural resources and the consequences of consumption, environmental impact is increasingly used as a decision criteria in combination with functionality and profitability. (Frota Neto, Bloemhof-Ruwaard et al. 2008, Guinee, Heijungs et al. 2010)

The second trend is the increasing digitalization and de-centralization of processes culminating in the vision of the 4th industrial revolution and an expected growth of additive manufacturing (AM) replacing conventional processes. As Huang, Liu et al. (2013) state, additive manufacturing allows design optimizations and customized production on demand, does not require the use of fixtures, cutting tools, coolants, or other auxiliary resources. Gibson, Rosen et al. (2015) highlight, that "it is difficult to provide flexible, scalable, "produce anywhere" services if one has to first fabricate a lot of tooling." Thus, AM can be regarded as one early, mandatory representative for the arising of the 4th industrial revolution. It enables flexible production and is therefore regarded as an imperative for Industry 4.0. The Boston Consulting Group (2017) expects, that these additive manufacturing methods will reduce batch sizes, transportation and stock on hand by highly customized products manufactured in high-performance, de-centralized additive manufacturing systems. (The Boston Consulting Group 2017)

Industry 4.0 is expected to significantly optimize both, functionality (by high customization) and profitability (by eliminating non-value adding steps such as over-production, waiting time, transportation, inventory, etc.) of manufacturing. Nevertheless, the question arises how will it impact performance (e.g., cost, responsiveness, and environmental sustainability) of industry? An emerging body of literature explores the impacts of AM. Most relevant to this thesis are life cycle assessments (LCAs) that assess the environmental impact of AM and analyses that examine the use of AM in the aerospace sector.

Life Cycle Assessment (LCA) is a predominant framework for assessing the environmental impact of product systems, from raw material extraction through manufacturing, distribution, use, and end-of-life. It is broadly standardized by ISO 14040 and 14044. While many different approaches are available and developed for specific applications, most can be categorized in either a bottom-up or a top-down approach. Process-LCA is a bottom-up approach that quantifies all relevant inputs from nature (e.g. water, energy, raw materials) and outputs to nature (e.g., emissions, waste) from each process in a product's life cycle. Environmentally Extended Input-Output (EEIO) analysis is a top-down approach that relates monetary transactions to inputs from and outputs to nature on an average industry basis. Both approaches result in a life cycle inventory, or an account of all inputs and outputs of the defined system, which is then translated into measures of environmental impact (e.g., global warming, human toxicity, ecotoxicity) using established characterization models. The results can be further aggregated into estimates of impact on resource availability, human health, and ecosystem quality, making the results easier to understand for non-experts and, therefore, helpful to support decision making. Several databases and specialized software are available to support this process.

Initial LCA studies (Faludi, Bayley et al. 2015, Chen, Heyer et al. 2015, Serres, Tidu et al. 2011) compare the environmental performance of additive manufacturing with conventional manufacturing in specific case studies, by replacing conventional manufacturing processes with additive manufacturing processes within an otherwise unchanged value chain. For example, Faludi et al. (2015) perform a comparative LCA of two products with different geometrical complexity being produced on a CNC milling machine versus two different three dimensional (3D) printing machines. They conclude that environmental performance is highly dependent on machine and tool utilization and therefore the lot sizes (economies of scale). While these studies are informative, they are incomplete in that they do considering the changes additive manufacturing will have on the supply chain.

Other studies consider changes in the supply chain based on the introduction of distributed manufacturing systems (DMS). Cerdas, Juraschek et al. (2017) perform a comparative LCA of low volume eyeglass frames produced via centralized manufacturing system (CMS) using conventional mass production technologies to those produced in a distributed manufacturing system (DMS) using additive manufacturing. They conclude that environmental performance is highly sensitive to energy consumption and the chosen material. Moreover, impacts due to transportation are found to be negligible.

Gebler, Uiterkamp et al. (2014) study additive manufacturing from a global perspective, quantifying changes in life cycle cost, energy consumption and CO2 emissions under forecasted growth of the additive manufacturing market until 2025. Due to the expected low share of 3D printing in mass production markets, they conclude a maximum global energy and CO_2 emissions reduction 5% from 3D printing.

The potential to benefit from AM in the aerospace industry, and there especially in the spare part market with high product availability requirements and low turnovers, has been identified and studied by different authors. Holmström, Partanen et al. (2010) observe cost saving potentials through changes in the supply chain from using additive manufacturing to replace inventory holding and distribution of spare parts within the commercial aviation industry. Their findings suggest a high potential for mitigating high inventory risk and achieving required service levels while eliminating downtime cost and avoiding supply chain disruptions with the adoption of the additive manufacturing. They suggest that the reduction in logistics operations could lead to reduced cost especially for slow moving parts. In a later study, discuss environmental risks and opportunities of additive manufacturing in operations and supply chain management. Without quantifying the environmental implications, they conclude that if considered separately, none of the identified promising paths for AM (localizing part production, on-demand production, and upgrading and refurbishing products in use) are expected to have significant environmental impacts. However, if considered all together, they see potentials from for example spare parts specifically re-designed for AM and on demand production and resulting simplifications in supply chain and operations as well as improved product functionality.

Another study by Khajavi, Partanen et al. (2014) compares the cost of manufacturing the F-18 Super Hornet air-cooling ducts in one centralized versus multiple distributed locations. While this study shows an interesting industry application with the advantages of distributed manufacturing systems (DMS), it assigns high importance to the utilization of the machines. These machines are assumed to be solely used for producing the investigated product, making the acquisition price and labor cost the major drivers of the distributed production system.

What most of the reviewed articles have in common is that additive manufacturing, which is in an early maturation phase (Gebler et al. 2014), is compared to highly mature and optimized manufacturing systems and technologies with supply chain concepts and infrastructure that have been evolving for decades. Although, it is expected that additive manufacturing will further develop, it is difficult to forecast how Industry 4.0 and additive manufacturing will evolve and how it will be implemented in the future. Robust data for this kind of forecasting is lacking. Therefore, this work focuses on an existing application, where additive manufacturing is already achieving a competitive edge.

Furthermore, the reviewed articles look at on-going developments mainly from single perspectives and under static conditions. This study aims to consider both, the economic performance and the environmental implications while ensuring competiveness of the production systems. It is believed that changes of such a magnitude and temporal range as they are expected for Industry 4.0 and direct digital manufacturing would be difficult to justify otherwise. Since technologies, markets, and polices change over time, it is necessary to consider the changes that may occur over a longer time frame such as the entire product life cycle versus current conditions as if they will remain static. Therefore, relevant changes that may impact the cost, performance and environmental impact of additive manufacturing over time, such as political developments, changing electricity mixes, and electric vehicle technologies, should be identified and implemented into a comprehensive evaluation of this emerging technology.

1.2 Problem statement

The potentials of Industry 4.0 and direct digital manufacturing seem promising and are expected to be far reaching. First niche products are available providing insight on how the industry will evolve over the coming decades. However, new operation models need to be evaluated to ensure their viability and sustainability. The economic and environmental potentials seem high but difficult to quantify.

As Holmström et al. (2017) say, "AM could be used in many ways, both good and bad for the environment". The U.S. Department of Energy (DOE) (2015), in its Quadrennial Technology Review 2015, highlights the relevance of additive manufacturing as a current research and development field. Further, they list the development of sustainability indicators for measuring AM processes and products as a current research opportunity.

For a new technology to be competitive in the marketplace, it must be cost effective and provide functional benefits. While this is not expected to change, environmental performance cannot be ignored for several reasons. First, the use of scarce natural resources and damage to the environment are increasingly translated into business risk (e.g., water competition, carbon taxes, and extended producer responsibility). In addition, customers, institutional investors, shareholders, regulators, and other important stakeholders are increasingly demanding more sustainable business practices and accountability from industry. As such, environmental performance should be a consideration in the technology development process, with environmental performance being understood and important environmental risks mitigated as early as possible in this process. At the same time, the most sustainable solution is worthless if the market is not interested in it or if it is not viable or competitive.

Therefore, the following objectives are established for this thesis:

(1) Perform a literature review to understand Industry 4.0 and direct digital manufacturing, including on-going developments;
(2) Identify an industry example for a case study;
(3) Integrate existing methodologies for benchmarking production and supply chain systems based on life cycle economic, environmental performance while ensuring competitiveness of the production system;

(4) Conduct a case study to assess the cost, supply chain, and environmental implications of additive manufacturing-enabled production and supply chain systems; and
(5) Analyze the results to understand the opportunities and risks of DDM and de-centralized manufacturing concepts for the economic and environmental performance of supply chain operation systems.

1.3 Literature Review

1.3.1 The evolution of 3D printing towards direct digital manufacturing (DDM)

3D printing emerged to support product design and development as a quick and cost efficient technology to create prototypes, demonstrators and mock-ups. The major advantages of 3d printing are that it does not require tooling, it can be used without sharing confidential design data to tool or mock-up suppliers, and it reduces the time to hardware significantly, so that designers can perform more improvement loops during a shorter time period. Although the investment costs might have been high at the beginning, manufacturing without tooling enabled companies to reduce cost on the long run. During this first phase the use of AM was limited due to a premature technology, high investment costs and the selection and quality of the available materials. It was originally developed around polymeric materials, waxes, and paper laminates. (Berman 2012, Gibson, Rosen et al. 2015)

During a second still on-going phase, advancements have been made in the technology, material choice and quality. Also more suppliers offer a wider choice of machines and technologies starting at lower prices. Additive manufacturing has been successfully used for some commercial niche products (e.g., orthodontic treatment braces, hearing aids, custom footwear) and have found its way to some private homes. Online communities are available, where computer-aided design (CAD) data is exchanged or even sold and some machine owners sell their service of printing parts to others. (Gibson, Rosen et al. 2015)

For a third phase, it is expected that additive manufacturing technologies will establish itself as a mainstream manufacturing technology. Together, with the developments of Industry 4.0, additive manufacturing has the potential to cause major changes to industry as well as the roles of the customers and designers. For some products, manufacturing could happen close to or possibly at customers' homes. The need for inventory, unsold finished goods, and many transportation and distribution networks could become redundant or at least be radically reduced. Esmaeilian, Behdad et al. (2016) identify the following five research pillars requiring further advancements prior to a successful large scale implementation of AM: design, materials, technology, software and quality control.

1.3.2 The paradigms of direct digital manufacturing

Under the assumption that direct digital manufacturing (DDM) will be the final development stage of additive manufacturing in Industry 4.0, the “parts will no longer be produced in a factory, assembled to final products and shipped to customers. Instead, these products are manufactured right at or close to the customer utilizing additive manufacturing and directly derived from a digital model.” (Chen, Heyer et al. 2015)

DDM together with Industry 4.0 have the potential to radically change industry and society. Due to the nature of radical change, it is hardly possible at this stage to forecast the impact of the new production paradigm in detail. However, several studies explore and summarize expected paradigm shifts.

Figure 1 shows an overview of the paradigms defining DDM that are derived from current literature and publications. The following sub-chapters 1.3.2.1 to 1.3.2.6 provide more detailed information.

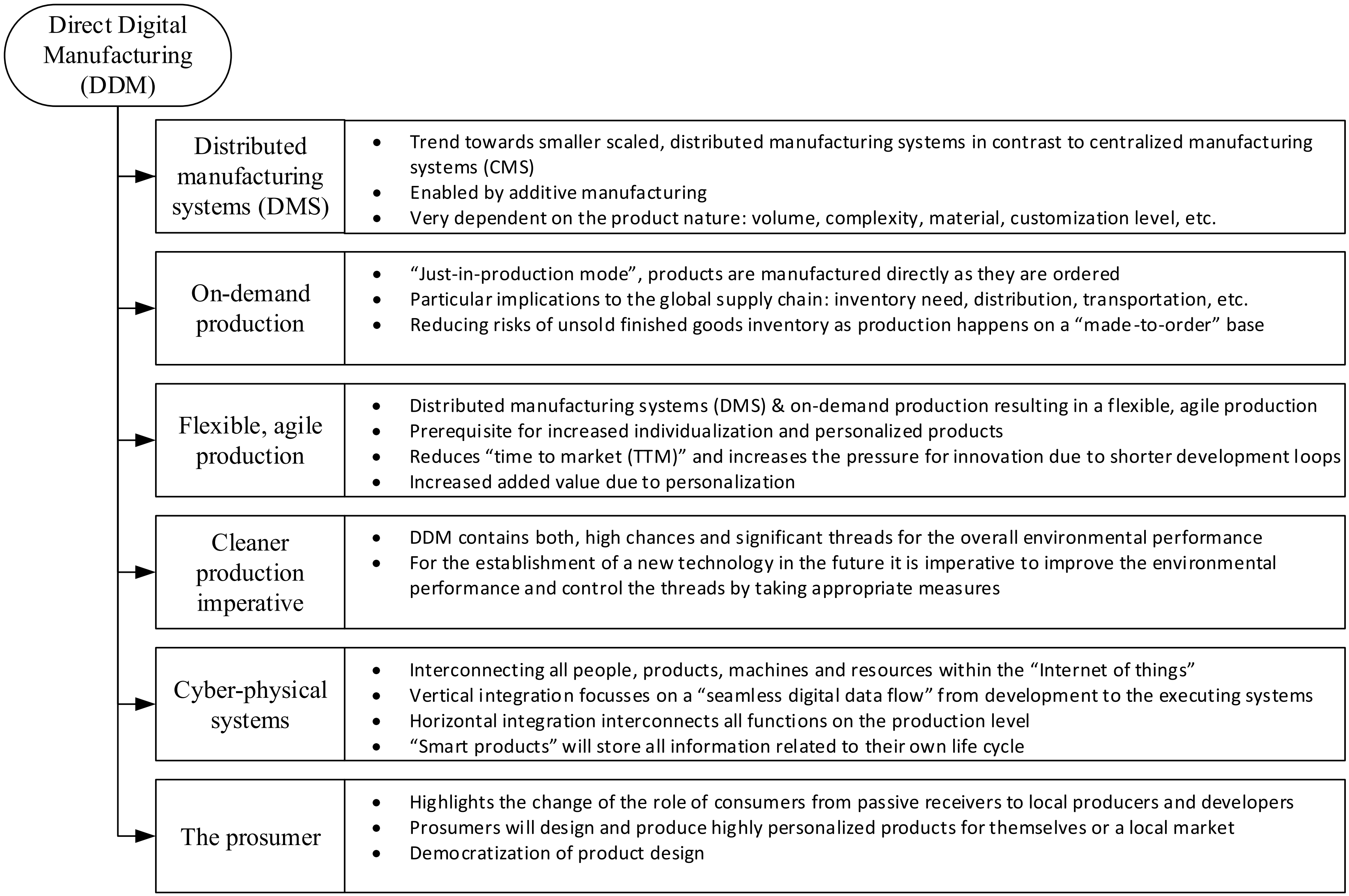


Figure 1: Summary of paradigm changes

1.3.2.1 Distributed manufacturing systems (DMS)

Distributed manufacturing systems (DMS) are a result of a de-centralized, low volume production enabled by additive manufacturing. The level of distribution depends mainly on the product nature, future developments and costs for additive manufacturing machines & materials. It can range from manufacturing in private households, e.g., “maker movement” (Gebler et al. 2014) or “DIY” (Kohtala 2015), to highly specialized local providers to large companies offering personalized products as an extension of modular product platforms. Figure 2 shows how a future market could potentially be divided into home producers, specialized local service providers and large companies depending on capabilities, quantities, material and process complexity etc. When compared to centralized manufacturing systems (CMS), significant impacts on production volume (economies of scale), supply chain configurations, and consumer-producer relationships are expected (Kohtala 2015). Drivers for such developments are based on the potential for DM to increase product customization, reduce costs and increase production sustainability, altogether, giving companies a competitive edge. (Ford, Despeisse 2016, Piller, Moeslein et al. 2004, Gibson, Rosen et al. 2015, Gebler, Uiterkamp et al. 2014)

Besides the potential positive outcomes, Matt, Rauch et al. (2015) also identify potential negative outcomes, such as high investment costs and lower efficiency of decentralized production as compared to automated central production factories.

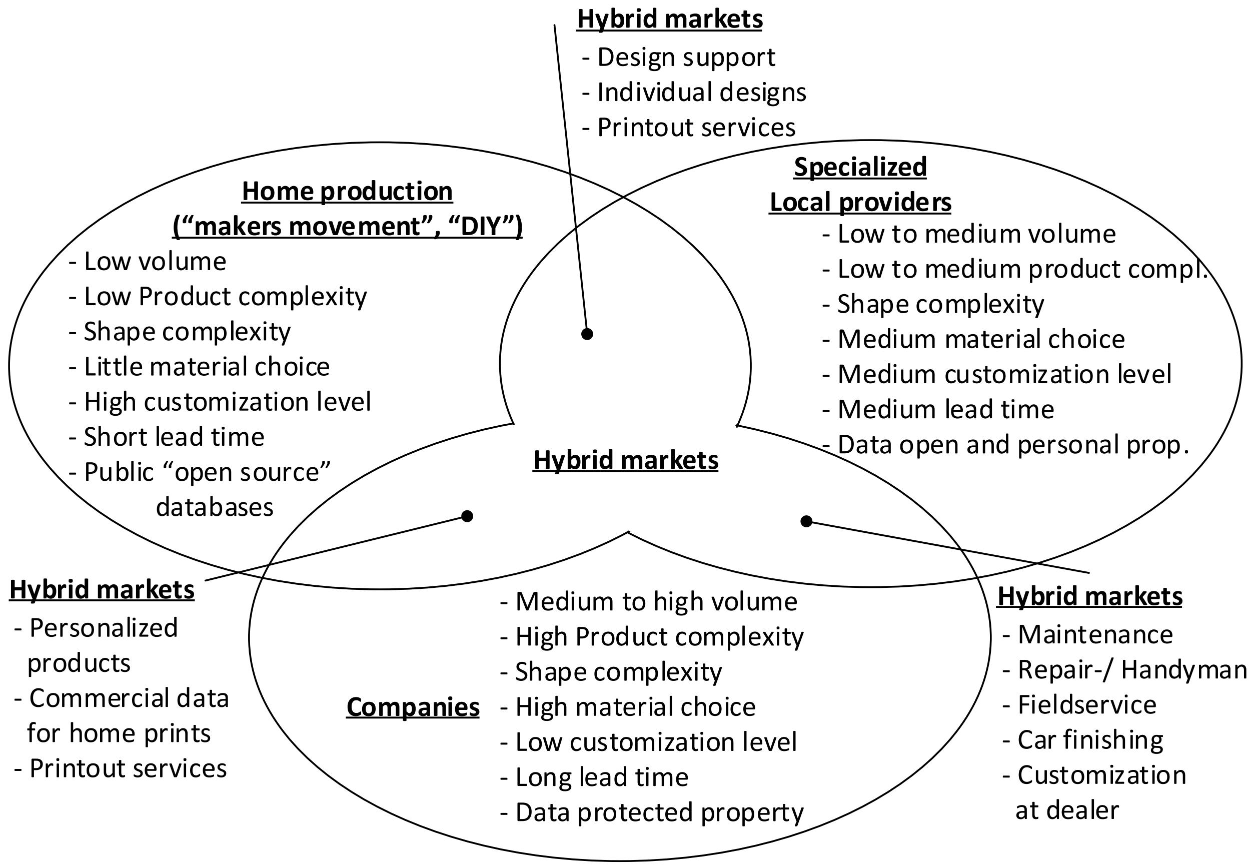


Figure 2: Potential division of a future DDM market

1.3.2.2 On-demand production

The possibility of manufacturing on-demand will have several impacts on industry, supply chain configurations and inventory management. Esmaeilian et al. (2016) compare the existing just-in-time approach with a new "just-in-production mode", where products are printed directly as they are ordered. They expect particular implications on global supply chains such as reduced need for storage and transportation as well as assembly work and ultimately a reduction in product time-to-market. Due to on-demand production, DDM reduces the risks and efforts associated with inventory and logistics as parts are only made to order rather than to a stock following market forecasts. In an ideal case, no unsold finished goods inventory is left (Berman 2012) and the in-process and in-transportation inventory levels of entire global supply chains can be reduced.

1.3.2.3 Flexible, agile production

On-demand production in distributed manufacturing systems significantly increases flexibility and agility which is essentially a prerequisite for increasing individualization (Anderl 2015). The increased flexibility, agility and adaptability of manufacturing systems will reduce time to market (TTM) (Esmaeilian et al. 2016), causing an even higher pressure for innovation. While Durao, Christ et al. (2016) state that the customer may be willing to pay a higher price in order to receive a more personalized product with a higher added-value. They indicate that such an increase would have to be moderate compared to mass production to be accepted by the market.

1.3.2.4 Environmental efficiency / Cleaner production imperative

DDM has the potential to reduce waste for a variety of reasons, including parts being build-up layer by layer instead of being subtracted from a raw material block, on-demand production instead of production to stock or wholesale steered by demand predictions, simplified supply chains carrying lower levels of inventory (work in process, semi-finished & finished goods), no need for long distance transportation of finished goods, and no need for tooling, tooling storage and tooling refurbishments. Thus, improvements in environmental sustainability could be achieved through supply chain simplifications as well as the transformation of the manufacturing.

Besides the potentials there are also threats for the environmental sustainability that need to be considered. In large centralized manufacturing systems with experienced and well-educated staff, certain production and quality standards have been established. For many industries they are consistent and certified against international standards such as ISO 9001. With smaller localized production or even home production there are risks that missing knowledge, inappropriate handling, such as wrong disposal of materials, wrong machine and material handling or wrong pre-treatments may have direct or indirect negative environmental impacts (e.g. reduced life time causing earlier replacement). (Durão et al. 2016, Kohtala 2015) Since additive manufacturing materials can be potentially hazardous and many instructions manuals and other documentation are currently lacking sufficient health and safety guidelines for users, this risk is particularly high. (Short, Sirinterlikci et al. 2015) Just imagine common home users, who are making 3d printouts with special settings a few times a year. They would usually need several attempts before achieving the desired result and might not invest time in reading manuals to comply with all safety and material handling requirements.

Moreover, the machines would be idle most of the time, potentially rendering the technology out of date and replaced before the machine reaches a certain amount of production. Of course, specialist companies also have lower yields and setup waste when new products are introduced, but in larger scale production the initial effort can be compensated for by economies of scale and high production volumes. In the worst case for DMS, this phenomenon could happen every time, when an operator tries to manufacture a one-off personalized product. Moreover, companies can be obliged by laws and regulations to take measures to protect their employees and the environment, such as risk management, workplace design (e.g. ventilation) and waste management measures. (Short et al. 2015)

Another important sustainability aspect has been highlighted by Cerdas et al. (2017). In comparing additive manufacturing to injection molding of a cellulose acetate product, they found that electricity consumption and the electricity mix selected for the printing processes significantly influenced the environmental performance of DMS. Nevertheless, Serres et al. (2011) come to a completely different conclusion when comparing additive manufacturing of a complex aerospace part made out of a Ti6Al4V alloy with conventional machining. They find an overall environmental impact reduction potential of 70% due to the application of AM based on product life-cycle assessment. These savings mainly result from upstream processes, the raw material production in particular, and long milling times of the hard material due to slow removal rates. As with all emerging technologies, the strengths of additive manufacturing will be realized within limits (e.g., realized in some applications, but not others). However these limits are yet to emerge. Hence, universal statements about the energy consumption are not possible and need to be considered case by case.

1.3.2.5 Cyber-physical systems, Internet of things

Anderl (2015) presents cyber-physical system (CPS) as the basis of a high-tech strategy for the German “Industrie 4.0” research platform. Specifically, he identifies interconnected and communicating cyber-physical systems (CPS), comprising CPS, the internet, components as information carriers, and a holistic concept for safety, security, privacy and knowledge protection, as being “the key technology approach” for Industrie 4.0.”. CPS aim to build a network that contains all relevant functions of the supply chain interconnecting all people, products, machines and resources. (Durão et al. 2016) Finally, this requires upgrading the internet into the “Internet of things,” which comprises both vertical and horizontal integration. Vertical integration focusses on a “seamless digital data flow” from the development and planning of functions down to executing systems. Meanwhile, horizontal integration aims to interconnect all functions on the production level, such as smart products, smart machines, smart factories, smart plants, and smart logistics. (Anderl 2015) Smart products include a “wide range of physical objects”, such as products, assemblies or single parts that will store all information related to their own life cycle. Information could be stored in a product memory and could be used to control manufacturing processes or route the product through the supply chain. (Anderl 2015)

1.3.2.6 The prosumer

The definition of a prosumer who is producer and consumer at the same time goes back to Toffler et al. (1981). It has gained significance in the context of DDM, as it highlights the change of the role of consumers from simple passive receivers to local producers and developers, who design and produce highly personalized products for themselves or a local market around them. (Chen, et al. 2015a) The prosumer leads to a democratization of product design, however there will still be a need for experts.

1.3.3 Life Cycle Assessment (LCA)

Life cycle assessment (LCA) is a prominent method for assessing the environmental aspects and potential impact of systems, products or services. ISO, the International Organization for Standardization, has published eleven (LCA related standards, with the LCA framework and requirements specified ISO 14040 and ISO 14044. LCA divides the life cycle into five main stages: material extraction, product manufacture, packaging and transportation, use and end of life (International Organization for Standardization 2006). It has been refined for a broad field of industrial applications, including process design, selection and optimization (Azapagic 1999, Burgess, Brennan 2001, Shin, Suh et al. 2017), product development (Wenzel, Hauschild et al. 2000, Santucci, Esterman 2015, Alting, Hauschild et al. 1997), production plant or strategy assessments (Cherubini, Bargigli et al. 2009, Koornneef, van Keulen et al. 2008), and environmental product declaration (eco-labelling) (Bombardier Commercial Aircraft 2016). These applications establish LCA as a tool to support decision making, which is essentially the overarching purpose of LCA. (Hertwich, Hammitt et al. 2000)

The US Department of Defense (DoD) has developed a framework for integrating sustainability assessments into the acquisition process. (Department of Defense 2016) The framework provides a recommended approach for assessing the direct, indirect, contingent, and external costs across the life cycle of defense systems. It combines life cycle cost analysis (LCCA) and LCA. LCCA is used to estimate cost to the end user over the life cycle of a product or service. LCA is used to estimate the impacts of resource requirements, environmental releases, and waste on resource availability, climate change, human health and the ecosystem quality, and translate these impacts into external cost. (Department of Defense 2016) The DoD has also provided resources for supporting the analysis. One such resource is the Defense Input-Output (DIO) dataset (Lloyd, Bruckner et al. 2016). The DIO dataset was generated using integrated hybrid LCA model. It combines data from EEIO models and process-based LCA. EEIO models relate resource use, environmental releases, and waste to monetary transactions within an economy at an industry sector level. Based on the monetary purchases from an industry sector, one can use EEIO to estimate the environmental impacts occurring in that industry sector as well as from its supply chain. Process-based LCA uses detailed input and output data from processes to estimate environmental impact. For example, process-based LCA can be used to calculate the resources required and emissions and waste generated from producing a unit of electricity using a coal-based power plant. An integrated hybrid LCA model computationally integrates the physical flows between processes, monetary transactions between sectors, and the links between the two to enable a rapid screening-level LCA. It is considered screening level because it use average data for common processes and industry activity rather than specific data from the products and processes being studied. The DoD ran the DIO model to estimate the impacts of one unit of industry activity, purchased good or service, and elementary on resource availability, climate change, human health and the ecosystem quality. The results are provided in a Microsoft Excel spreadsheet on the Department of Defense Environment, Safety and Occupational Health Network and Information Exchange website (DENIX 2016). The resulting "scoring factors" can easily be integrated into other methodologies to enable estimation of life cycle environmental impact without requiring the application of specialized LCA software or the need to perform in-depth LCAs. This DIO dataset is advantageous to this study as it has been developed for industry applications within the US market. It has been used in assessing the economic and environmental impacts of several aerospace applications. For example, GE used the DoD method to evaluate the potential implications of using additive manufacturing to produce fuel nozzles for the CFM LEAP jet engine (MSRI 2014, Scanlon, Lloyd 2017) It has also been used to evaluate exterior coating alternatives for the Boeing P-8 Poseidon Aircraft and the Sikorsky MH-60R Seahawk Helicopter (Scanlon and Lloyd, 2017), brush plating alternatives for repairing US Air Force aircraft components (Lloyd, Bruckner et al. 2017), electroplating alternatives for repairing US Navy aircraft components (Bruckner, Henderson et al. 2018), and an anti-corrosive coating that incorporates multi-walled carbon nanotubes and titanium dioxide nanoparticles with recent applications (Ong, Henderson et al. 2018).

1.4 Research gap

Direct digital manufacturing (DDM) enabled by additive manufacturing (AM) technologies has been identified as a promising area for further research. Besides established performance measures such as cost, product quality, and availability, environmental performance has been found to be an imperative performance measure for assessing DDM.

Recent studies investigating supply chain changes resulting from direct digital manufacturing concepts exist, but consider mostly single perspectives. Others have considered additional performance measures, such as those related to energy consumption and environmental impact. However, they tend to concentrate on the replacement of single process steps and take a static perspective, therefore failing to capture the overall implications of Industry 4.0, and direct digital manufacturing in particular. Holmström and Gutowski (2017) discuss the sustainability potential of additive manufacturing on operation and supply chains. Recognizing the importance of challenges with estimating the economic, engineering, energy, and environmental performance of advanced materials manufacturing from a life cycle perspective, the US Department of Energy identified further development of methods for predicting performance as important for successfully developing advanced manufacturing methods and materials (DOE 2015).

No actual models have been found for assessing or benchmarking operations and supply chain systems taking into account the cost, environmental, and supply chain performance. To be informative, such methods must look at the life-cycle and therefore consider potential external factors. External factors may include changing markets, public policies, technology diffusion, and other local, national, or global changes that complicate the decision making process. Such a model can help public policy-makers assess the consequences of their decisions on specific industry sectors and their competitiveness. It can also help private sector decision-makers better understand the competitiveness of and risks and opportunities associated with specific research and development initiatives.

1.5 Contribution of this thesis

To evaluate the potential impacts of DDM on production and supply chain systems, this research develops a framework for assessing the economic, supply chain performance, and ecologic aspects of an emerging technology. Moreover, a thorough evaluation is only meaningful when it reviews the entire lifecycle. This is a particular important when developing and advancing technologies that require high investments and are not easily reversible.

The example of the newly developed GE fuel nozzle for the CFM International LEAP engine has been identified as a relevant industry example to study. This fuel nozzle is being produced using additive manufacturing technologies in one centralized location and is replacing its predecessor, the fuel nozzle of the CFM56 engine which has been produced successfully using conventional metal joining processes over decades. A telephone interview with the lead engineer of GE Additive, Mr. Joshua Mook, was conducted and confirmed that distributed manufacturing capabilities are being considered for this application.

This study is built on four major aspects. (1) It benchmarks different supply chain operation systems representing centralized and de-centralized production capabilities. (2) It considers the advantages of additive manufacturing in a case study looking at a product that can be regarded very advantageous and therefore a successful early representative of the new emerging technology DDM. (3) It includes the economic, environmental and supply chain performance to build a performance measure for assessing and benchmarking the systems. (4) It looks at the life cycle of the product considering a time frame of 30 years and identifies external factors that could potentially influence the system performance.

2. Research Methodology and Data Collection

2.1 Introduction

This study is conducted in three major steps. In the first step, data and information is collected to extend an existing LCA of GE's additive manufactured fuel nozzle (Flanagan et al. 2017) into an extensive case study of three different production and supply chain systems further referred to as production scenarios 1, 2 and 3. Production scenarios 1, 2 and 3 represent conventional centralized high volume, additive centralized high volume and additive distributed low volume production.

In the second step, simulation models are developed representing the airline operations on the US and Canadian market. Based on airline operations, random customer arrivals to 7 MRO repair shop locations and eventually random aftermarket fuel nozzle demand is generated. The simulation models provide a realistic environment for simulating the behavior of the three supply chain operation scenarios and estimating system performance over a future period of 30 years.

In the third step, data envelopment analysis is used for benchmarking the three production and supply chain systems. Based on the performance estimates from the simulation models, system inputs and outputs are selected to define a relative technical efficiency score based on economic, supply chain and sustainability performance. Varying market projections, expected future technology changes and different supply chain setups such as different anticipated service levels are considered. For each set of unique inputs one new consecutively numbered experiment or decision making unit (DMU) is created and incorporated into the optimization program. Using linear programming, the most beneficial relative technical efficiency for each DMU is found. The relative technical efficiency score allows for benchmarking of the three production systems, but also for drawing conclusions of the influence different supply chain setups or superior developments such as political decisions or varying market forecasts can have on one or all the systems.

2.2 Information flow model

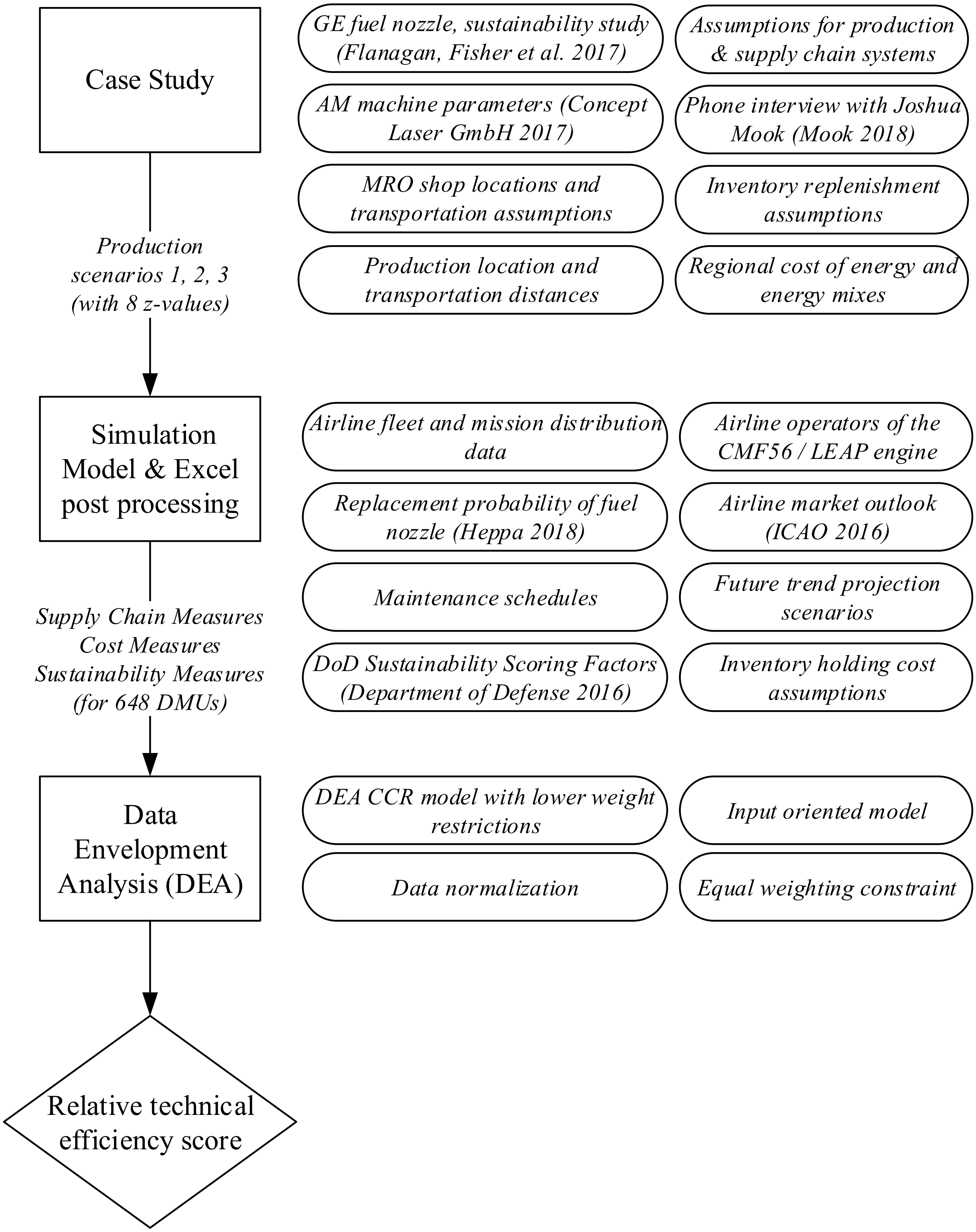


Figure 3: Information flow chart

2.3 Step 1: Case study

2.3.1 Case background

The LEAP engine is a next generation high bypass turbofan jet engine built by a joint venture of General Electric (GE) and Snecma called CFM International. This LEAP engine contains 19 fuel nozzles that are manufactured by GE using additive manufacturing (AM) technology. According to the specification of the manufacturer the new fuel nozzle design reduces the weight by 25%, reduces the number of used material alloys from four to only one, and improves the part life by factor 5 as compared to its predecessor. All this is possible due to the greater freedom of additive manufacturing in producing complex hollow geometries. (Flanagan et al. 2017)

GE has performed an LCA comparing the environmental performance of the fuel nozzle being produced using additive or traditional manufacturing (Flanagan et al. 2017). Relevant data is taken from this presentation and is complemented by data obtained from or derived based on other sources. To complete the picture of the fuel nozzle production process, a telephone interview has been conducted with Joshua Mook, the Engineering Leader of GE Additive on January 19th, 2018. (Mook 2018)

According to MRO-network.com the LEAP engines predecessor, the CFM56 has been the most successful engine in commercial aviation history being introduced almost 25 years ago on the Boeing 737 Classic. Among others it powers the high volume single aisle short- to medium-range aircraft families Airbus A320 and Boeing 737. Production of the CFM56 is planned to phase out by 2020 with decreasing production each year between now and then while the LEAP engine production volume increases. (Derber 2017) As the LEAP engine is relatively new to the market and therefore has not yet required significant maintenance or repair, this case study will assume the existing MRO supply chain network of its predecessor, the CFM56, remaining in place.

Currently, the fuel nozzles are being manufactured in one centralized manufacturing location, i.e., GE Aviation’s new manufacturing plant in Auburn, Alabama. The parts are being shipped to the different demand locations, where they are used as replacements during engine maintenance. For comparing the centralized with a distributed manufacturing system both scenarios need to be modelled based on the available data and estimations as summarized in this chapter.

The traditional fuel nozzle of the CFM56 engine is assembled from 19 components. 14 of these components are being formed in a total of 63 shaping and joining processes. (Flanagan et al. 2017) As no public data is available for the detailed production process a simplified production system is modelled that acts as a baseline to simulate lifecycle cost and emissions from operations and logistics. Chapters 2.3.5 and 2.3.6 summarize how the supply chain systems have been modelled. The energy demand, raw material consumption, emissions and cost are calculated on a per part basis and are determined as shown in this chapter.

2.3.2 Definition of the three production scenarios 1, 2 and 3

In this case study three production and supply chain systems have been developed. Production scenario 1 represents high volume production applying conventional technology in one centralized location. Production scenario 2 uses additive high volume production in one centralized location. Production scenario 3 represents low volume production applying additive technology in distributed locations located close to the demand locations and can therefore be regarded a realistic example for direct digital manufacturing (DDM).

All production systems are designed to follow a Q,r inventory replenishment strategy and recalculate Q and r depending on the average demand and the demand fluctuation of the previous one year period. Q represents the reorder quantity and is calculated using the Efficient Order Quantity (EOQ) model formula while r represents the reorder point (equations 2.1 and 2.2). As soon as the inventory level reaches or drops below the reorder point r, a new order is placed for the quantity Q. As demand is random and the lead time is considered constant within each scenario in this study, safety stock is held to cover demand fluctuations during lead time. Therefore, the average demand and the standard deviation of demand are being recalculated for the lead time period over the previous year. The level of safety stock held is regulated by the z-value which is altered during the simulation model as an input value to simulate the effect of different inventory levels. The ordering cost is assumed to be relatively low and is set to USD 200,- for all three models.

$$Reorder\ point\ r = Mean\ orders\ during\ lead\ time + z\ value\ x\ Std.Dev.of\ orders\ during\ lead\ time \quad (2.1)$$

$$Order\ quantity\ Q = \sqrt{\frac{2\ x\ Ordering\ cost\ x\ Mean\ oders\ of\ previous\ year}{Annual\ holding\ cost}} \quad (2.2)$$

Lead times for the different production systems vary as a result of different production technologies, lot size or single piece production, different machine technology assumptions and so on. Table 1 provides a definition of the three production scenarios. Appendix 02 gives an overview of all considered parameters.

	Scenario 1	**Scenario 2**	**Scenario 3**
Production technology	Conventional	Additive	Additive
Production volume	High volume	High volume	Low volume
Production location(s)	Centralized	Centralized	Distributed

Table 1: Overview of production systems

2.3.3 Manufacturing of the fuel nozzle

As General Electric states in its press release, by 2020 “GE is expected to operate more than 50 printing machines in Auburn, producing more than 35,000 engine fuel nozzle injectors annually using additive technology”. Furthermore, the machines are running “around the clock”. (General Electric Company 2016a, General Electric Company 2017) GE has acquired two European additive manufacturing machine suppliers, Concept Laser from Germany and Arcam AB from Sweden (General Electric Company 2016b). The Concept Laser GmbH machines apply Direct Metal Laser Melting (DMLM) and the Arcam AB machines use Electron Beam Melting (EBM) technology. Both technologies process powders from a powder bed. For fuel nozzle production, GE currently uses Concept Laser machines, which “are capable of processing various powder materials including titanium, nickel-base, cobalt-chromium and precious metal alloys, as well as hot-work and high-grade steels and aluminum”. (General Electric Company 2016b) The Concept Laser GmbH specifies its product line “M LINE FACTORY” for “economical series production of additive metal parts, supported by a unique safety concept.” It provides four lasers with a laser power of up to 1,000 Watts each and can produce laser thicknesses of 20 – 100 µm with a maximum speed of 4.5 m/s. (Concept Laser GmbH 2017)

Considering a 3 shift operation with one shift equaling 40 hours per week and a total of 52 working weeks a year with a planned machine utilization of 80%, 50 machines have the capacity to produce 35,000 parts when one part is being produced every seven hours.

For the centralized location in Auburn, Alabama, it is assumed that the fuel nozzles are being produced in lot sizes of 12 parts using Concept Laser M3 Liner machines with 4 lasers and a laser power of up to 1,000 Watts per laser and a standby energy consumption of 0.7 kW. The lot size of 12 parts is assumed based on a video published by GE Aviation showing the additive production of the fuel nozzle. (GE Aviation 2014) Although lot size can be adjusted, it is assumed a realistic scenario for the centralized production reducing changeover times and considering the size and the processing space of the Concept Laser M3 Liner machines.

For all distributed locations of scenario 3 it is assumed that smaller machines of the modular type range Concept Laser M3 Liner are used with one laser and a laser power of up to 1,000 Watts and the same standby energy of 0.7 kW. Parts will be produced in lot sizes of one representing on-demand production.

The production lead time for one fuel nozzle including all required assembly, surface treatment and quality inspections is estimated to be 14 days for scenario 1, 10 days for scenario 2 and 7 days for scenario 3 considering no capacity restrictions and therefore no queuing of parts. As no detailed process information is available from the parts manufacturer, the production lead times need to be estimated. Based on the top down capacity assessment in 2.3.3, scenario 2 needs to produce one part every 7 hours. Considering a lot size of 12 parts and a changeover time of 2 hours, the production time for one lot equals approximately 3.5 days. Another 6.5 days estimated for quality inspection, pre or post treatments and part handling resulting in a total lead time estimation of 10 days. The same per part production time is used to estimate the lead time of scenario 3 with the changeover time of 2 hours being applied to each part rather than to a lot of 12 parts. The total lead time is estimated to a total of 7 days, also assuming 6.5 days for quality inspection, pre or post treatments and part handling. For the baseline scenario 1 the total lead time is estimated to be 14 days considering a conventional production facility with component supply and assembly work, quality inspection, pre or post treatments at different levels of the value stream as well as part handling. It is assumed that component production in Scenario 1 is de-coupled from the assembly. Therefore, component lead times are not considered in the model.

All manufacturing locations provide a finished goods inventory stock from which customer orders are filled. It is assumed that the production facility is informed in advance of a version upgrade and can take the required measures to build up stock. The delivery time depends on the different locations and is estimated based on the online calculation system from UPS. (United Parcel Service of America, Inc.) As production scenario 3 produces right at the demand locations, no delivery times are considered.

	Scenario 1	**Scenario 2**	**Scenario 3**
Equipment used	Not considered	Concept Laser M3	Concept Laser M3
Lot size	Not considered	12	1
Lead time	14 days	10 days	7 days
Delivery time	1-3 days	1-3 days	0 days
Changeover (C/O) Time (3)	Not considered	2h	2h
Process time per lot (4)	Not considered	83.5 hours	6.33 hours
Total time incl. C/O Time per lot (4)	Not considered	85.5 hours	8.33 hours
Process time per part (4)	Not considered	7 hours	6.33 hours
Total time per part incl. C/O (4)	Not considered	7.15 hours	8.33 hours

Table 2: Overview of equipment, lot size, and lead time assumptions

Machines are assumed to be 80% utilized in all distributed and centralized manufacturing system scenarios. It is assumed that any additional capacity is used to produce other products, potentially for other customers, in an open market. No machine downtown is considered in this study. Given the limited number of components currently produced via additive manufacturing, this may not be realistic today. In fact, past studies have found the machine utilization being a major driver for the cost and environmental performance as it significantly influences how machine investments and up-stream emissions from building the machines are broken down to a per part calculation. (Faludi, Bayley et al. 2015, Lindemann, Jahnke et al. 2012) However, with the expected growth in additive manufacturing, machine utilization is expected to improve. The assumption of an 80% machine utilization, enables a focus on the required resources and capacities on a per part basis in a future scenario in which DDM machines are fully utilized. Also, no machine or equipment amortization and investment costs are considered within this study.

Although not much information about the cobalt-based alloy used for additive manufacturing is publicly available, one GE additive company has been identified in Québec, Canada. This company called AP&C is currently expanding its capacities to manufacture metal powders from titanium and other customized super alloys by building a new facility in St-Eustache, Québec. According to their website they are expending their capacities from currently 500 tonnes to a future production of 1250 tonnes of metal powder for additive manufacturing. The raw material demand for fuel nozzle production can be calculated to maximize 35 tons per year for a maximum rate of 40,000 fuel nozzles per year and a per part start weight of 0.85 kg. (Flanagan et al. 2017) Therefore, St-Eustache, Québec has sufficient capacities to supply raw material for all fuel nozzle manufacturers and is assumed as the location for raw material powder production. It is assumed that this highly customized material will be produced on order at a minimum order quantity of 5 tons for the centralized production location. It is further assumed for the distributed scenario that the MRO locations are restricted to use this material and supplier as it is often the case in the aerospace industry and that they can order the material from the same location with minimum order quantities of 500 kg. It is assumed that raw material is shipped via truck transport. Road distances are calculated using google maps and raw material transportation is considered in the simulation model.

2.3.4 The demand locations

For the CFM56 a wide range of service providers exist, as CFM has kept the aftermarket for the CFM56 open. Services are offered by independent MROs, airline affiliates and the OEMs, i.e., General Electrics (GE), SAFRAN Aircraft Engines and their joint venture CFM International. According to Derber (2017), CFM Services has a market share of about one third in the global aftermarket.

For an estimation of the US aftermarket for the CFM56 engine, press statements (StandardAero 2016, Lockheed Martin Corporation 2016, Southwest Airlines Co. 2016, Shay 2017, DELTA AIR LINES 2007, Mecham 2012) of the involved companies and airlines were reviewed. In addition, most of the airlines also publish information about their current fleets on their websites. In cases where they do not, data about airline fleets and aircraft movements are derived from public website (Airfleets 2018). Taken together, this information was used to develop an inventory of aircraft operated out of the US and Canada that use the CFM56 or LEAP engines, and identify MRO providers and locations for these aircraft.

Table 3 gives an overview of the relevant companies and locations identified to perform maintenance service on the CFM56 engine family. Seven MRO locations were identified, four in the U.S., two in Canada, and one in Brazil. Table 3 also identifies the airlines serviced at these maintenance locations and the number of airplanes with CFM56 engines operational in their current fleets. This included twelve airlines, eleven operating out of the U.S and one operating out of Canada. Within their fleets, aircraft from the Airbus A320 and Boeing 737 families utilize the CFM56 or LEAP engine. The only other commercial aircraft type planning to use the LEAP engine is the Comac C919 with a planned market introduction in 2021. At the moment it is not known, if any US or Canadian airlines are planning to operate this airplane. Therefore, the Airbus A320 and Boeing 737 aircraft were simulated in this study.

No.	Company	Company Address	Customers	A/C with CFM56/LEAP engine
001	GE Aviation Strother Field	Strother Fld Arkansas City KS 67005, USA	Virgin America Alaska Airlines Sun Country Airlines Air Transat Sunwing Airlines	67x A319/A320/A321 232x Boeing 737
002	GE Aviation Celma	R. Alice Hervé 356 – Bingen Petrópolis – RJ 25669-900 Brazil	70% of the Southwest fleet	485x Boeing 737
003	StandardAero	1885 Sargent Ave, Winnipeg, R3H 0E2 Canada	30% of the Southwest fleet Westjet	327x Boeing 737
004	Lockheed Martin Commercial Engine Sol.	7171 Boulevard de la Côte-Vertu Saint-Laurent H4S 1Z3, Canada	Frontier Airlines	76x A319/A320/A321
005	AMERICAN AIRLINES Technical Ops. & Maintenance	3900 NORTH MINGO ROAD TULSA, OK 74116 USA	American Airlines Allegiant Air	205x A319/A320/A321 306x Boeing 737
006	DELTA TechOps	1775 M.H. Jackson Service Road ATLANTA, GA 30354, USA	DELTA AIR LINES INC	150x A319/A320/A321 171x Boeing 737
007	United Airlines Maintenance Base	4849 Wright Rd # B Houston TX 77032, USA	United Airlines	329x Boeing 737

Table 3: Overview of service locations with assigned customers and airplane volumes

Figure 4 and Figure 5 show a summary of the eight identified MRO shops (demand locations) from Table 3 and the location of the centralized production location in 400 Innovation Dr, Auburn, AL 36832, USA, where GE Aviation has established a new facility for additive manufacturing high volume production. (Zaleski 2017)

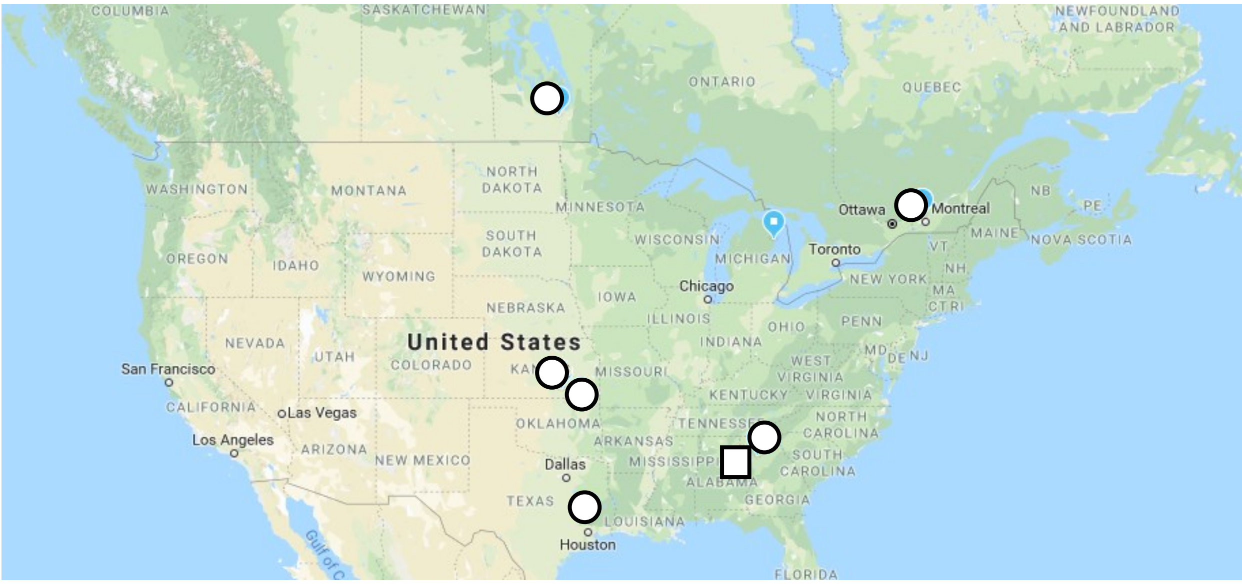


Figure 4: Overview of demand locations in North America

- The white circles show the demand locations for the centralized and distributed manufacturing system (CMS & DMS). For the DMS, these are also the production locations.

- The white square shows the production location of the centralized manufacturing system (CMS) and is not relevant for the distributed manufacturing system (DMS).

Figure 5: Overview of demand locations in South America

- The white circles show the demand locations for the centralized and distributed manufacturing system (CMS & DMS). For the DMS, these are also the production locations.

2.3.5 The centralized manufacturing location (CMS)

GE Aviation has been investing heavily into additive manufacturing technology and has established a new facility in Auburn, Alabama for manufacturing the fuel nozzle. At full production this new facility will have capacities for manufacturing 35,000 - 40,000 fuel nozzles per year. (General Electric Company 2017) Considering 19 fuel nozzles per engine and a planned output for serial production of 2,000 engines per year by 2020 these capacities will be almost fully utilized by a demand of 38,000 fuel nozzles per year. (Broderick 2017) Without taking measures to expand capacities a maximum of 2,000 fuel nozzles could be delivered to the aftermarket based on these estimates.

Figure 6 shows the supply chain concept for production scenarios 1 and 2 in one centralized location with subsequent part distribution to the customers (repair shops). The centralized manufacturing location produces all parts required by the MRO repair shops in the US, Canada, and Brazil. Raw material is assumed a low value item with relatively low holding cost and therefore stocked plenty. Within the simulation, simplified raw material replenishment with high tolerances is used and raw material stocks are reviewed yearly to ensure that production is not disputed due to missing raw material in the following year. Costs and environmental impacts related to manufacturing, inventory holding, and transportation are estimated.

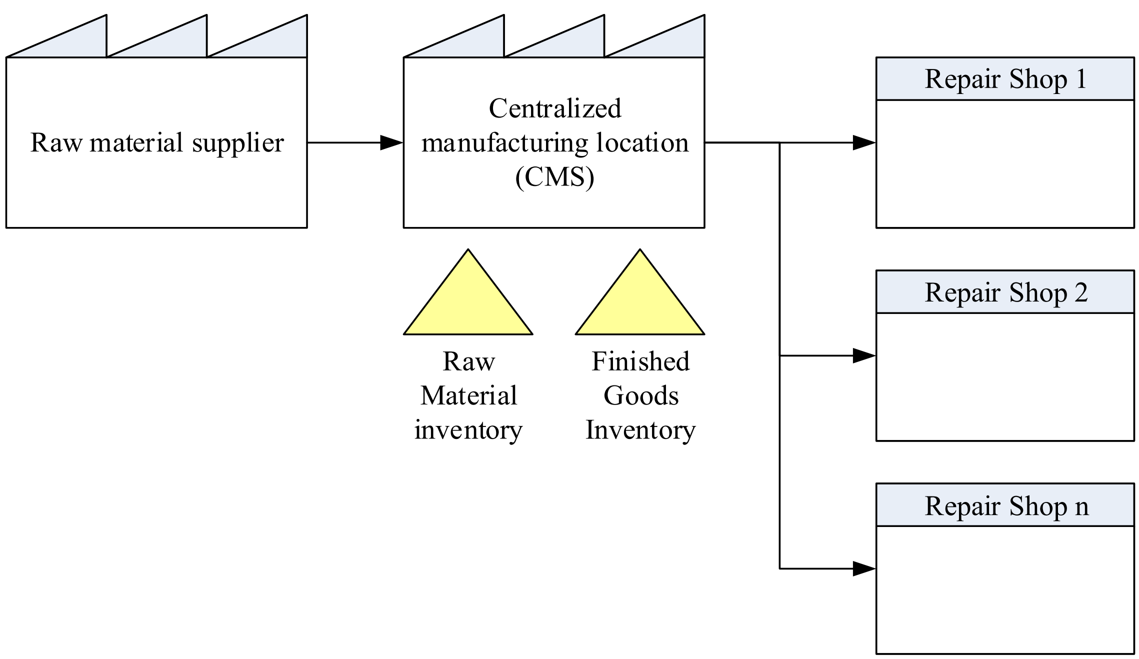


Figure 6: Supply chain of the centralized production system

2.3.6 The distributed manufacturing system (DMS)

For production scenario 3, i.e., the distributed manufacturing system (DMS), it is assumed that parts are produced at the repair shops, i.e., at the fuel nozzle point of demand. In this case the seven demand locations in Figure 4 and Figure 5 are considered to accommodate the required production infrastructure.

Figure 7 shows the supply chain concept for production scenario 3. Each distributed manufacturing location produces the parts required for the specific repair shop. Raw material is considered a low value item with relatively low holding cost and therefore stocked plenty. Unlike the centralized supply chain, all distributed locations require raw material and finished goods inventory stocks.

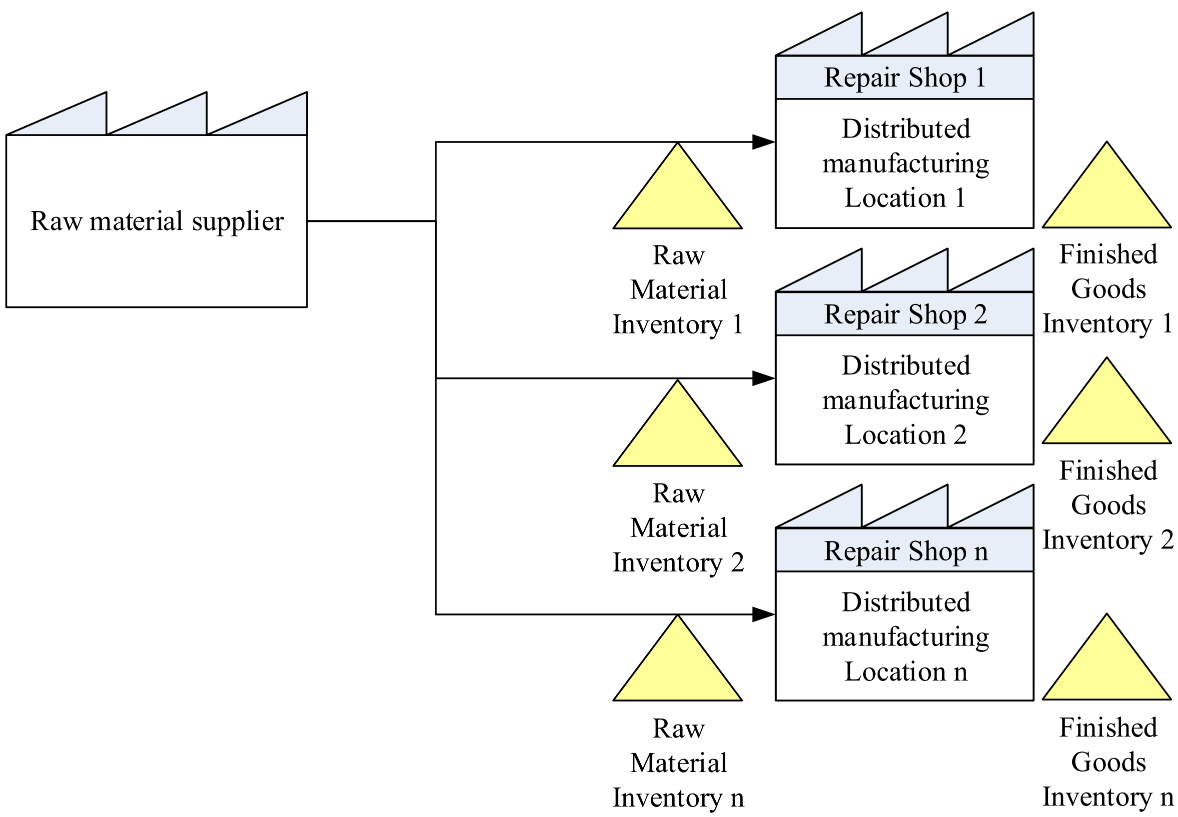


Figure 7: Supply chain of the distributed production system

2.3.7 Life-cycle inventory

The purpose of the life-cycle inventory is to define the boundaries of the reviewed system from an environmental perspective and to define what exchanges with nature are considered. The assessment of the environmental performance of the three production systems considers the electric energy consumption from fuel nozzle production (pre and post processing as well as part shaping), electric and fossil energy consumption from raw material transportation to either the centralized production location in Auburn, Alabama in scenario 2 or directly to the seven de-centralized MRO repair shop locations in scenario 3, and finally electric energy consumption from transportation of the final fuel nozzle product to the seven demand locations (MRO repair shops) in scenarios 1 and 2. In scenario 3 the de-centralized MRO repair shops produce the final fuel nozzles themselves. Therefore, no distribution is considered. Inventory risks deriving from inventory obsolescence are causing additional production and are therefore considered as part of this life-cycle inventory. Figure 8 provides a flowchart showing the considered life-cycle inventory. For scenario 1 no raw material transportation is considered as it does not use powder material. Moreover, it is assumed that all component production activities happen at the same location. This is a simplifying assumption for scenario 1 as no detailed information of the component supply chains are available. Due to significantly higher per part efforts it is expected that this simplification does not change the overall picture significantly. Production scenario 3 does not require transportation to the MRO locations as the final parts are manufactured right at these locations.

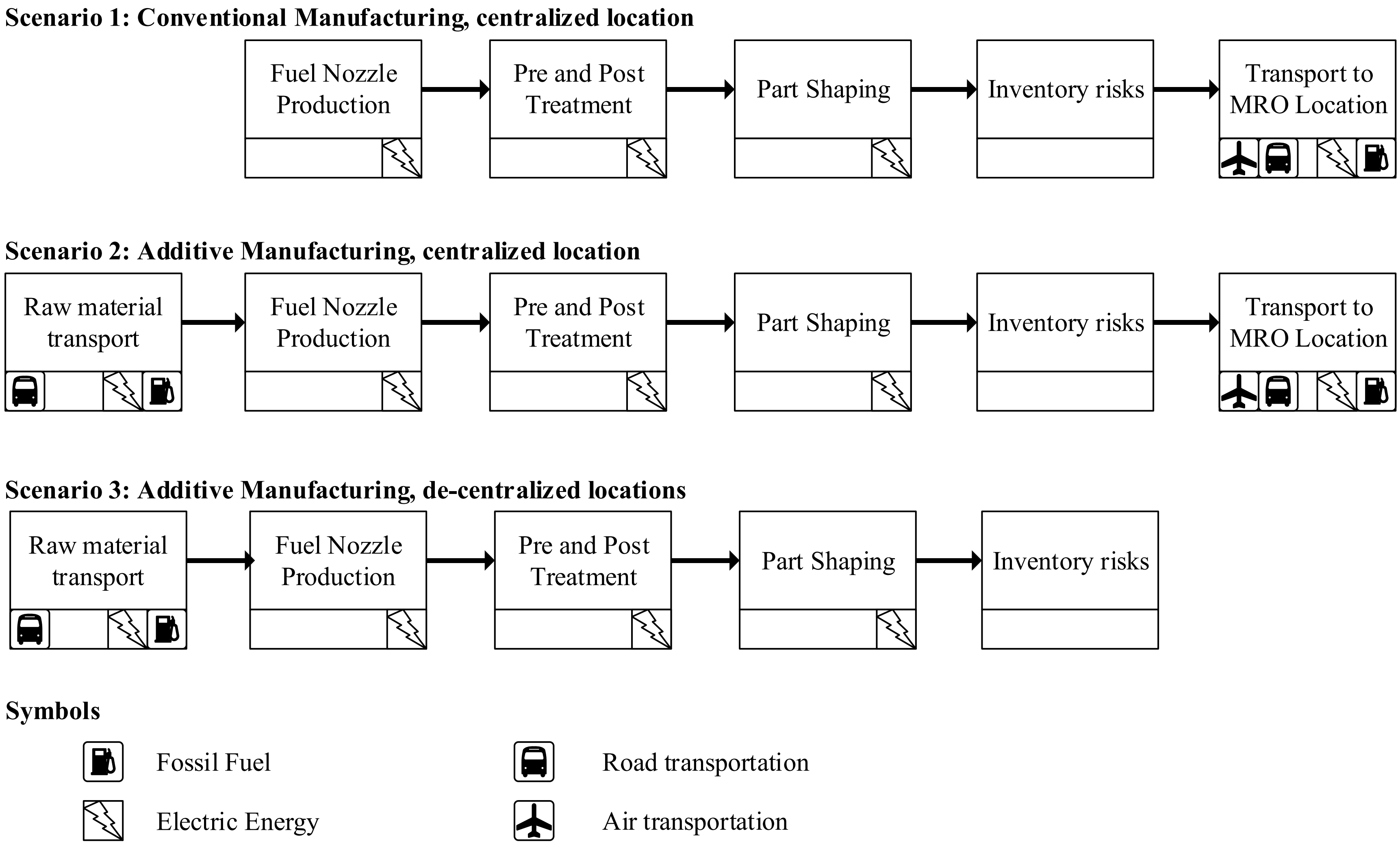


Figure 8: Life-cycle inventory diagram

2.3.8 Energy and resource consumption on a per part basis

The energy consumption per part is derived from Flanagan et al. (2017). Flanagan et al. (2017) do not provide complete detailed information about the electricity consumptions, so that the information available is completed by estimations, machine data sheets (Concept Laser GmbH 2017) and information from current literature (Kellens, Mertens et al. 2017a). Based on these information, the required electrical energy per part is assumed to be 81.4 kWh for scenario 1, 48 kWh for scenario 2 and 49.32 kWh for scenario 3.

Flanagan et al. (2017) provide a graph showing the cumulative energy requirement of approximately 14.000 kJ for part shaping of the traditional fuel nozzle (slide 15). Another graph (slide 18) shows the relation of the required energy for all considered life cycle phases of the traditional and additive fuel nozzle. The part shaping process is found to account for approximately 0.5% of the energy demand of the traditional fuel nozzle. The largest portion "Aircraft operation – Replacements" is ignored as it is covered by the simulation model and a higher probability of part replacements for scenario 01 and should thus not be considered twice. The relevant portions of pre and post processing as well as part shaping account for approximately 11.9% or 293,186 kJ or 81.4 kWh.

Applying the same procedure for the additive manufactured fuel nozzle an energy demand per part of approximately 48 kWh is considered for the pre and post processing and the part shaping. Approximately 40 kWh account for pre and post processing while the remaining 8 kWh account for the part shaping process. With a standby energy of 0.7 (Kellens et al. 2017a), a laser power of max. 1 kW (Concept Laser GmbH 2017) and an estimated production time of 7 hours per part the machine would require approximately 11.9 kWh if operating at full power. As the required laser energy is dependent on the layer thickness and the layer thickness has a high impact on part quality, it is assumed that a sensitive aerospace part like the fuel nozzle would rather be produced at lower layer thicknesses. Each laser of a Concept Laser M3 machine can produce a layer thicknesses of 20 – 100 µm with a maximum speed of 4.5 m/s. (Concept Laser GmbH 2017)

Assuming that the relationship between the layer thickness and the required laser energy is linear scenario 03 would require approximately 9.32 kWh and 8.33 hours to build up one fuel nozzle with a layer thickness of the minimum range of 20 to 40 µm. This estimation includes changeover times and standby energy requirements. Applying the same settings for scenario 2, one lot containing 12 fuel nozzles would require 95.65 kWh of electricity or 7.97 kWh per part and it would take approximately 84.5 hours to produce one lot.

Table 4 summarizes assumptions related to energy consumption for the three production systems.

	Scenario 01	**Scenario 02**	**Scenario 03**
Average power standby	Not considered	0.7 kW	0.7 kW
Minimum layer thickness	Not considered	20 µm	20 µm
Maximum layer thickness	Not considered	100 µm	100 µm
Layer thickness assumed	Not considered	20 - 40 µm	20 - 40 µm
Laser power assumed	Not considered	25%	25%
Maximum power laser	Not considered	1 kW	1 kW
Number of lasers	Not considered	4	1
Energy required for part shaping per part	0.8 kWh	8 kWh	9.32 kWh
Accumulated energy for required pre and post processing per part	80.6 kWh	40 kWh	40 kWh

Table 4: Overview of assumptions related to energy consumption

The traditional fuel nozzle is assembled from 19 pieces comprising 4 different alloys. The additive fuel nozzle is printed from only one alloy and does not require additional components. The following table summarizes the raw material consumption per part for the traditional and the additive manufactured fuel nozzle. All numbers are taken from (Flanagan et al. 2017).

Materials / Alloys	Start Weight [kg]	Finish Weight [kg]	Excess [kg]
Traditional fuel nozzle			
Inconel 625	0.76269	0.22625	0.53644
Hastelloy X	0.06788	0.027	0.04088
Haynes 188	0.51089	0.08147	0.42942
Rene 80	0.04926	0.02211	0.02715
Total	1.39072	0.35683	1.03389
Additive fuel nozzle			
CoCrMo	0.84879	0.26762	0.58117

Table 5: Summary of raw material consumption and excess

The cost of electricity depends on the location of the production facilities and is defined as follows: (U.S. Energy Information Administration (EIA) 2018b, Natural Resources Canada 2017)

	State / Province / Location	Industrial Electricity Rate
1	Oklahoma	4.98 US cents per KWh
2	Arkansas	5.44 US cents per KWh
3	Texas	5.26 US cents per KWh
4	Alabama	5.97 US cents per KWh
5	Georgia	5.54 US cents per KWh
6	Kansas	7.15 US cents per KWh
7	Winnipeg, Manitoba, Canada	4.5 US cents per KWh
8	Montreal, Quebec, Canada	5.63 US cents per KWh
9	Brazil	11.6 US cents per KWh

Table 6: Overview of electricity cost

2.3.9 Transportation efforts

Transportation distances and part weights are needed to estimate the amount of freight transport associated with transporting the fuel nozzles in between the centralized manufacturing location and the MRO locations. Transportation distances are used in combination with shipment weights to estimate the ton-miles required for air and ground transport. These values are then multiplied by the DIO scoring factors for air ("Transport, aircraft, freight") and truck transportation ("Truck transport, class 6, medium heavy-duty (MHD), diesel, short-haul, load factor 0.5") to estimate the potential environmental impact from air and ground transport of the fuel nozzles.

The DELTA TechOps MRO in Atlanta, Georgia is located a little more than 100 miles from the centralized manufacturing plant in Auburn, Alabama. In this case it was assumed that the nozzles will be shipped by truck solely. For all other locations, the nearest major airport served by UPS cargo was identified from UPS's lists of US and global airports (UPS Air Cargo 2017b, UPS Air Cargo 2017a). The selected airport for each MRO is listed in Table 6. For these, it was assumed that the fuel nozzles will be shipped first via truck to Hartsfield–Jackson Atlanta International Airport (IATA Code: ATL), the closest major airport to the centralized manufacturing plant in Auburn, Alabama. They are then assumed to be shipped by air directly from Hartsfield–Jackson Atlanta International Airport (IATA Code: ATL) to the nearest major airport, identified in Table 6, without the need of stopovers. Finally, they are assumed to be shipped via truck from this airport to the MRO location. All road distances are determined using google maps and the locations from Table 3. The shortest distances estimated by google maps is assumed. For all UPS air deliveries, air transportation distances are estimated using the website https://www.world-airport-codes.com/distance/, which offers distance calculations between airports.

Table 7 provides estimates of the air and ground shipping distances from the centralized manufacturing plant in Auburn Alabama to each of the seven MRO locations.

	Nearest UPS Airport Code	Distance Road [miles]	Distance [miles]		
			Road (to ATL)	Air (to nearest UPS airport)	Road (to MRO)
GE Aviation	TUL	883	105	672.45	134
GE Celma	GRU	n/A	105	4666.44	795.24
StandardAero	YWG	1655	105	1299.65	3.38
Lockheed Martin Commercial Engine Solutions	YUL	1322	105	994.33	13.17
AMERICAN AIRLINES Technical Operations & Maintenance	TUL	778	105	672.45	6.3
DELTA TechOps		108			
United Airlines Maintenance Base	IAH	693	105	688.17	0.70

Table 7: Summary of shipping distances

Flanagan et al. (2017) report a weight saving potential of 25% for the fuel nozzles by applying additive manufacturing technology. According to the report the weight per fuel nozzle can be reduced from 0.35683 kg to 0.26762 kg.

Based on the per part weight, the shipment weights are estimated as shown in Table 8. It is assumed that extra precautions, including use of specialty packaging materials, will be taken to keep the fuel nozzles stable and damage free during shipping. These packaging materials as well as paper documentation are considered in the shipping weight estimates. The total additional weight is assumed to be 1 kg for a package that contains one to nine fuel nozzles and 2 kg for a package that contains 10 – 19 fuel nozzles.

Package content	Part Weight [kg]	Package Weight [kg]	Package Weight [lb]	UPS Billable Weight [lb]
1 – 3 fuel nozzles	0.27 – 0.81 kg	1.27 – 1.81 kg	2.8 – 3.99 lb	< 4 lb
4 – 6 fuel nozzles	1.08 – 1.62 kg	2.08 – 2.62 kg	4.6 – 5.8 lb	< 6 lb
7 – 9 fuel nozzles	1.89 – 2.43 kg	2.89 – 3.43 kg	6.4 – 7.56 lb	< 8 lb
10 – 14 fuel nozzles	2.7 – 3.78 kg	4.7 – 5.78 kg	10.4 – 12.74 lb	< 13 lb
15 – 19 fuel nozzles	4.05 – 5.13 kg	6.05 – 7.13 kg	13.3 – 15.4 lb	< 16 lb

Table 8: Shipment weights overview

For evaluating the shipping time and cost, the online calculation system from UPS is used. (United Parcel Service of America, Inc.) Taking into account the package weight and the demand locations listed in *0*, the shipping cost and times from the manufacturing location in Auburn, Alabama to the identified demand locations are derived. Table 9 summarizes the resulting cost and transportation time that is used in the simulation model.

Adressee	Cost [USD]					Transportation time
	< 4 lbs	< 6 lbs	< 8 lbs	< 13 lbs	< 16 lbs	
GE Aviation	85.46	109.58	122.22	164.93	185.15	1 day
GE Celma	234.66	326.74	412.60	539.67	657.42	5 days
StandardAero	80.17	95.66	105.94	129.78	143.77	1 day
LMCS	80.17	95.66	105.94	129.78	143.77	1 day
AMERICAN AIRLINES Tech. Ops.	90.35	106.64	119.28	161.99	182.21	1 day
DELTA TechOps	35.55	44.35	45.28	55.83	59.27	1 day
United Airlines Maintenance Base	82.53	106.64	119.28	161.91	182.21	1 day

Table 9: Transportation time and cost

2.3.10 Holding cost and fuel nozzle spare part price assumptions

Several companies from the MRO industry have been approached for an estimation of the spare part price for the fuel nozzle. Most of them did not reply or replied that the catalogue price cannot be shared for confidential reasons. Two answers have been received setting a range from USD 9,500,- to USD 18,000. This high variation can be explained by different engine versions, different fuel nozzle versions even within the same engine and by different suppliers such as OEM and third party suppliers.

The spare part price of the fuel nozzle is set to be USD 10,000 for all fuel nozzle versions for simplicity reasons as it is only used for estimating the holding cost. This simplification also means that no cost reductions or increments in part production resulting from Industry 4.0 concepts are considered in this model. Due to the much higher number of fuel nozzles that are needed for the conventional manufacturing system based on (Flanagan, Fisher et al. 2017) a cost saving resulting from a much simplified design of the additive fuel nozzle is expected to have a negligible impact on the total result unless it would be extraordinary. With required high investments into new machines and infrastructure as well as high cost of initial research, an extraordinary cost saving cannot be expected even if the per part recurring cost would be reduced significantly.

As no actual holding cost information is available, the cost of holding a part for a period of one year is assumed to be 20% of the products value. This includes the cost of damaged parts, cost of storage space and labor as well as opportunity cost due to tied capital.

2.4 Step 2: The Simulation Model

2.4.1 Simulation model conception

This work aims to quantify the overall impact of Industry 4.0 and direct digital manufacturing in particular based on a given example from the industry. To address these questions three major production and supply chain models are developed in ARENA Simulation software, Version 15 by Rockwell Automation Technologies, Inc. that are used for simulating varying conditions set by attributes and recording performance output measures on a monthly basis. Figure 9 shows the principle conception of the simulation model while Figure 10 provides a schematic overview of the three developed production and supply chain system scenarios Scenario I, II and III.

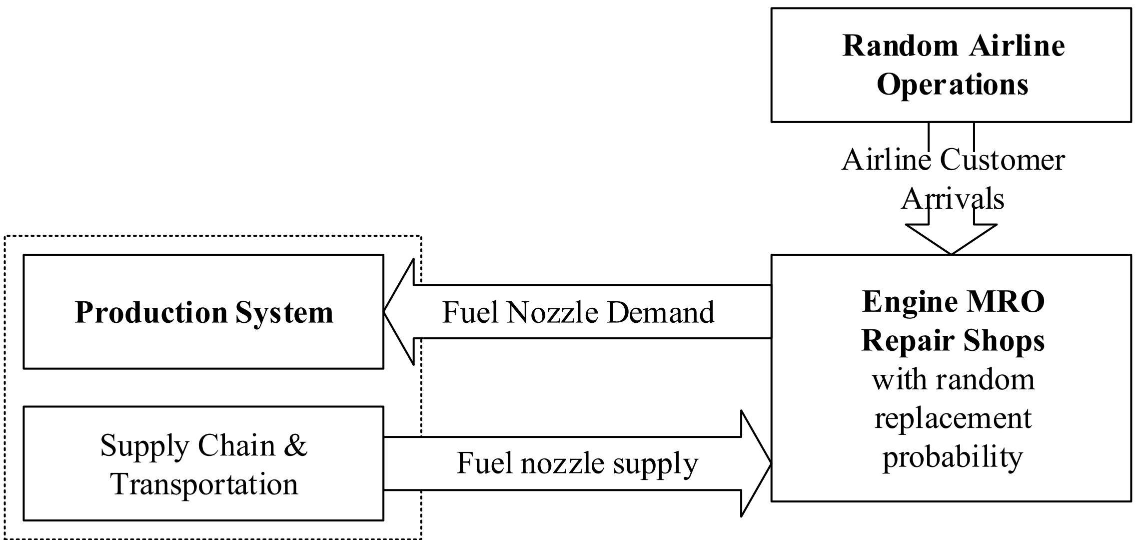


Figure 9: ARENA Simulation flow chart

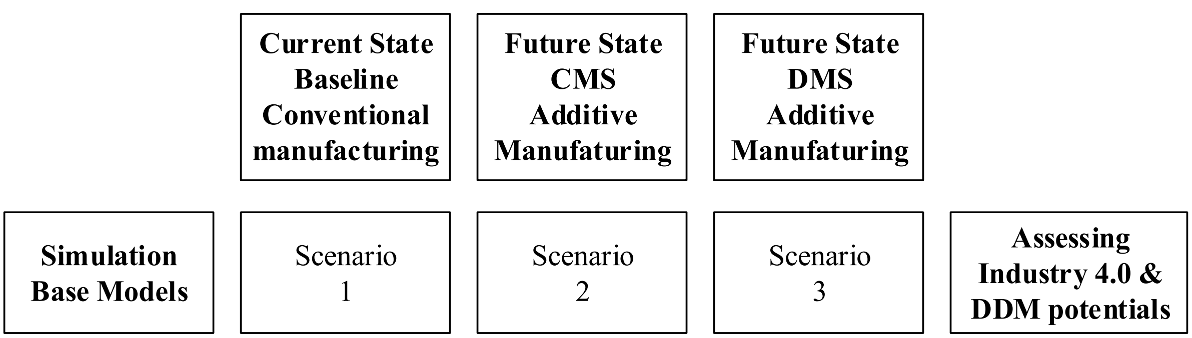


Figure 10: Schematic overview of scenarios

The models have not been simulated on static conditions as of today but rather are subject to changing technology over time which is considered by projections. For each of the three considered technology changes (changes in the electricity mix, growth of the electric truck market and implementation of carbon tax) three scenarios representing low, mid and high developments have been modeled as defined in 2.4.8. Combined with three different supply chain configurations and 8 different input values for the anticipated service level (z-value) a total of 648 (3 x 3 x 3 x 8 x 3) different unique input combinations have been investigated. Appendix 03 provides an overview of all 648 unique input set combinations that have been considered in this work. Table 11 shows an overview of all considered inputs. Not all of them are independent of each other. The first three inputs production location(s), manufacturing method and production lead time define the three production scenarios, as shown in Table 10. For the location parameter, 0 represents production in one centralized location, whereas 1 represents production in multiple distributed locations. For the manufacturing method parameter, represents traditional manufacturing, whereas 1 represents additive manufacturing. Production scenario 1 [0, 0, 14] produces in one centralized location using conventional technologies and has a lead time of 14 days. Production scenario 2 [0, 1, 10] produces in one centralized location using additive technologies and has a lead time of 10 days. Production scenario 3 [1, 1, 7] produces in distributed locations using additive technologies and has a lead time of 7 days.

Production & Supply chain system	**Production Location(s)**	**Manufacturing Method**	**Lead Time (days)**
Scenario 1	0	0	14
Scenario 2	0	1	10
Scenario 3	1	1	7

Table 10: Definition of production & supply chain systems (production scenarios 1, 2, 3)

Category	**Input**	**Unit**	**Description**
Supply chain	Production location(s)	boolean	0 means production in one centralized location 1 means production in distributed locations
Supply chain	Manufacturing method	boolean	0 means production technology is traditional 1 means production technology is additive manufacturing
Supply chain	Production lead time	Days	Defines production lead times for production systems I, II, III (7, 10 and 14 days)
Supply chain	Anticipated service level (z-value)	n/A	The z-value defines the number of standard deviations in demand that should be covered by safety stock assuming a normal demand distribution
Global forecast	Carbon tax	USD	Carbon tax forecast considering three forecast cases: low, mid, high based on "Spring 2016 National Carbon Dioxide Price Forecast" (Luckow, Stanton et al. 2016)
Global forecast	Electricity mix fraction	misc.	Projected mix of electricity generation technology in the US considering three cases based on "Annual Energy Outlook 2018" by the U.S. Energy information administration: (low: Low Oil and Gas Resource and Technology, mid: Reference Case, high: High Oil and Gas Resource and Technology) (Coyle 2018)
Global forecast	Electric truck fraction	[%]	Projected fraction of electric road freight in relation to conventional road freight considering three cases: (low: Early adoption phase, mid: Reference Case high: Late adoption phase) (Tryggestad, Sharma et al. 2017)

Table 11: Configuration parameters

The observation period is set to be 30 years. Depending on random operations factors like average flight cycles and average flight hours but also economic considerations an aircraft is expected to operate for a timeframe of approximately 30 years. Therefore, this timeframe provides a good overview for an aircraft fleet using this technology before successors are developed that might use improved or completely different technologies. All simulation models start on January 1st, 2018 and simulate a timeframe of 30 x 365 days. One year is defined to be 365 days long and one month within the simulation model is defined to have 365/12 days. To be in line with Flanagan et al. (2017), an aircraft is disposed and replaced with a new one after reaching 60,000 flight cycles or 120,000 flight hours, whichever occurs later.

2.4.2 The ARENA Simulation model

All simulation models are build up following the same concept. Figure 11, Figure 12, and Figure 13 shows how the sub-models containing airline operations, repair shops, the production systems CMS or DMS and the raw material supplier are arranged. One sub-model is created for each airline operator. Figure 14 exemplarily shows the sub-model created for the operations of A319, A320 and Boeing 737 airplanes of American Airlines. All airplanes for all airlines are initially created within the simulation run with an age distribution defined in 2.4.3. They then operate on a daily basis according to statistical distributions as summarized in 2.4.3. When reaching a certain amount of flight hours or flight cycles as defined in 2.4.4, an airplane leaves the sub-model of its airline operator and is send to one of the seven repair shops in the “Repair Shops” column. (Figure 11) Figure 15 shows the repair shop activities at American Airlines in the Tulsa location. Airplanes arrive and are routed depending on the engine type, as all engines are found to have different maintenance procedures. Engines are being demounted, parts being checked and the number of fuel nozzles requiring replacement is defined according to a probability distribution as described in 2.4.4. Figure 16 and Figure 17 show the distributed and centralized production system, which in general work very similar. First the order arrives with a specific order quantity coming from one of the MRO repair shops. It is checked if on-hand inventory is sufficient to fulfill the order. If yes, demand is fulfilled and the on-hand inventory position variables are updated. Next, it is checked whether the inventory position reached or dropped below the reorder point. If it did not, the order is fulfilled from stock, the ordered parts are being shipped to the repair shop based on the assumptions in 2.3.9. Figure 19 shows how parts are being routed according to their package weights and the addressee repair shop location. Transportation efforts like cost and ton-miles (road) or ton-miles (air) are being recorded for later processing. If the inventory position reached or dropped below the reorder point, production is initiated. Also, if on-hand inventory is not sufficient in the first place, the order enters the backorder loop and remains there until new parts are being finished. Number of parts entering the backorder loop are being recorded on a monthly basis for supply chain performance measures. For scenario 1 parts are being produced one by one, for scenario 2 a batch of 12 parts needs to accumulate before production starts. After recording all production related parameters and delaying the production lots according to lead time definitions (see 2.3.2), the parts are being delivered to stock and all inventory variables are being updated. The total demand is being recorded on a monthly basis for statistics and on a lead time basis for forecasting and recalculating the production quantity Q and the reorder point r. Figure 18 shows how the variables for the average demand and the demand standard deviation are being continuously re-calculated based on the last years demand. Every quarter year the production quantity Q and the reorder point r are being recalculated based on the average demand, the demand standard deviation and the pre-defined z-value.

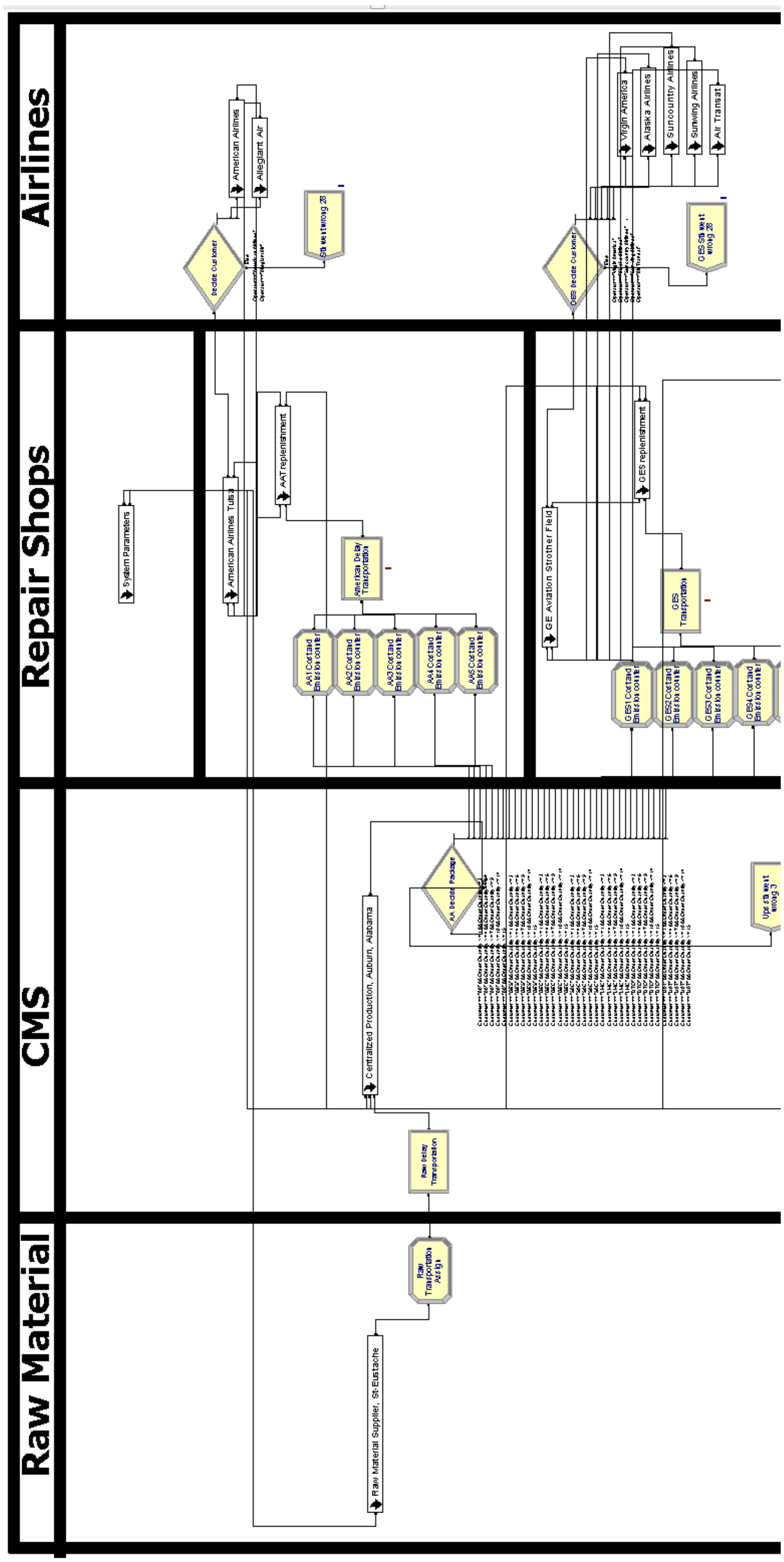


Figure 11: Overview of ARENA Simulation model 1/3

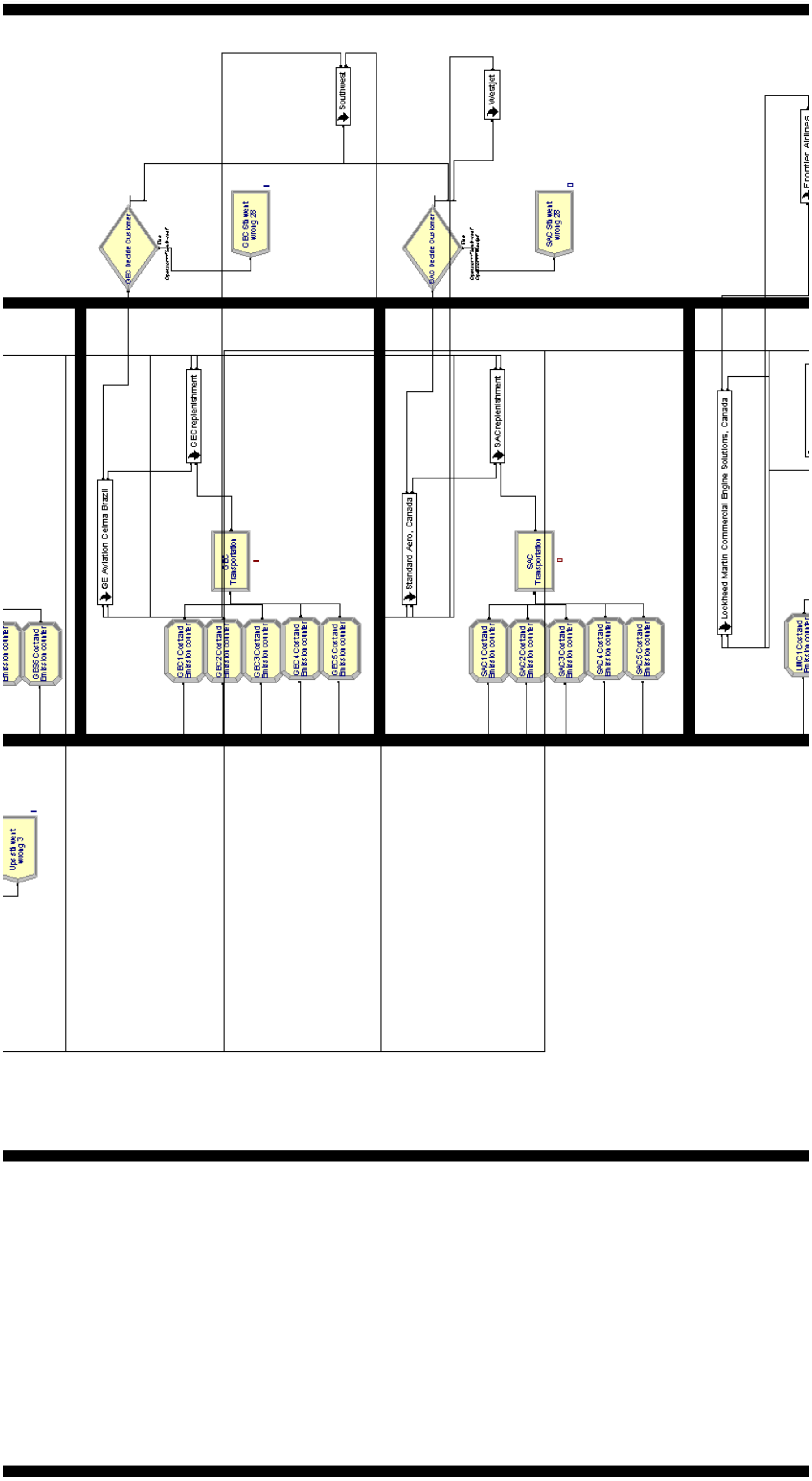


Figure 12: Overview of ARENA Simulation model 2/3

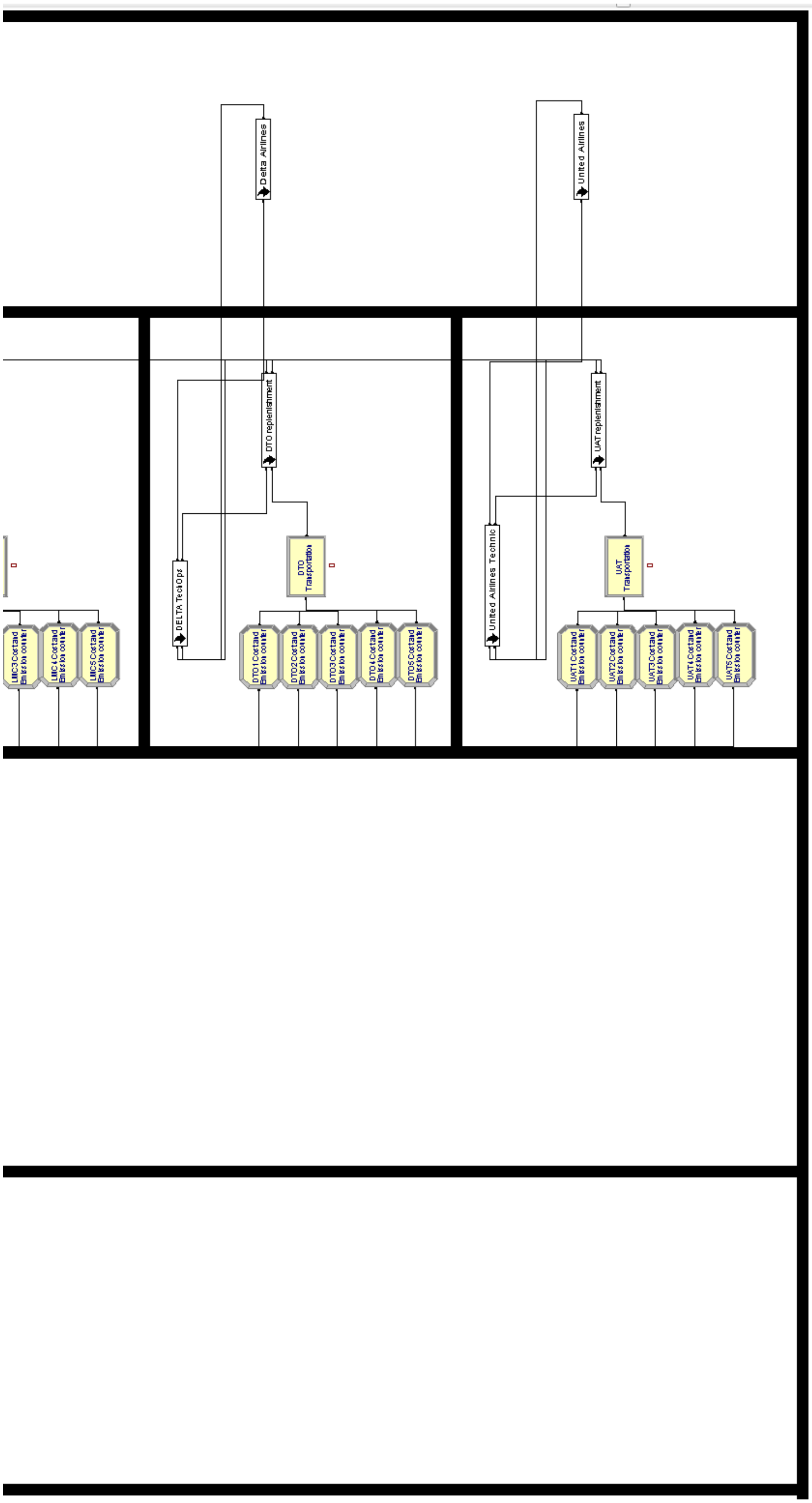


Figure 13: Overview of ARENA Simulation model 3/3

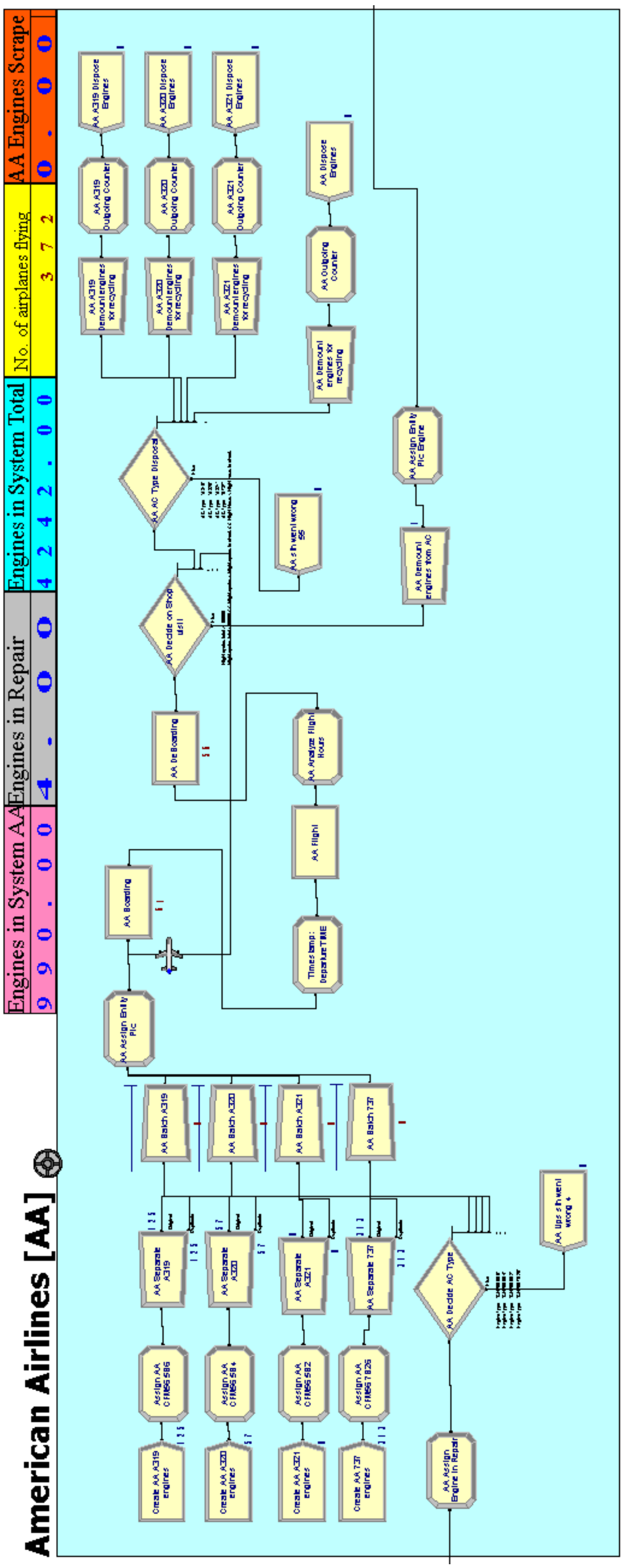


Figure 14: ARENA Submodel for American Airlines [AA]

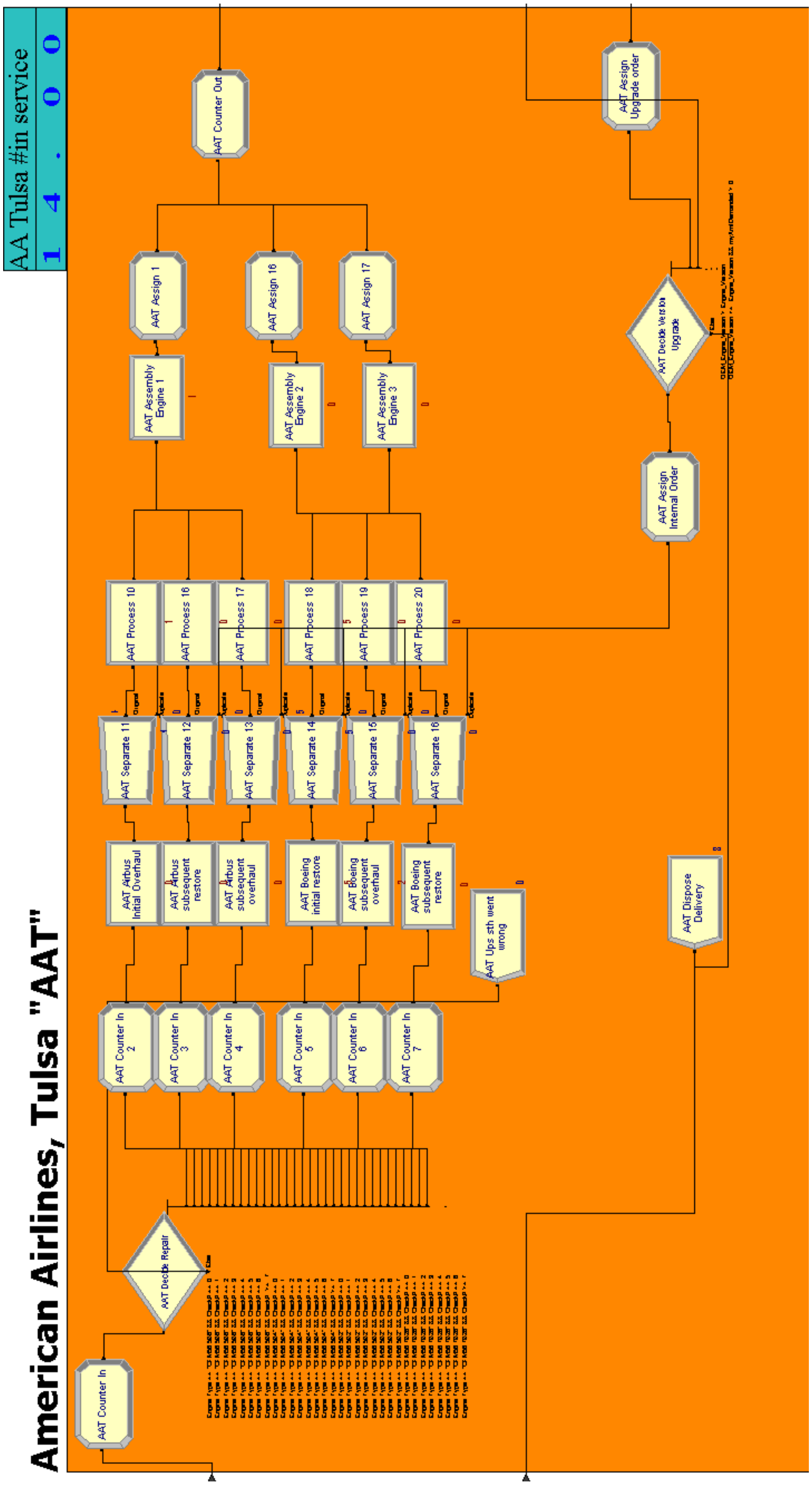


Figure 15: ARENA Submodel for American Airlines, Tulsa

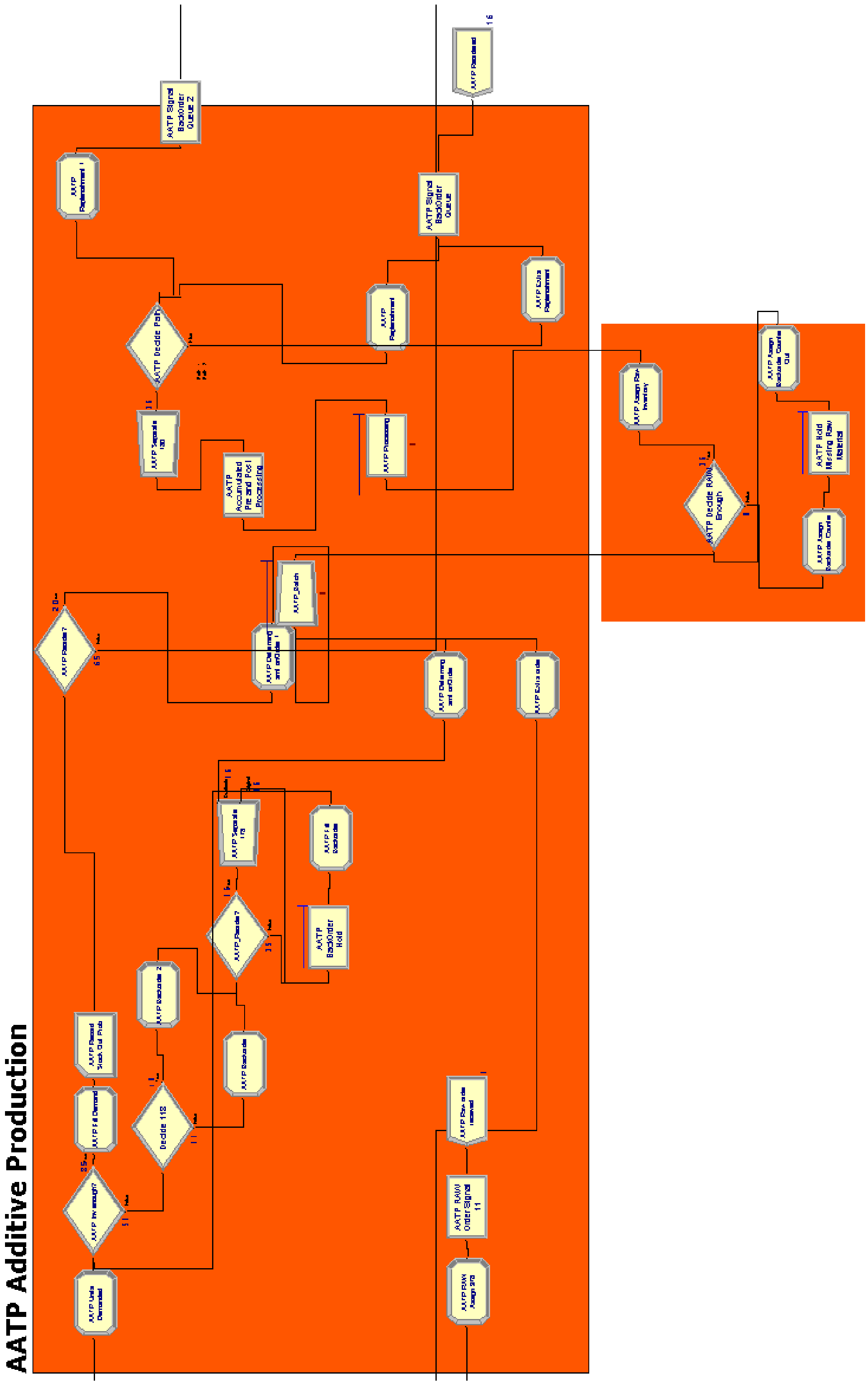


Figure 16: ARENA Submodel AATP Additive, distributed Production

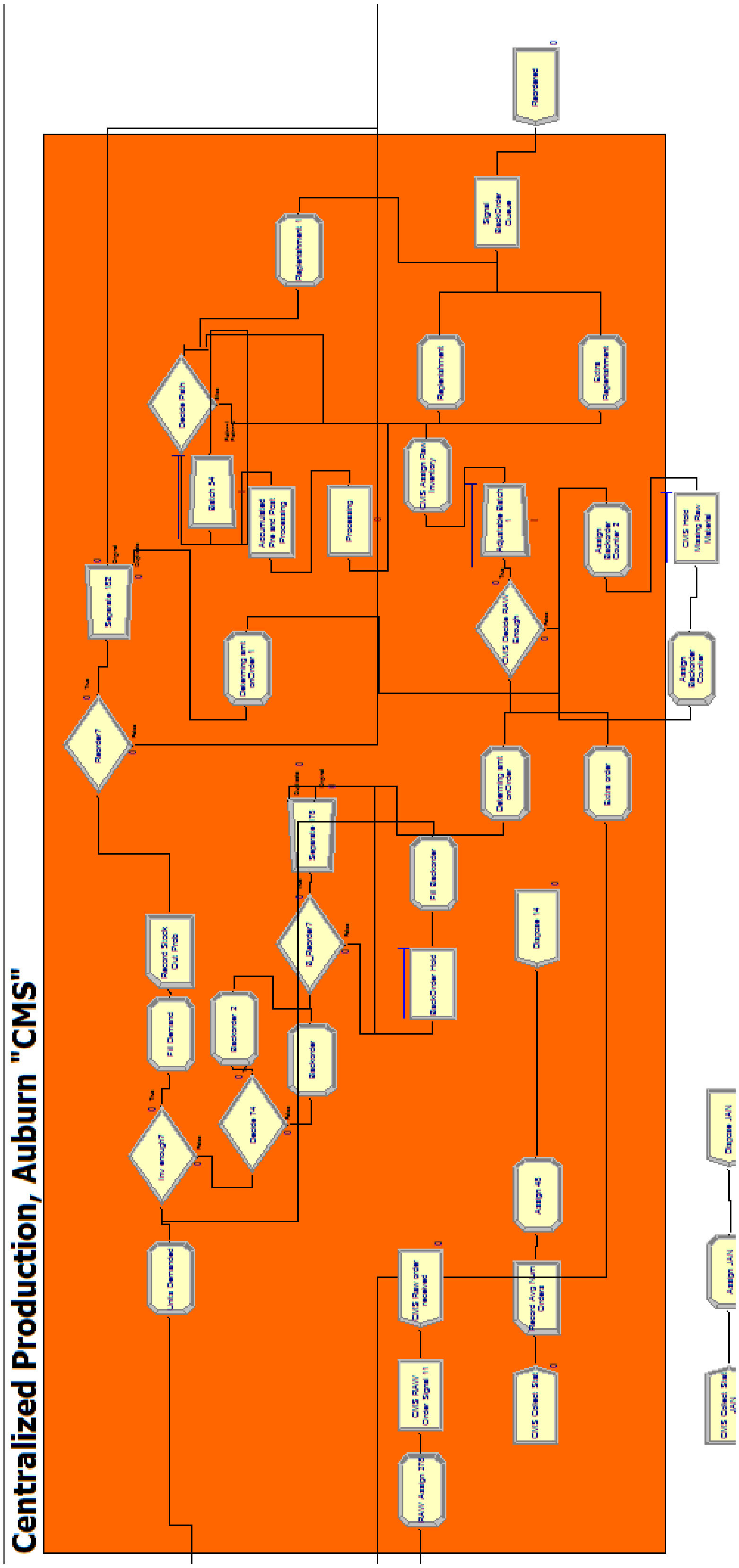


Figure 17: ARENA Submodel Centralized Production

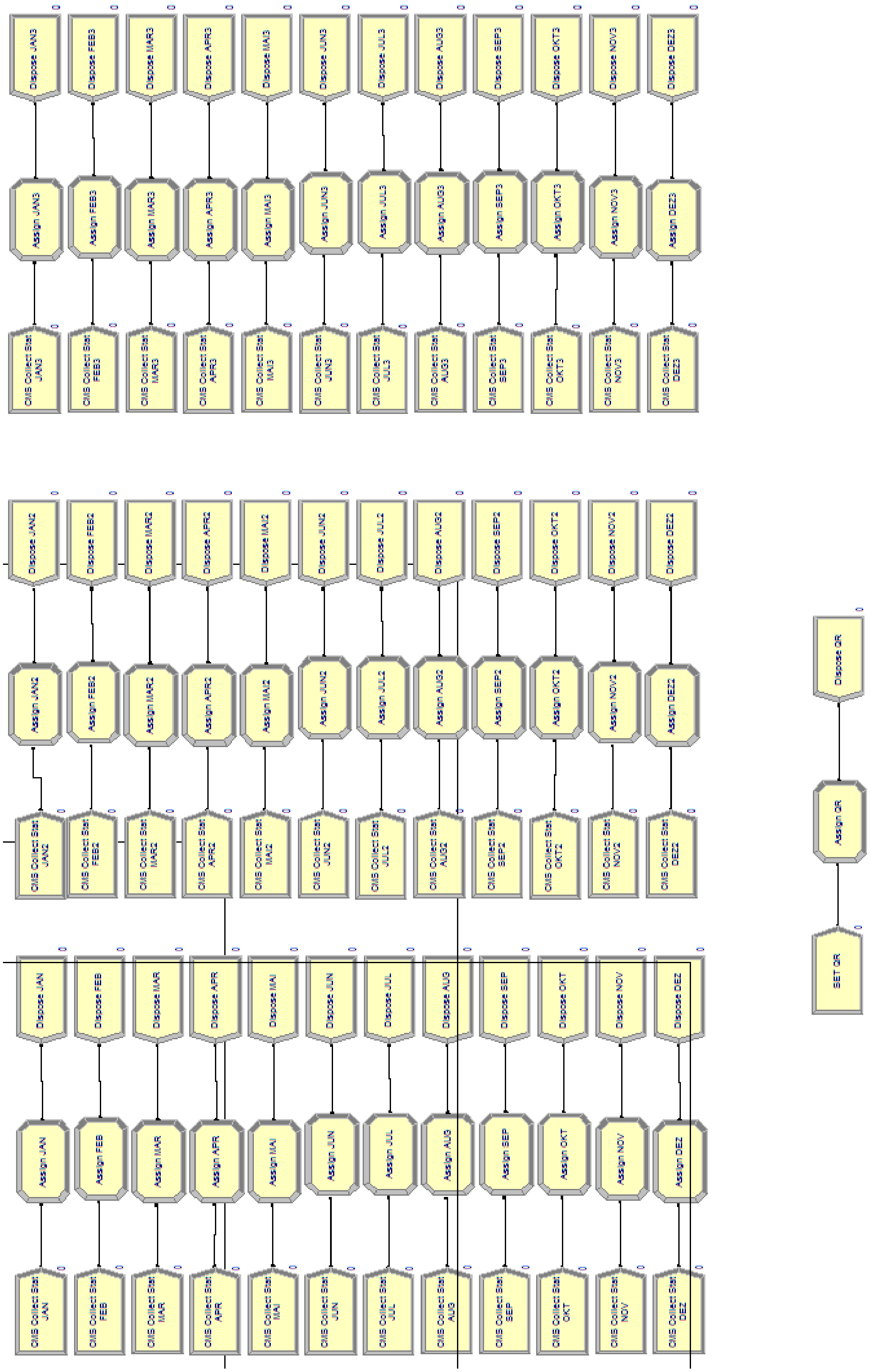


Figure 18: Q,r calculation and demand forecasting

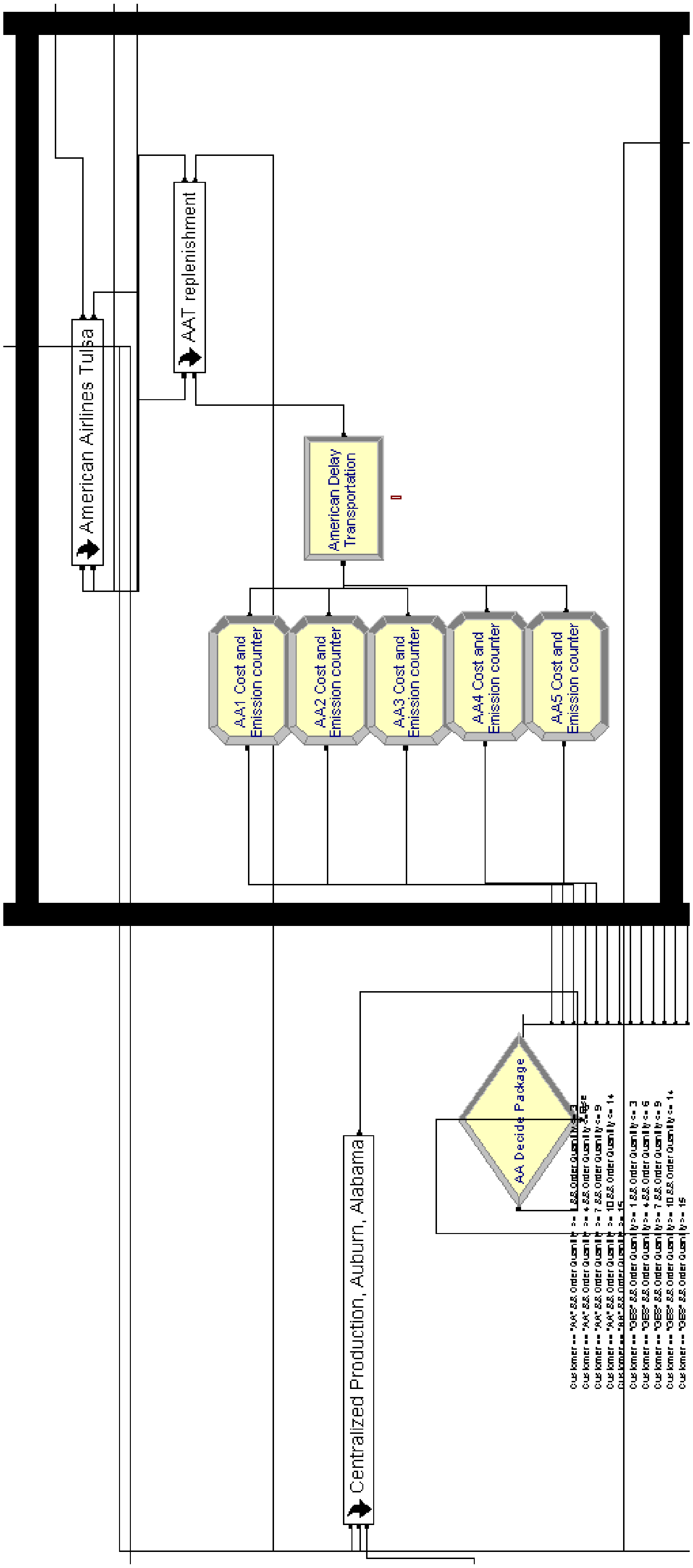


Figure 19: Part transportation from CMS to American Airlines

2.4.3 Random Airline operations

Appendix 01 gives an overview of the initial airline fleets, providing the numbers of each aircraft type, their average age in years, and the resulting age distribution for each airline. The website planespotters.com is a civil aviation database that collects information about all current and historic civil aircrafts. The datasets can be filtered by airline and aircraft type among others. Using this function all aircrafts per considered airline and aircraft type are counted and listed with their age information. ARENA Input Analyzer is used for generating statistical age distributions of these raw data sets per aircraft type per airline. During initiation of the simulation model, the current aircraft fleet numbers are generated with the age distribution as summarized in Appendix 01.

Data for the average missions, such as average flight cycles per day and average flight hours per day, is obtained for each airline from the Massachusetts Institute of Technology Global Airline Industry Program's Airline Data Project (ADP) (Massachusetts Institute of Technology 2017). The data for the Airbus A319 and A320 is selected from the category "small narrowbody aircraft (e.g. Boeing 737-700, Airbus A320)", while the average data for the Boeing 737 and the Airbus A321 is taken from the category "large narrowbody aircraft (e.g. Boeing 737-800, Boeing 737-900, Boeing 757, Airbus A321)". As the Boeing 737 airplane family is considered as one aircraft type in this study, it is assigned to the category, in which it is represented the most. As of September 2018, about 82% of the delivered airplanes of the 737NG family are of type 737-800 or 737-900 and therefore, large narrowbody aircrafts. (Boeing 2018) Data for average flight hours and average departures per day were obtained for the year 2016. It is available for American Airlines, Delta Airlines, United Airlines, Frontier, Virgin America, Alaska and Allegiant Air covering 92% of simulated airplanes. For the remaining airlines, Air Inuit, Air Transat, Air North, Sunwing Airlines and Westjet of which no data sets are available, the average of the airlines for which data is available is assumed for small and large narrowbody aircrafts. Table 13 shows the mean flight duration and how it is used in the beta distribution.

The maximum flight time value is estimated based on the maximum range of the airplane type and available regular non-stop flight routes found in online flight trackers. The longest non-stop route found for an A319 was Air Canada's transatlantic flight from St. John's, Newfoundland to London, UK, which can take up to 5 hours 30 minutes. (Economy Class & Beyond 2014) The longest non-stop route found for the A321 was 5 hours and 51 minutes operated by American Airlines between Los Angeles, USA (LAX) and Kauai in Hawaii, USA (LIH). (Leff 2015) For the A320, the longest route identified is the connection between New York City, JFK and Los Angeles, LAX operated by Alaska Airlines. (Dozer 2018) Although, an extended range version of the A321, the A321LR is available on the market, Air Transat has just recently become the first North American customer for the A321LR and operates its remaining Airbus fleet with the Pratt & Whitney engine option. (Darcy, Brunet 2017) Therefore, this airplane version has not been considered in this study. Based on these findings, the maximum flight time was set to 5 hours 30 minutes for the Airbus A319, 6 hours 25 minutes for the Airbus A320, and 6 hours for the A321.

For the Boeing 737 airplanes the route between Chicago O'Hare International Airport and Ted Stevens Anchorage International Airport operated by United Airlines and Alaska Airlines is found to be one of the longest, fully utilizing the maximum range of this airplane. (Lazare 2018) It takes 6 hours and 49 minutes according to the United Flight schedule.

	Maximum Range	**Longest route identified**	**Operator**	**Flight time**	**Max flight time defined**
A319	3750 nm	YYT - LHR	Air Canada	5 hours 26 minutes	5.5 hours
A320	3300 nm	JFK - LAX	Alaska Airline	6 hours 14 minutes	6.25 hours
A321	3200 nm	LAX - LIH	American Airlines	5 hours 51 minutes	6 hours
737	3010 nm	ORD - ANC	United Airlines, Alaska Airlines	6 hours 49 minutes	6.8 hours

Table 12: Summary of defining non-stop routes for the airplanes

The minimum flight mission for all airplanes is estimated to be 0.1 hours. As very few regular flight routes are existing close to this very short flight time, this setting represents a case in which the airplane has to return to the airport right after take-off for technical or other reasons.

Variation in aircraft flight mission is represented by a beta distribution in the simulation model. Different from the triangular distribution which would have been another feasible option, the beta distribution can be adjusted to have very little probabilities for missions close to the minimum value, the highest probability for flight missions in the range of the average and still relevant probabilities for longer flight routes. In this case it is a realistic representation as these aircraft categories operate on domestic routes with a majority of routes connecting the major US hubs with each other and with other smaller cities. The following Table 13 summarizes the beta distributions defined per aircraft per airline based on the mean, the minimum and the maximum values:

Airline	Aircraft Type	Mean	Min. value	Max. value	Distribution
American Airlines	A319	1.79	0.1	5.5	0.1 + 5.4 * beta (2, 4.4)
	A320	1.79	0.1	6.25	0.1 + 6.15 * beta (1.9, 5)
	737	3.16	0.1	6.8	0.1 + 6.7 * beta (2.1, 2.5)
Delta Airlines	A319	1.58	0.1	5.5	0.1 + 5.4 * beta (2, 5.3)
	A320	1.58	0.1	6.25	0.1 + 6.15 * beta (2, 6.3)
	A321	2.82	0.1	6	0.1 + 5.9 * beta (2, 2.35)
	737	2.82	0.1	6.8	0.1 + 6.7 * beta (2, 2.93)
United Airlines	737	3.51	0.1	6.8	0.1 + 6.7 * beta (4.15, 4)
Southwest	737	2.24	0.1	6.8	0.1 + 6.7 * beta (2, 4)
Frontier	A319	2.38	0.1	5.5	0.1 + 5.4 * beta (2, 2.75)
	A320	2.38	0.1	6.25	0.1 + 6.15 * beta (2, 3.4)
	A321	2.29	0.1	6	0.1 + 5.9 * beta (2, 3.4)
Virgin America	A319	3.13	0.1	5.5	0.1 + 5.4 * beta (2.5, 2)
	A320	3.13	0.1	6.25	0.1 + 6.15 * beta (2, 2.1)
	A321	3.13	0.1	6	0.1 + 5.9 * beta (2.1, 2)
Alaska	737	2.97	0.1	6.8	0.1 + 6.7 * beta (2, 2.65)
Allegiant Air	A319	2.03	0.1	5.5	0.1 + 5.4 * beta (2.8, 5)
	A320	2.03	0.1	6.25	0.1 + 6.15 * beta (1.8, 4)
Sun Country Airlines	737	2.70	0.1	6.8	0.1 + 6.7 * beta (2, 3.1)
Air Transat	737	2.70	0.1	6.8	0.1 + 6.7 * beta (2, 3.15)
Sunwing Airlines	737	2.70	0.1	6.8	0.1 + 6.7 * beta (2, 3.14)
Westjet	737	2.70	0.1	6.8	0.1 + 6.7 * beta (3, 4.75)

Table 13: Summary of Aircraft missions distribution

To be in line with the study conducted by Flanagan et al. (2017), a total engine life of 60’000 take-off and landing cycles is assumed. After reaching 60’000 flight cycles, the simulation assumes that the engine is scrapped and replaces it with a new engine.

2.4.4 Engine MRO repair shop visits

This engine life can be divided into a different amount of on-wing intervals depending on the engine type and its thrust ratings as well as on the engines average mission. In between these intervals there is always a repair shop visit for which the engines are taken off the wing. Depending on the age of the engine model, different scopes of work are performed. Shop visits can be divided into scheduled and unscheduled shop visits.

Unscheduled shop visits can be further categorized as engine related and non-engine related. Unscheduled, engine related shop visits contain failures of the engine hardware and can further be sub-divided into light and heavy shop visits. Unscheduled, non-engine related engine shop visits are caused by special events such as bird strikes or foreign object damages (FOG). (Aircraft Commerce 2014) AIRCRAFT COMMERCE (2014) suggests to consider heavy engine related shop visits and shop visits following non-engine related events together. They interrupt "the schedule of planned removals and shop visits, and also reduce the average planned removal interval." Although shop visits following heavy events are also used to expedite planned maintenance work, the randomness of these events "means that they can occur shortly before a planned event or halfway between planned events, thereby reducing the average planned interval, rather than adding a full additional shop visit." (Aircraft Commerce 2014) According to AIRCRAFT COMMERCE 2014 "heavy and non-engine related events occur on average once every 70,000EFH". (Aircraft Commerce 2014) This would correspond to one or maximum two unscheduled shop visits on average per engine life in this example. Due to the complexity of modelling unscheduled shop visits and lack of information about the probability that fuel nozzles would be affected during unscheduled shop visits, they are not considered separately within this study.

For scheduled visits most airlines follow different strategies. All of these strategies are based on obtaining the maximum time between shop visits with the goal of reducing cost per-engine flight hour. The major driver is the exhaust gas temperature (EGT) margin, which declines with increasing operation. The engine gas temperature margin is the difference of the maximum engine gas temperature, the engine has been certified for and the maximum gas temperature measured during operations. It is usually measured during the take-off phase. The EGT margin is highest, when the engine is new. AIRCRAFT COMMERCE (2006) states that "most CFM56-3s recover about 70% of the original exhaust gas temperature (EGT) margin after the first shop visit". The rate at which engine performance deteriorates depends on many factors, inducing mission characteristics and CFM56 engine model. Experience of airline operators show a relation between engine removals and engine flight hours (EFH) or engine flight cycles (EFC). (Aircraft Commerce 2014) Whether it is engine flight hours (EFH) or engine flight cycles (EFC) being the crucial factor of the on-wing interval depends on its prior mission. As Markus Kleinhans, propulsion systems engineer for the CFM56-3/-7B at Lufthansa Technik states in AIRCRAFT COMMERCE (2006), "EFC has more impact on the on-wing interval than EFH for average EFC times of 1.0-1.5 EFH. On longer average sectors, however, where EFC time is 2-3x EFH, the accumulated number of EFH on-wing has more of an influence on interval."

Based on this, it is assumed that the engine flight cycles (EFC) govern the scheduled shop visits for average engine cycles smaller than two flight hours. For average cycles greater than or equal to two flight hours the engine flight hours (EFH) are defined to be the determining factor. As removal intervals are significantly different for different engine models and are highly dependent on the engine thrust rating, four reference engine models are selected to represent the engines that power the aircrafts of the Airbus family (A319, A320, A321) and the Boeing 737. Three of these are selected to represent the A320 family (CFM56-5B6 for A319, CFM56-5B4 for A320 and CFM56-5B2 for A321). For the Boeing 737, the CFM56-7B26 model is selected as a representative engine since it is used on more than 50% of 737NG airplanes. (Aircraft Commerce 2013) As this work aims to investigate one part used in the successor of the CFM56 engine, only the newest models of the CFM56 family are used, although many airplanes might still operate older engines. On-wing intervals have significantly increased between the first CFM56 engines on the market and the latest version and the same can be expected for its successor, the LEAP engine.

Table 14 gives an overview of the engine model that are assigned to each airplane model in this study. It also defines the maintenance patterns used in the simulation model for the different engine models. It shows the flight cycles (EFC) and engine flight hours (EFH), after which the engine is removed for shop maintenance and the scope of the work performed during these visits. These pattern are summarized information published by AIRCRAFT COMMERCE (2013) and

AIRCRAFT COMMERCE (2014) and are a simplification of the earlier described, very complex and individual maintenance strategies that the airline operators apply.

Airplane type	**Engine model**	**Thrust**	**1st removal**	**Subsequent removal 2nd, 3rd, 4th, etc.**	**Condition**
Airbus A319	CFM56-5B6[1]	23,500 lbs[1]	20,000 EFC[1]	every 10,000 EFC[1]	Av. EFC < 2h
Airbus A319	CFM56-5B6[1]	23,500 lbs[1]	36,000 EFH[1]	every 18,000 EFH[1]	Av. EFC ≥ 2h
Work scope			Overhaul[1]	rotating restore, overhaul,… [1]	
Airbus A320	CFM56-5B4[1]	27,000 lbs[1]	20,000 EFC[1]	every 10,000 EFC[1]	Av. EFC < 2h
Airbus A320	CFM56-5B4[1]	27,000 lbs[1]	36,000 EFH[1]	every 18,000 EFH[1]	Av. EFC ≥ 2h
Work scope			Overhaul[1]	rotating restore, overhaul,… [1]	
Airbus A321	CFM56-5B2[1]	31,000 lbs[1]	15,000 EFC[1]	10,000 EFC[1]	Av. EFC < 2h
Airbus A321	CFM56-5B2[1]	31,000 lbs[1]	27,000 EFH[1]	18,000 EFH[1]	Av. EFC ≥ 2h
Work scope			Overhaul	rotating overhaul, restore,…	
Boeing 737[2]	CFM56-7B26[2]	26,300 lbs[2]	14,000 EFC[2]	11,000 EFC[2], 9,000 EFC[2], 11'000 EFC[2], 9'000 EFC[2]	Av. EFC < 2h
Boeing 737	CFM56-7B26[2]	26,300 lbs[2]	27,000 EFH[3]	21,000 EFH[3], 17,000 EFH[3], 21,000 EFH[3], 17,000 EFH[3]	Av. EFC ≥ 2h
Work scope			Restore	overhaul, restore, overhaul, restore	

Table 14: Summary of scheduled shop visits

[1] *(Aircraft Commerce 2014)*
[2] *(Aircraft Commerce 2013)*
[3] *Calculated based on 1.9EFH per EFC (Aircraft Commerce 2013)*

According to the Engineering leader of GE Additive, Mr. Mook, it is an accepted industry standard that about 10% of fuel nozzles need replacement during maintenance shop visits. Mr. Mook also states that the new additively manufactured fuel nozzles generally last the life of an engine, but non-normal wear related issues can occur during operations. The replacement probability of 10% covers all kind of damages that occur during aircraft operations as well as the maintenance and cleaning process and special events such as bird strikes or foreign object damage (FOD). These events can result in secondary effects like local overheating that damage single fuel nozzles. (Mook 2018) In the simulation, the number of fuel nozzles replaced during a shop visit is defined by a Poisson distribution with mean 2 for scenarios 2 and 3.

According to Flanagan et al. (2017) the part life of the new additive manufactured fuel nozzles is expected to be five times longer than its traditionally manufactured predecessor, which is considered in scenario 1. In the simulation model this is covered by 5 times the Poisson distribution with mean 2 for scenario 1.

Based on the conference call with Mr. Mook, replacements resulting from upgrades or modifications that improve performance (e.g. reduce weight, fuel consumption) are common. These upgrades happen unpredictably, but might punctually cause high demand volumes during scheduled maintenance. In such a case, all fuel nozzles are typically replaced when an airline decides to implement an available upgrade. (Mook 2018)

The occurrence of version upgrades has a high impact on the demand as suddenly all fuel nozzles need to be replaced. Moreover, available inventory is disposed. To maintain comparability of the three production systems, one sample for the version upgrades is pre-defined based on an exponential distribution with mean 10 years and used for simulation runs. Version upgrades will occur after 18, 38, 52 and 158 months. Exponential distribution is chosen as it is expected that during the early stage of a product life cycle a lot of engineering work is still being conducted to overcome initial issues which usually accompany a product introduction. Later with a mature product very few, punctual modifications and improvements are being implemented as required to improve the performance or extend the product life. In the last stage the product support is being reduced resulting in a very low probability for version upgrades.

2.4.5 Simulation of the production and supply chain systems

For the simulation model, the initial combined U.S. and Canadian fleet is comprised of 2,578 airplanes utilizing the LEAP or CFM56 engines from 12 airline operators. For each airline, information about the aircraft age, missions, and maintenance schedule was collected from publicly available sources as described in the next two sections. Based on this information, airline/aircraft operations (i.e., take-off and landing flight cycles and collecting flight hours) are simulated on a daily basis for each aircraft independently. Ground handling times and night flying restrictions are considered with the goal of achieving a simulation model as close to reality as possible as these times reduce the availability of an aircraft. After an aircraft reaches the amount of flight cycles or flight hours defined in its maintenance schedule, the simulation routes the airplane to its identified maintenance service provider, where engine maintenance is conducted and fuel nozzles replaced if necessary, per the replacement probability defined in section 2.4.11. If replacement is deemed necessary, the maintenance service provider then orders replacement fuel nozzle(s) either from the centralized production location (production scenarios 1 & 2), where part production and inventory replenishment are simulated, or initiate production themselves (scenario 3) following a Q,r replenishment strategy and with safety stocks. For all transportation and production activities, annual cost and environmental impacts as well as supply chain performance measures are recorded. Airline market growth projections are simulated as described in section 0. Besides demand resulting from day-to-day operations, version updates that require replacement of all fuel nozzles are also considered. When an update is initiated, as described in section 2.4.4, each aircraft will have the fuel nozzles replaced during its next scheduled maintenance. All order quantities and reorder points are re-calculated periodically every 4 months within the model based on the demand and demand fluctuation of the previous year and the specified z-value following a Q,r replenishment policy. On-hand inventory and the inventory position are reviewed continuously and new production is initiated as soon as the inventory position reaches or drops below the reorder quantity.

2.4.6 Aerospace market outlook

Several studies have been assessed to quantify the market growth for the observation period of 30 years. (Boeing Commercial Airplanes 2017, AIRBUS 2017, ICAO 2016) All three studies forecast a significant worldwide growth of the commercial aviation sector for the coming decades and also provide detailed forecasts for the different world regions. While the ICAO (2016) forecasts focus on the development of passenger and cargo volumes until 2042, Boeing Commercial Airplanes (2017) and AIRBUS (2017) both build on air travel demand forecasts but also include other factors (e.g. low cost carriers, increasing nonstop connections, smaller airplanes with higher frequencies, airline consolidations, etc.) to ultimately generate product demand forecasts for the different regions. With an average annual growth rate of 3% for the North American single aisle market two overlapping trends are covered, an increasing number of passengers and a growing market share of single aisle airplanes resulting from low cost market growth and customer preference for direct non-stop flight connections. Using the annual growth data from the past years 2002 until 2017 (United States Department of Transportation 2017) a normal distribution is found to provide a good fit using ARENA Input Analyer. The suggested distribution of NORM(1.02, 0.033) has been adjusted for a mean value of 1.03 (3% growth rate) and a standard deviation keeping the unpredictability, i.e., the coefficient of variation unchanged.

$$cv = \frac{\sigma_1}{\mu_1} = \frac{\sigma_2}{\mu_2} \qquad (2.3)$$

$where$

$cv\ is\ the\ coefficient\ of\ variation$

$\mu_1\ is\ the\ mean\ value\ of\ the\ past\ 15\ years\ growth\ period$

$\sigma_1\ is\ the\ standard\ deviation\ of\ the\ past\ 15\ years\ growth\ period$

$\mu_2\ is\ the\ mean\ value\ of\ the\ future\ 30\ years\ growth\ period$

$\sigma_2\ is\ the\ standard\ deviation\ of\ the\ future\ 30\ years\ growth\ period$

Eventually, the annual growth rate in the simulation model is described by the normal distribution NORM(1.03, 0.033). As for the version upgrades defined in 2.4.4, the market growth is found to have a high impact on the performance of the systems as well. To achieve comparability of the three scenarios, the following sample data set is pre-defined from this normal distribution function and used for all scenarios in all simulation runs.

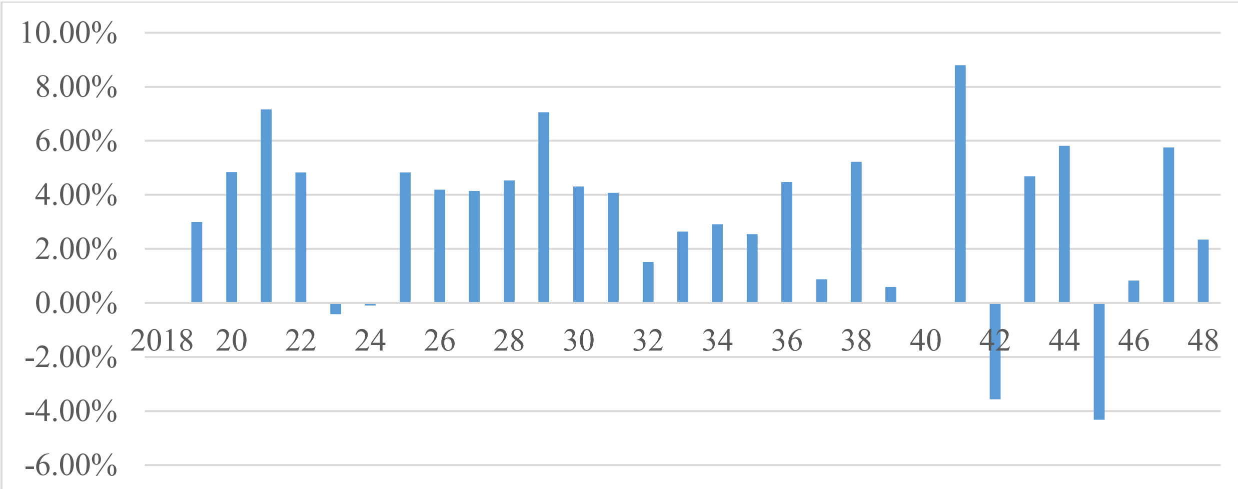


Figure 20: Sample data set defining annual growth rate of the aviation market

2.4.7 Sustainability analysis inputs

To measure the environmental performance, the DIO scoring factors made available by the DoD and described in section 1.3.3 are used. This framework provides environmental scoring factors in an excel spreadsheet and can be multiplied with the accumulated activity outputs recorded by the simulation model. This fact enables incorporation of this dataset into a study outside of existing life-cycle assessment software. The DIO provides scoring factors at the midpoint and endpoint level. Midpoints are provided for specific environmental issues (e.g., toxic releases, water consumption) and represent indicators of potential impacts. Cause-effect models are used to translate midpoint impacts into endpoint impacts for specific areas of concern (e.g., human health). As such, endpoints represent the potential damage to these areas of concern. The DIO model provides scoring factors for four endpoints, i.e., resource availability, climate change, human health and ecosystem (Department of Defense 2016). This study uses the endpoint scoring factors to evaluate the performance of the CMS and two DMSs over the lifecycle, including electricity used during part production, fuel or electricity used during supply chain transportation, and fuel used during aircraft operations.

Due to the lack of publicly available information, it was not possible to accurately estimate the environmental impacts associated with producing the materials used in the conventional or additive manufactured fuel nozzles. The materials used to produce fuel nozzles via conventional manufacturing are different than those used to produce fuel nozzles via additive manufacturing. The quantity of material used in the two additive manufacturing scenarios is unlikely to vary significantly. While there are differences in the types and quantities of materials used, the environmental impacts associated with material production are relatively small compared to those with other life cycle stages, as was found by Flanagan et al. (2017). Exclusion of material production will not change the overall conclusions of this analysis. Nonetheless, the environmental, health, and safety implications of these materials should be considered.

A complete list of the considered activities can be found in Appendix 04. Through exchanges with developers of the DIO model, it was determined that the DIO model assumed all electricity mixes used a similar supply chain regardless of the mix of energy sources used to generate the electricity. That is, the DIO model provides scoring factors for 1 MJ of electricity produced from each state. The outputs (e.g., emissions) for each of these are estimated based on the type of energy sources used to produce the electricity. However, the inputs (i.e., purchases from other industry sectors) are assumed to be the same as the average US electricity mix. They are simply scaled based on a relative comparison of the average cost of electricity in the state to the average cost of electricity in the U.S. For example, if the average cost of electricity in a given state is 10% higher than that of the U.S, it is assumed that the purchases for each industry sector are estimated as 10% higher regardless of the underlying energy mix. In actuality, the supply chain for electricity generated in renewable sources would be quite different from a supply chain for electricity generated from fossil fuels. As it stands, the DIO model is insufficient for characterizing and contrasting the life cycle impacts associated with using electricity to produce fuel nozzles at different locations. To address this, a member of the DIO development team created new activities and generated scoring factors for electricity generated from coal, oil, gas, a renewable energy, and a zero emissions renewable energy mix. The renewable mix is based on the breakdown of renewable energy sources currently used in the US, and assumes 13.2% biomass, 66.3% hydro, 18.2% wind, 0.2% solar, and 2.2% geothermal sources (U.S. Environmental Protection Agency, 2018). The zero emissions renewable mix removes biomass from this mix and assumes zero emissions. Using state resource mixes (eGrid2016) published by the U.S. Environmental Protection Agency (EPA) and the new scoring factors provided by the DIO development team, new endpoint impacts are calculated per MJ of electricity consumed for each of the relevant locations as well as for the US average. (U.S. Environmental Protection Agency 2018)

Four environmental impact measures are quantified. Resource Availability characterizes the potential impact to resource availability from using natural resources, including fossil fuels, minerals, and water. It is measured in MJ extra, which reflects the additional energy required to extract and deliver marginal units of water to future end users. Climate Change characterizes the potential damage to human health and ecosystems from global warming. It is measured in kilograms of carbon dioxide equivalent (kg CO2 eq), which reflects the global warming potential of greenhouse gas emissions. Human Health characterizes the potential damage to human health. It is measured in disability-adjusted life years (DALYs), which reflects the number of years lost due to ill-health, disability or early death (e.g., from carcinogenic, non-carcinogenic, and respiratory effects from chemical releases). Environmental Health characterizes the potential damage to ecosystems. It is measured in units of the potentially disappeared fraction of species over a certain area (m^2) during a year (PDF*m2*yr), which represents the fraction of species lost from relevant impacts (e.g., acidification; eutrophication; ecotoxicity; water use; and land use).

2.4.8 External developments and future trend projections

Benchmarking three systems over a lifecycle of 30 years requires to identify and consider relevant external developments and to assess their influence on the systems. The potential implications of three trends are considered. This includes electricity mix projections, carbon tax developments, and electric truck projections over the next 30 years. However, the ARENA model can be used to test the effect of any kind of technology or policy change over the defined period as long as sufficient projections are available or can be generated.

The U.S. Energy Information Administration (EIA) has published three different electricity mix projections for the Unites States through 2050. The reference case assumes “trend improvements in known technologies along with a view of economic and demographic trends reflecting the current views of leading economic forecasters and demographers” and further that “current laws and regulations affecting the energy sector” remain unchanged unless they have already defined sunset dates. The other two cases assume a low and a high development of oil and gas resources and technology. (U.S. Energy Information Administration (EIA) 2018a). In the low oil and gas case, the share of renewable energy is higher than that of the reference case. In the high oil and gas case, the share of renewable energy is lower than that of the reference case. Hereinafter, these three cases are referred to as E-Mix 1 (i.e., reference case), E-Mix 2 (i.e., low oil and gas, high renewable energy), and E-Mix 3 (high oil and gas, low renewable energy) as defined in Table 15. Appendix 06 shows the development of the energy generation technologies and the cost for the three projection cases normalized to the year 2018.

Electricity mix projection case	**Case represented**	**Share in the US by 2050** (U.S. Energy Information Administration (EIA) 2018a)				**Average cost per MWh in the US by 2050**
		Coal	**Gas**	**Nuclear**	**Renewable**	
E-Mix 1	Low oil and gas resources and technology	30.11 %	17.45 %	14.80%	37.64%	USD 86.53
E-Mix 2	Reference case	25.14 %	33.44 %	14.02%	27.40%	USD 72.81
E-Mix 3	High oil and gas resources and technology	16.48 %	51.81 %	9.88%	21.83%	USD 65.53

Table 15: Overview of electricity mix projection values for 2050

No such detailed forecasts are available on a regional level. These normalized projection data sets are applied to the local energy mixes as off 2018 making the assumption that the energy mixes relatively develop the same at each location as they do on US average. Exceptions are the production locations in Quebec, Manitoba and Brazil where energy is already mainly produced from renewable sources in 2018. No changes will be considered for these locations. Figure 21 illustrates how this approach has been used for creating the electricity mix projection for the

Alabama location as a projection of the US average for the "low oil and gas resources and technology" case (E-Mix 1). (U.S. Energy Information Administration (EIA) 2018a) Using the scoring factors for electricity generated from coal, oil, gas, and renewable energy as defined in 2.4.7 as multipliers, the forecasted data has been used to generate absolute scoring factors for electricity generated per MJ per location per year for the period 2018 until 2050.

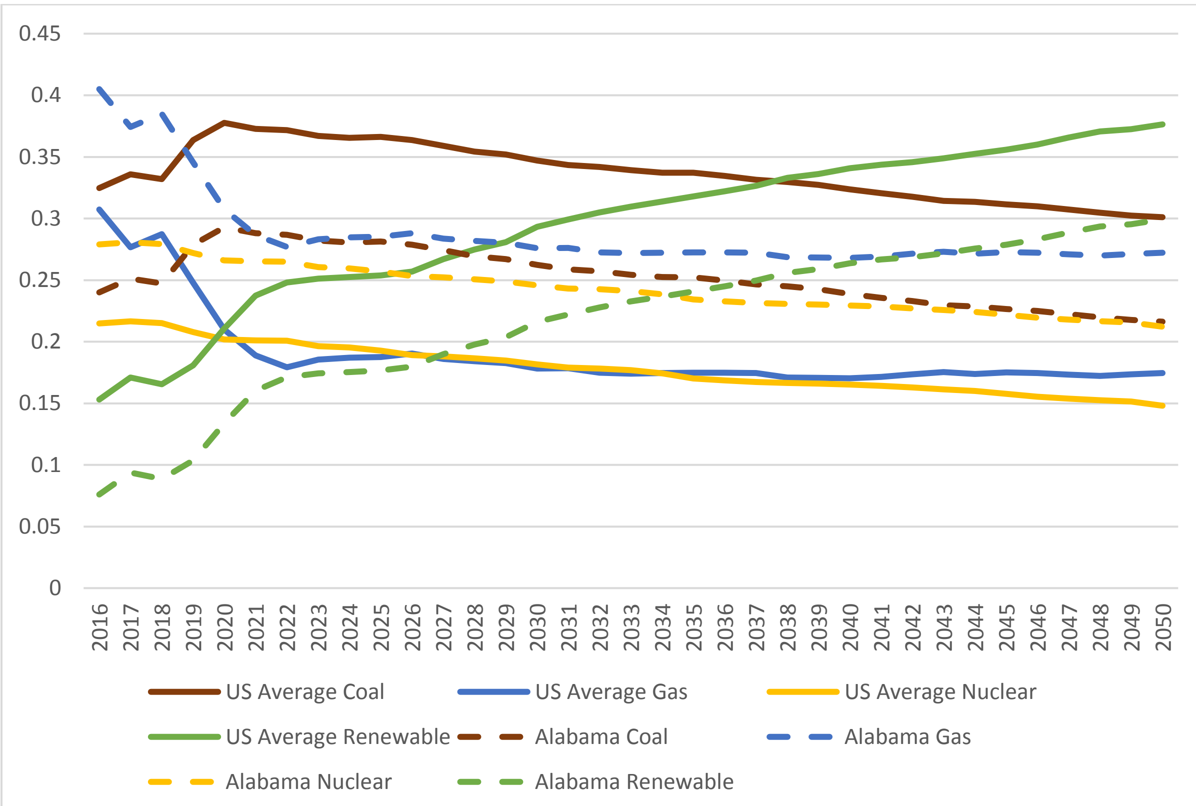


Figure 21: Electricity mix projection (E-Mix 1) US Average and Alabama

Luckow, Stanton et al. (2016) have published three carbon tax projections representing low, mid and high CO2 prices for the United States from 2022 to 2050. Their projections are based on "information from federal regulations, state and regional climate policies, and utility CO2 price forecasts" as well as their own analysis of the EPA (US Environmental Protection Agency) Clean Power Plan and complementary policies. The mid and high cases are developed based on the assumption that more stringent federal policies would extend the requirements of the Clean Power Plan. Figure 22 shows the three scenarios from Luckow, Stanton et al. 2016a. The cost is given in USD per ton of emitted carbon dioxide.

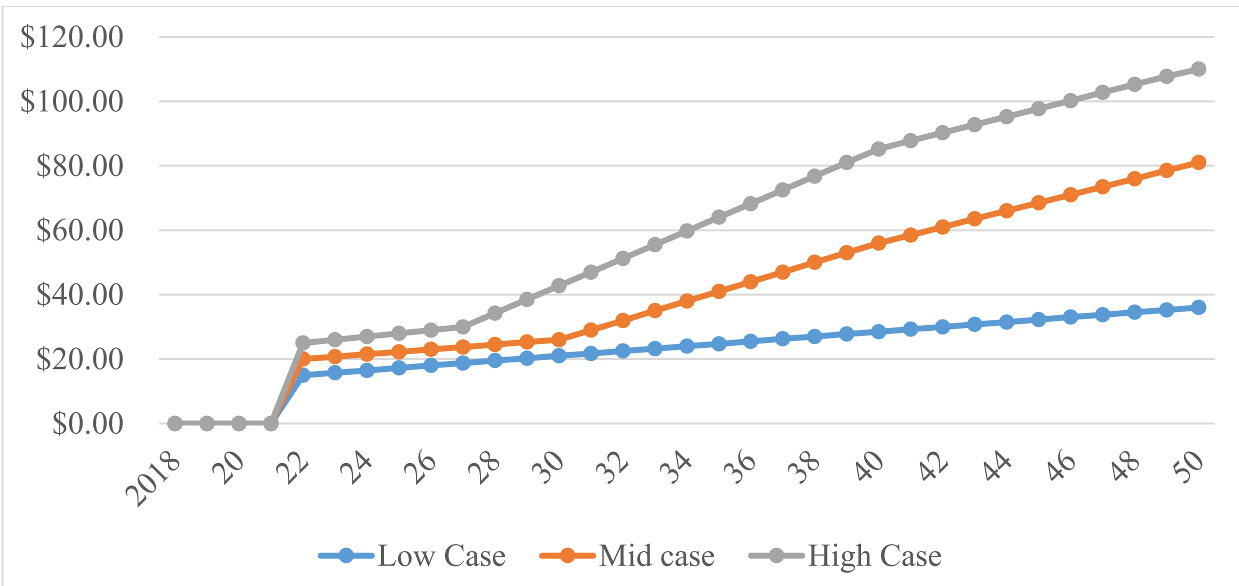


Figure 22: Carbon tax case projections

McKinsey Energy Insights, McKinsey Center for Future Mobility has published a study estimating the potentials of the electric truck market with two different case projections until 2030 (early and late electrification scenario). A third one representing a medium electrification scenario is calculated from the early and late electrification scenarios and added manually. Through the year 2030 they project the highest growth rates for light duty trucks (LDT) expecting to reach cost parity with diesel by 2025. For applications like parcel delivery and small retail delivery, this study is expecting economic benefits for operating electric trucks provided that charging infrastructure and the first models like e.g. DHL's StreetScooter Work XL and Tesla's Semi are successfully introduced to the market. Other drivers could be urban diesel bans and "tightening emissions targets for carbon dioxide (CO2) and oxides of nitrogen (NOx)". (Tryggestad, Sharma et al. 2017) Based on the information for light duty trucks (LDT) on the US market, three linear projections are created for a late (E-Cars 1), mid (E-Cars 2) and early (E-Cars 3) electrification scenario as shown in Figure 23.

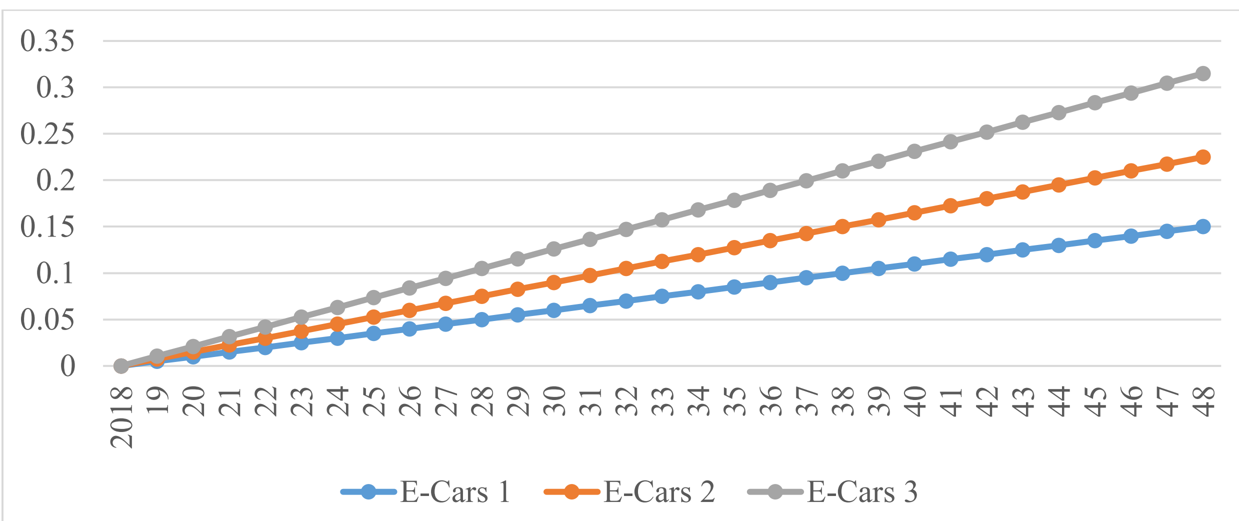


Figure 23: Projections for truck market electrification scenarios

2.4.9 Excel Post Processing

A total of 24 models for 3 production scenarios with 8 different z-values are simulated. On a monthly basis the simulation models record the following parameters.

- Monthly demand
- Monthly parts produced
- Monthly backorders
- Monthly parts obsolescent
- Monthly raw material consumption
- Monthly on-hand inventory
- Monthly electricity consumption per location
- Monthly transportation efforts (LBxRoadmiles, LBxAirmiles and transportation cost)

Using Excel post processing, these values for these 24 models are combined with the values from the DIO LCA dataset as shown in 2.4.7 for the 27 possible combinations of the future projections for electricity mix, carbon tax, and electric truck diffusion as defined in 2.4.8, resulting in a total of 648 experiments (i.e., 24 models x 27 projections). In addition, the monthly, annual average and total average service levels are calculated for each experiment.. For an overview of the 648 experiments or DMUs, see Appendix 03.

2.5 Step 3: Data Envelopment Analysis (DEA)

This section aims to develop the methodology which allows benchmarking of the different production and supply chain systems based on their cost, environmental, and supply chain performance. Data envelopment analysis (DEA) is used to rank the investigated experiments based on their relative technical efficiency and to analyze the technical efficiency value Te depending on different projections of long-term global developments. It allows for assessing the sensitivity of the investigated concepts and helps decision makers understanding their decision not only under static conditions but rather under all circumstances they are willing to consider.

Data Envelopment Analysis (DEA) is a non-parametric benchmarking methodology used for comparing the relative efficiency of systems based on the relation of inputs to outputs. As a relatively young method, it has been initially proposed by Charnes, Cooper and Rhodes in 1978 with the introduction of the “CCR model”. A set of inputs in DEA terms is called decision making unit (DMU) and a DMU is characterized as an object that transforms inputs into outputs. Inputs and outputs do not need to be of the same units, but to ensure comparability of DMUs the same inputs and outputs should be used along all of them. While other benchmarking methods either require previous weighting of inputs and outputs or subsequent analysis steps and setting priorities to find the aspired optimum, DEA is applying linear programming to find the optimum set of weights for each DMU that (a) maximizes the efficiency of each DMU under the constraint, that (b) all other DMUs maintain an efficiency lower than or equal to 1 with the same set of weights applied. This is referred to as the “benefit of the doubt” in literature, meaning that DEA tries to make each DMU look as efficient as possible compared to all other DMUs. (Sherman, Zhu 2006) Using the data of all DMUs a frontier is created that represents the empirical optimum of the set of DMUs under investigation. (Cooper, Seiford et al. 2006, 2nd ed. 2007)

2.5.1 Mathematical formulation

DEA maximizes the ratio of the sum of weighted outputs and the sum of weighted inputs for each DMU independently, where the weights are variable.

$$Maximize\ \theta_k = \frac{\sum_{i=1}^{N} u_i y_{ik}}{\sum_{j=1}^{M} v_j x_{jk}} \tag{2.4}$$

This maximization is subject to the constraints that all weight variables are non-negative and that the efficiency values for all DMUs are not greater than one.

$$subject\ to\ u_i, v_j \geq 0 \quad for\ all \quad i = 1, 2, \ldots N;\ j = 1, 2, \ldots M \tag{2.5}$$

$$\theta_k = \frac{\sum_{i=1}^{N} u_i y_{ik}}{\sum_{j=1}^{M} v_j x_{jk}} \leq 1 \quad for\ all \quad k = 1, 2, \ldots P \tag{2.6}$$

For the linear program this formulation has been transformed into its multiplier form:

$$Maximize\ \theta_k = \sum_{i=1}^{N} u_i y_{ik} \tag{2.7}$$

$$subject\ to$$

$$\sum_{j=1}^{M} v_j x_{jk} = 1 \tag{2.8}$$

$$u_i, v_j \geq 0 \quad for\ all \quad i = 1, 2, \ldots N;\ j = 1, 2, \ldots M \tag{2.9}$$

$$\theta_k = \sum_{i=1}^{N} u_i y_{ik} - \sum_{j=1}^{M} v_j x_{jk} \leq 0 \quad for\ all \quad k = 1, 2, \ldots P \tag{2.10}$$

$where$:

$k\ is\ the\ number\ of\ DMUs$

$m\ is\ the\ number\ of\ observed\ inputs$

$n\ is\ the\ number\ of\ observed\ outputs$

The linear program has been developed and executed using IBM ILOG CPLEX Optimization Studio, version 12.7.1.0 and the final code including all constraints is attached in Appendix 05.

2.5.2 Performance measures

To assess the cost, environmental, and supply chain impacts of the production systems, performance outputs of two categories are defined. The average and the lowest annual service level as well as the sum of six total life-cycle cost components (raw material cost, inventory obsolescence cost, inventory holding cost, energy, carbon tax and transportation cost) allow an evaluation of the supply chain performance while the resource availability, climate change, human health and environmental quality are aggregated measures (endpoints) of 16 sustainability impacts (midpoints) and therefore, allow evaluating the systems environmental performance. While the two service level outputs are considered desired outputs with the goal of maximizing them, both the cost and the sustainability impacts are considered undesired outputs with the goal of minimizing them. All undesired outputs will be treated as inputs in the DEA.

Category	**Indicator**	**Unit**	**Description**
Sustainability Impact	Resource Availability	[MJ extra]	Characterizes the potential impact to resource availability from using fossil energy and minerals.
Sustainability Impact	Climate Change	[kg CO2-eq]	Characterizes the potential damage to human health and ecosystems from global warming.
Sustainability Impact	Human Health	[DALY]	Characterizes the potential damage to human health from relevant impacts
Sustainability Impact	Environmental Quality	[PDF*m2*yr]	Characterizes the potential damage to ecosystems from relevant impacts
Total Life-Cycle Cost		[USD]	Sum of the six total life-cycle cost components: Raw material cost, Inventory obsolescence cost, Inventory holding cost, Carbon tax cost, Energy cost, Transportation cost

Table 16: Summary of undesired Outputs regarded as inputs

Category	Indicator	Unit	Description
Supply chain	Average service level	[%]	Provides the fraction of demand being fulfilled from stock (average).
Supply chain	Minimum annual service level	[%]	Provides the fraction of demand being fulfilled from stock (worst case).

Table 17: Summary of desired output measures

2.5.3 Relative technical efficiency score Te

DEA uses the relation of weighted outputs to weighted inputs to calculate an efficiency score for each DMU. It applies linear optimization to maximize this efficiency value for each DMU by varying the weight variables. This optimization is performed for each DMU separately while all remaining DMUs become part of the set of constraints. DEA finds the optimum set of weights for each DMU that maximizes its efficiency, while fulfilling the constraint that all remaining DMU efficiencies are smaller or equal to one.

The relative technical efficiency Te in this work is defined by the following equation:

$$Rel.Technical\ Efficiency\ Te = \frac{u_1 SL_{Av.\ TLC} + u_2 SL_{Min.Annual}}{v_1 SI_{RA} + v_2 SI_{CC} + v_3 SI_{HH} + v_4 SI_{EQ} + v_5 C_{Total}} \quad (2.11)$$

$where$:

$SL_{Av.\ TLC}$ $is\ the\ average\ service\ level\ over\ the\ observation\ period$

$SL_{Min.Annual}$ $is\ the\ minimum\ average\ annual\ service\ level$

u_1, u_2 $are\ the\ variable\ output\ weights$

SI_{RA} $is\ the\ aggregated\ Resource\ Availability\ [MJ\ extra]\ measure$

SI_{CC} $is\ the\ aggregated\ Climate\ Change\ [kg\ CO2-eq]\ measure$

SI_{HH} $is\ the\ aggregated\ Human\ Health\ [DALY]\ measure$

SI_{EQ} $is\ the\ aggregated\ Environmental\ Health\ [PDF*m2*yr]\ measure$

C_{Total} $is\ the\ aggregated\ life\ cycle\ cost\ [USD]\ measure$

v_1, v_2, v_3, v_4, v_5 $are\ the\ variable\ input\ weights$

For benchmarking and rating the production systems under investigation the CCR relative technical efficiency score is used. Additional measures like boundaries for the input and output weights are taken for further diversification of the results as the CCR model tends to find the majority of DMUs being CCR efficient or very close to an efficiency score of one. All measures have in common that they are limiting or constraining the linear program in finding higher scores for the DMUs and therefore result in overall lower efficiency scores. (Cook, Seiford 2009) It is important to mention, that the relative technical efficiency scores of the production systems are only valid for the benchmark under investigation, under the defined constraints and relative to the defined set of DMUs. Consequently, a low or high relative technical efficiency score for one production system should not be mistaken for an absolute or universal performance judgement of the affected location.

2.5.4 Definition of a DMU

As mentioned earlier, a total of 648 DMUs is considered in this work. One DMU is characterized by one unique set of configuration parameters. These DMUs are then benchmarked using the same set of performance measures. Appendix 03 gives an overview of all 648 DMUs and their definitions.

2.5.5 Input vs. Output oriented

DEA can be applied either input- or output-oriented. The input-oriented model focusses on reducing the inputs while maintaining at least the given output level and the output-oriented model tries to increase the outputs at fixed input levels. (Cooper, Seiford et al. 2006, 2nd ed. 2007) This work has the clear focus to reduce cost and environmental impacts which are undesired outputs and therefore, inputs per definition. Therefore, an input-oriented focus is considered for this study.

2.5.6 Equalized weighting of output variables constraint

The output measures are set to be of equal weight u_1 and u_2 with $u_1 = u_2$ to ensure that the same importance is assigned to the two service level performance measures, the total average service level and the minimum annual service level of the production system. During the first runs of the DEA model, it has been found that full output weight flexibility results in balancing the two output measures in such a way that weaker performance measures usually are underrated or neglected while stronger performance measures are overrated leading to very high relative technical efficiency measures for almost all DMUs. Equalizing the weights of the two output variables has been found to be a very efficient solution that sorts out DMUs as technically inefficient when one or both service level measures are unsatisfying. Furthermore, it prevents masking up weak input performance measures by setting excessively different output weights.

2.5.7 Minimum weight constraints

As Tracy, Chen (2005) state, the strength of DEA often becomes a weakness in practical applications as for the basic DEA models knowledge of the underlying processes of transforming inputs into outputs is neither needed nor considered. Several approaches are being investigated to address the undesired consequences or “unacceptable weight schemes” resulting from full weight flexibilities. (Cook, Seiford 2009) For this work it is decided to use absolute weight restrictions. Absolute weight restrictions “prevent the inputs or outputs from being over emphasized or ignored in the analysis”. (Allen, Athanassopoulos et al. 1997) For this study, weight restrictions have been defined with the goal of considering all inputs and outputs as important as possible without making the linear program infeasible. To achieve this, the lower weight bound is increased incrementally until reaching a condition of infeasibility. Then, it is set back to the last feasible value. For the output weights, no absolute limit is defined as it is the objective of the maximization function to increase the nominator as much as possible without violating the other constraints. Still, the relationship defined in 2.5.6 limits the relationship between the outputs. For the input values, an upper bound results from the linear program itself, where the sum of the weighted inputs must always be equal to one.

2.5.8 Mean data normalization and unit independency

To overcome scale imbalances in between the different inputs and outputs, mean normalization is applied as recommended by Avkiran (2006). Besides reducing the impact of different magnitudes, this method also improves unit independency. In mean normalization all values are divided by the mean value of the same category across all DMUs. The resulting scales are equal or greater than zero, the new average is equal to one and majority of values from the data sets can be found in the range of greater than zero and smaller than 2.5. The following equations explain the process of mean data normalization as recommend by Avkiran (2006). Table 18 provides an exemplary overview of the normalized data set for this study.

$$VNorm_{ni} = \frac{V_{ni}}{\bar{V}_i} \tag{2.12}$$

$$\bar{V}_i = \frac{\sum_{n=1}^{N} V_{ni}}{N} \tag{2.13}$$

where

V_{ni} *is the actual value of an input or output i and a DMU n before normalization*

$VNorm_{ni}$ *is the normalized value of an input or output i and a DMU n*

$\bar{V}_i$ *is the average value over all DMUs for an input or output column i*

N *is the total number of DMUs*

DMU No.	Output 1	Output 2	Input 1	Input 2	Input 3	Input 4	Input 5
DMU 001	1.048205	1.118151	2.31218	2.23739	1.56625	2.18355	1.65773
DMU 002	0.510346	0.148903	0.32149	0.36053	0.69087	0.38925	0.41235
DMU 003	0.989582	1.041209	0.31538	0.35408	0.70427	0.38955	0.41062
DMU 004	1.048597	1.139417	2.32814	2.25277	1.57705	2.19858	1.66950
(…)	(…)	(…)	(…)	(…)	(…)	(…)	(…)
DMU 648	1.044356	1.146574	0.32415	0.36184	0.71487	0.39284	0.85889
$\bar{V}_i$	1	1	1	1	1	1	1

Table 18: Data normalization results

3. Experiments and results

3.1 Experiment structure

All three production and supply chain scenarios are simulated with eight different input values for the anticipated service level, the z-value (z = 0, 1, 1.5, 2.5, 3, 3.5, 4 and 5). In a subsequent step the recorded output measures are multiplied with different projections of the electricity mixes, the carbon tax and the electric truck market development. Table 19 illustrates how the experiment structure is build up for supply chain configuration 1, a z-value of 0 and a low electricity mix projection. The same principle is applied for all three scenarios and eight z-values as well as electricity mix projections mid and high resulting in a total of 648 experiments or DMUs. The complete structure of experiments or decision making units (DMUs) can be found in Appendix 03.

	Supply Chain Configuration 1, z=0.0	**Electricity mix projection low**	**Electricity mix projection mid**	**Electricity mix projection high**	**Carbon tax projection low**	**Carbon tax projection mid**	**Carbon tax projection high**	**Electric trucks market projection low**	**Electric trucks market projection mid**	**Electric trucks market projection high**
DMU No.	001	x			x			x		
DMU No.	025	x			x				x	
DMU No.	049	x			x					X
DMU No.	073	x				x		x		
DMU No.	097	x				x			x	
DMU No.	121	x				x				X
DMU No.	145	x					x	x		
DMU No.	169	x					x		x	
DMU No.	193	x					x			X

Table 19: Exemplary illustration of experiment / DMU structure

3.2 The benefit of flexibility on supply chain operations

Due to its high flexibility resulting from short production lead times and no subsequent distribution needs, scenario 3 shows a high responsiveness to sudden increases in demand. As a consequence, the lowest overall service level for scenario 3 and a z-value of 0 is recorded at 94% with the lowest annual service level dropping to 84% in year 12. For the same z-value, scenario 2 reaches an overall service level of 49% and a minimum annual service level of 12%. Such low service levels are not acceptable for aerospace aftermarket applications and are underlining the need to hold higher safety stock levels for satisfying the external demand requirement. The impact of the low service levels on the performance of scenario 2 are illustrated in Figure 24 showing a weak relative technical efficiency score for scenario 2 at low z-values, an increasing one for increasing z-values and an area of saturation for z-values greater than 4. This saturation can be explained by growing cost and emissions with no further significant improvement of the service levels. Production scenarios 1 and 3 perform relatively consistently across all safety stock levels. Although scenario 1 also faces longer lead times, it does not require high safety stock levels since it has a different demand profile than scenario 2 and 3. This is further discussed in 3.3. The higher total demand for scenario 1 due to a shorter life time of the conventional fuel nozzle and a higher per part production effort explains the overall weaker performance of scenario 1.

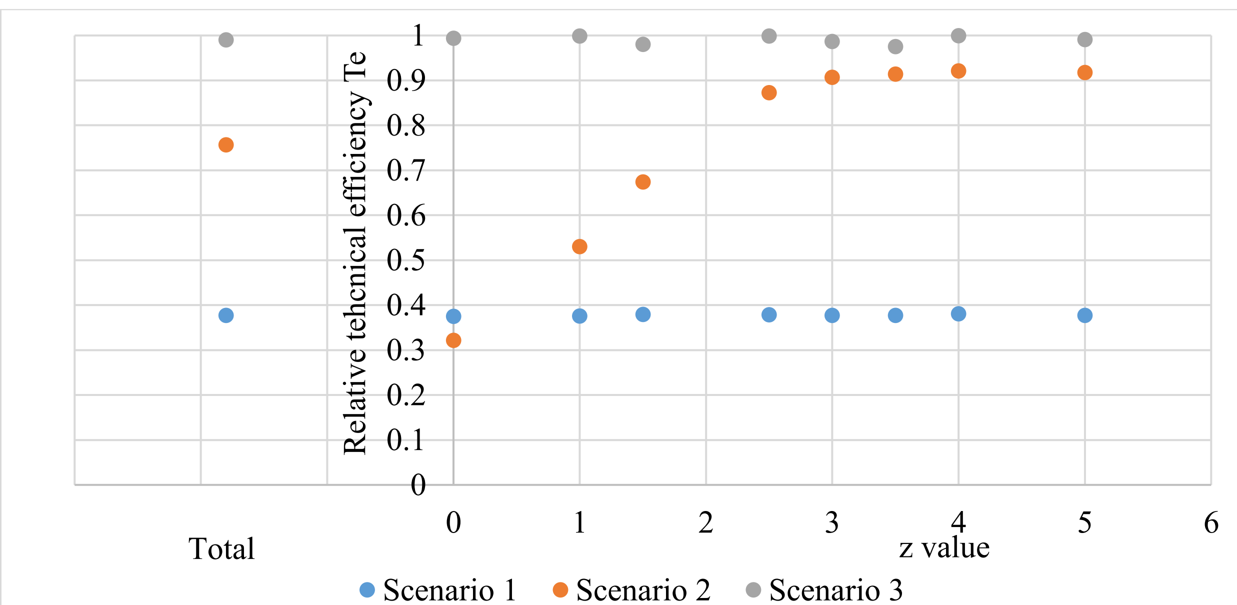


Figure 24: Rel. technical efficiency Te over z-value (average values)

3.3 Fuel nozzle demand resulting from random aircraft operations

For all three scenarios the fuel nozzle demand is based on the same aircraft fleet operation simulation. The shorter life expectation of the conventional fuel nozzle is represented in the simulation model by a higher probability for fuel nozzle replacements during a repair shop visit. This leads to a higher total demand for scenario 1 as can be seen in Figure 25. The main drivers impacting demand are the aerospace market growth, fuel nozzle version upgrades and the aging of the airline fleets causing a higher frequency of repair shop visits. As Figure 25 shows, the first 15 years of the simulated period are mainly influenced by version increments. During this period the demand of scenario 1 and scenarios 2 and 3 develop relatively similar if viewed on a yearly basis. If a version upgrade occurs, all fuel nozzles of an engine are replaced during the next planned shop visit disregarding the replacement probability. If viewed on a monthly basis as shown in Figure 26 however, it can be seen that a version upgrade has a lower impact on the demand of scenario 1 than on scenarios 2 and 3. This is due to the fact that scenario 1 replaces a higher number of fuel nozzles out of a total of 19 per engine anyways during a regular repair shop visit. Thus, if all fuel nozzles need replacement following a version upgrade, this leads to a higher demand increase for scenarios 2 and 3 compared to scenario 1. Therefore, the demand of scenario 1 is better predictable making the performance of scenario 1 more independent of safety stock levels as shown in 3.2. Moreover, Figure 26 shows that the impact of version upgrades on demand is higher if occurring less frequently. This relates to the assumption that airlines prefer to wait for the next scheduled maintenance shop visit for an implementation of a new product version. If another version upgrade is released before an engine has been upgraded, the simulation model skips one version and implements the latest version instead. This explains why the 1st and the 4th version upgrade shown in Figure 26 cause a significant increase in demand while the impact of the 2nd and 3rd version upgrades on the demand curves are hardly recognizable. During the second half of the simulated period no fuel nozzle version upgrades occur anymore. As a consequence of the higher fuel nozzle replacement probability, market growths and ageing aircraft fleets, the demand in scenario 1 increases almost linearly while the demand curves of scenarios 2 and 3 recover from a more intense phase, maintaining a relatively stable level with only slow growth rates.

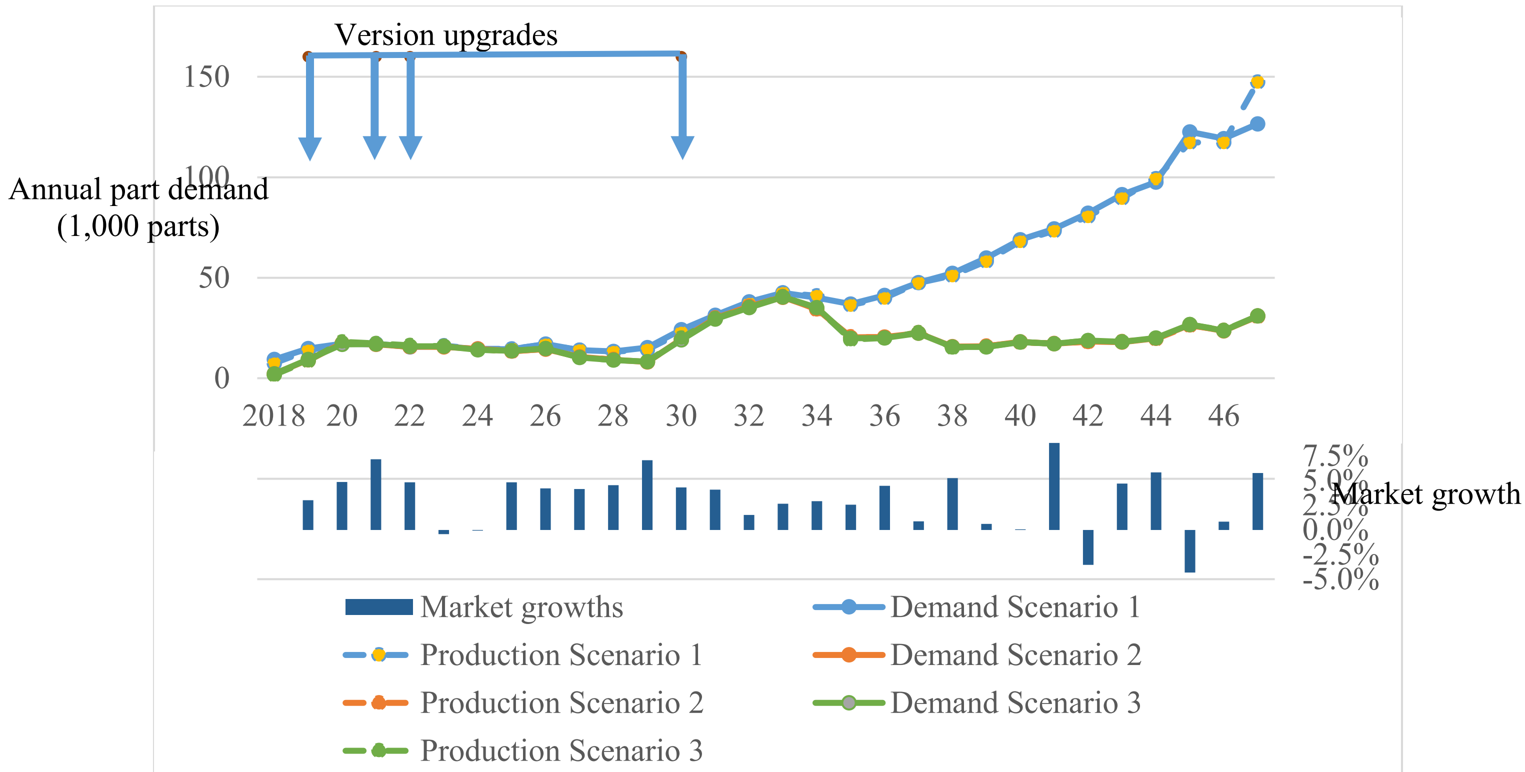


Figure 25: Annual demand & production (thousand parts), market growths & version upgrades

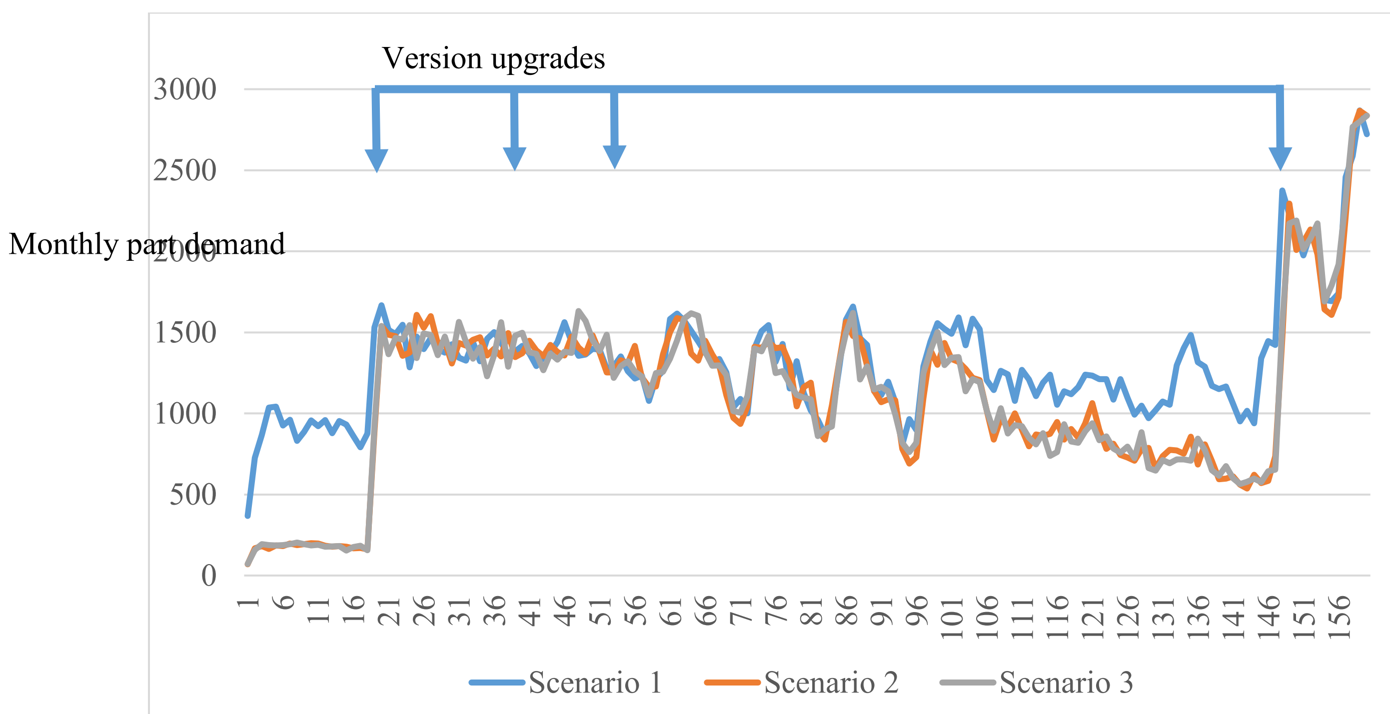


Figure 26: Monthly demand months 1 to 160

3.4 Efficient supply chain operations

As it is the goal of this study to compare production systems in an efficiently operating condition, i.e., when fulfilling the external demand requirement, the production scenarios are further analyzed and discussed at individually selected z-values (scenario 1 with z = 0, scenario 2 with z = 4 and scenario 3 with z = 1). Within this subset of selected experiments all scenarios have an overall service level of about 97% or higher and do not accumulate unnecessary inventory risks that would cause higher cost and environmental impacts. Table 20 shows the selected combination and also the impact on cost and service levels if operating the same systems at very low (z = 0) and very high (z = 5) z-values. All three production systems generally show the same trends towards higher inventory obsolescence and inventory holding costs with higher z-values as can be seen in Table 20. The impact of the z-value on transportation cost is found to be negligible.

Scenario	z-value	TLCC: Inventory obsolescence [USD]	TLCC: Inventory holding [USD]	TLCC: Transportation [USD]	Overall Service Level	Min. annual Service Level
Sc. 1	0	23,953,600.00	52,757,466.67	23,581,656.75	0.997	0.886
Sc. 2	4	11,693,000.00	27,407,010.00	19,663,338.51	0.986	0.758
Sc. 3	1	10,914,700.00	27,185,368.51	4,585,100.22	0.969	0.891
Sc. 1	0	23,953,600.00	52,757,466.67	23,581,656.75	0.997	0.886
Sc. 2	0	1,357,200.00	4,907,743.33	19,523,155.68	0.485	0.118
Sc. 3	0	5,293,900.00	15,424,971.16	4,623,202.28	0.941	0.825
Sc. 1	5	30,766,400.00	99,376,533.33	23,532,825.95	0.998	0.963
Sc. 2	5	14,583,400.00	34,267,246.67	19,627,453.94	0.989	0.759
Sc. 3	5	34,711,750.00	78,704,918.37	4,578,463.82	0.994	0.909

Table 20: Impacts of safety stock on cost and service levels

The changes in the environmental impact measures from increasing safety stocks are found to be relatively small. These measures are solely connected to activities such as production and transportation within the simulation model. Although higher safety stock levels cause an increase in the total number of parts produced mostly as a compensation for higher part obsolescence numbers, this increase is found to be relatively small. Higher inventory levels themselves do not have an impact on the environmental measures within this model. Table 21 presents the environmental measures for the subset of scenarios 1, 2 and 3 at individually selected z-values, at very low (z = 0) and very high (z = 5) z-values. The results are presented for medium carbon tax level projections (Carbon Tax Mid), medium electricity mix projections (E-Mix 2) and a medium development of the electric car market (E-Cars 2).

Scenario	**z-value**	**Resource Availability [MJ extra]**	**Climate Change [kg CO2-eq]**	**Human Health [DALY]**	**Environmental Quality [PDF*m2*yr]**	**Exp. Ref. Number**
Sc. 1	0	1,671,599,506	698,083,072	301	48,286,224	313
Sc. 2	4	232,675,801	108,813,951	130	8,586,746	332
Sc. 3	1	218,922,383	105,476,975	128	8,601,321	318
Sc. 1	0	1,671,599,506	698,083,072	301	48,286,224	313
Sc. 2	0	232,675,801	108,813,951	131	8,586,746	314
Sc. 3	0	218,877,472	105,445,628	128	8,600,673	315
Sc. 1	5	1,718,898,116	717,939,192	310	49,664,277	334
Sc. 2	5	233,639,233	109,263,396	131	8,621,893	334
Sc. 3	5	220,241,559	106,122,980	129	8,651,433	336

Table 21: Impacts of safety stock on environmental impact measures

3.5 Supply chain operations measures

This chapter aims to summarize the recorded simulation results for production, supply chain and transportation activities of the three production scenarios and to provide an overview of the magnitudes in which they operate over the considered life cycle of 30 years. Figure 27 summarizes the production and supply chain measures for scenario 1 with a z-value of 0, scenario 2 with a z-value of 4 and scenario 3 with a z-value of 1. It shows that the total demand for production systems 2 and 3 over 30 years is approximately 60% lower than the demand for production system 1. This is a result of the technology advancements and design improvements enabled by Industry 4.0 and additive manufacturing in particular and one of the main drivers for the low relative technical efficiency scores of production system 1 in the data envelopment analysis. Besides that, the advantages in the areas of on-hand inventory, obsolescent parts and backorders of scenario 3 over scenario 2 are indicated. All numbers are given as total number of parts over the assumed lifecycle of 30 years.

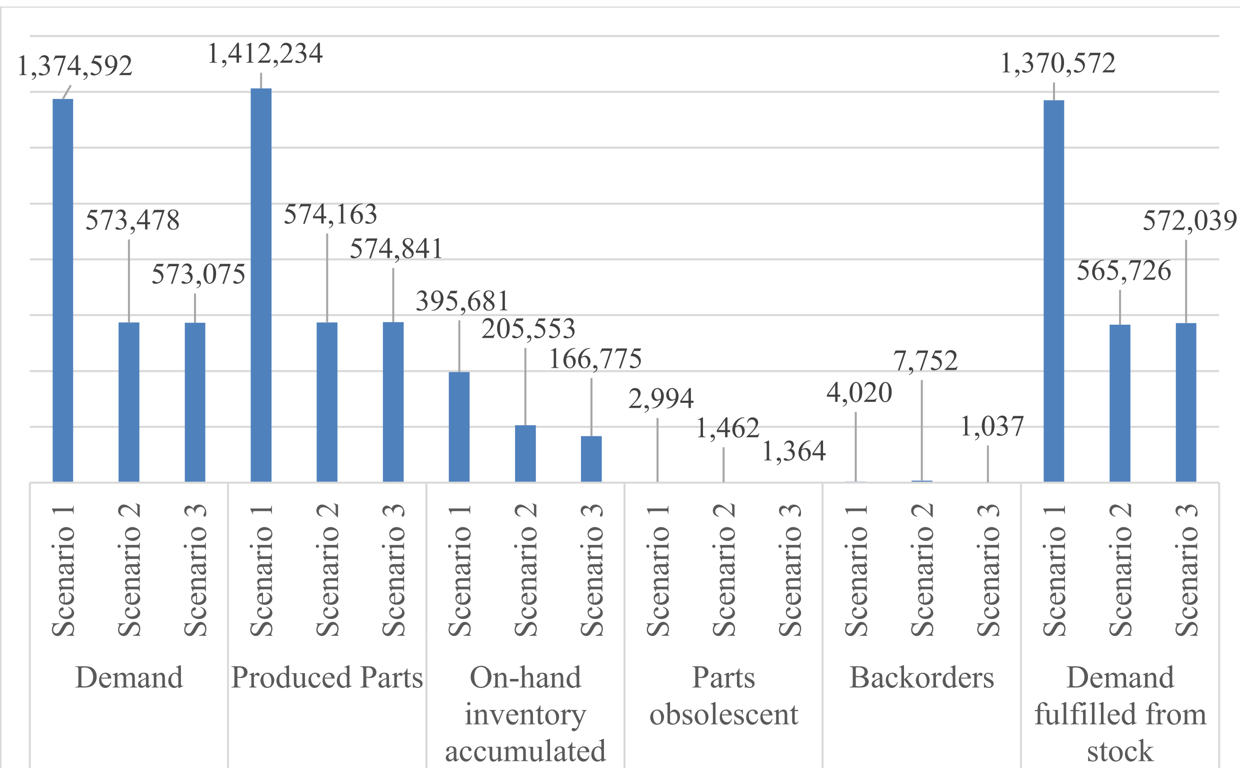


Figure 27: Total production and supply chain measures recorded over the life cycle

Figure 28 shows the total air and road transportation measures as well as the electricity consumption recorded over the considered life cycle of 30 years. As expected, scenario 1 has the highest numbers of accumulated tkm for air transportation and the highest absolute electricity consumption. The relatively low number of accumulated tkm for road transportation results from the assumption that all components of the conventional fuel nozzle are manufactured in the centralized Auburn, Alabama location, where the final fuel nozzle is assembled as well. Therefore, no road transportation for raw material or component transportation is recorded for scenario 1. The raw material transportation for scenarios 2 and 3 is carried out solely by road transportation which explains the higher efforts for scenario 3. As only the distribution of the final product is assumed to use air transportation in this work, scenario 3 has no tkm recorded from air transportation.

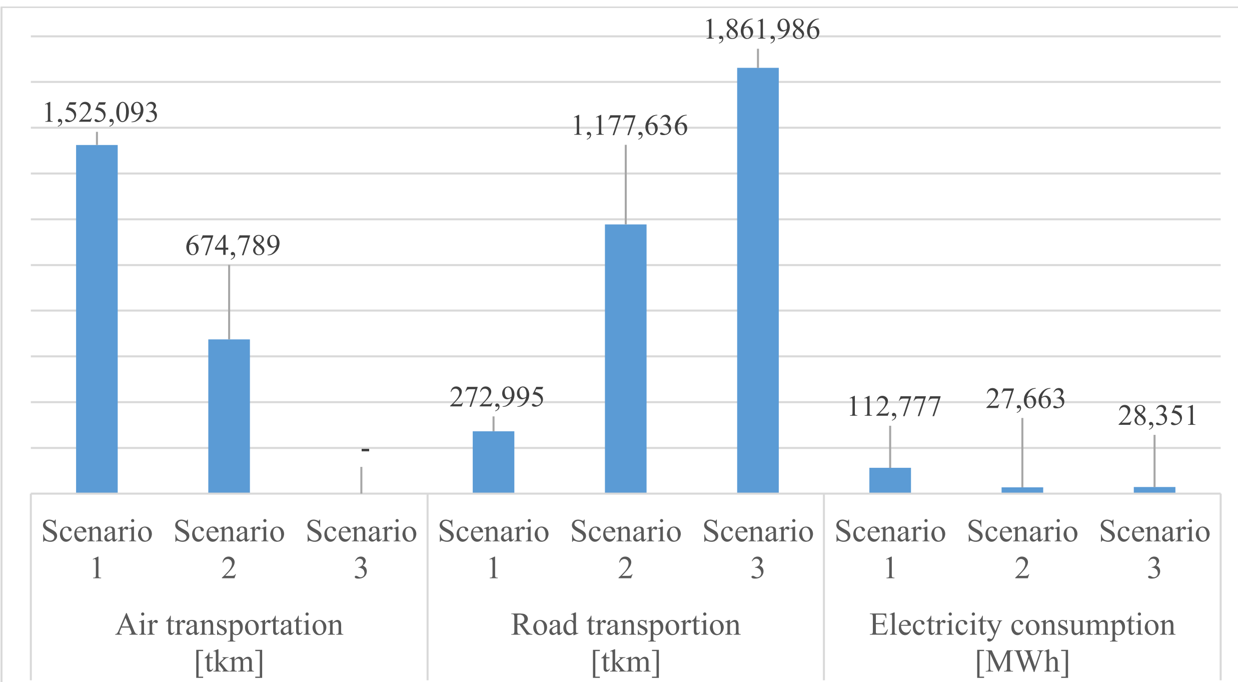


Figure 28: Total transportation and electricity consumption recorded over the life cycle

3.6 External developments and future trends projections

As part of the experiment structure, the potential implications of three trends are considered. This includes electricity mix projections (E-Mix 1, E-Mix 2 and E-Mix 2), carbon tax developments (Carbon Tax Low, Mid and High), and electric truck projections (E-Cars 1, E-Cars 2 and E-Cars 3). For all three production systems the development of the carbon tax and the electricity mixes are found to have a relatively strong impact on the performance while the expected developments on the electric truck market seem negligible. This particularly highlights the importance of considering present electricity mixes as well as regional policies and electricity mix projections when selecting a new production site. Figure 29 shows for scenario 1, Figure 30 for scenario 2 and Figure 31 for scenario 3 how the efficiency changes for the three considered trends.

The distributed production scenario 3 reacts insensitive to changes in the electricity mix while production scenarios 1 and 2 react sensitive and contrary towards the three defined electricity mix projections. Scenario 1 reacts as expected being more efficient when the electricity mix contains a higher ratio of renewable energy. The contrary happens in scenario 2. Other than expected, the relative technical efficiency decreases with increasing levels of energy from renewable sources. To understand this behavior, a deeper analysis of the electricity mix projections of the Alabama production location and their impact on the performance measures is required and is conducted in 0. The different projections of the electric truck market (E-Cars 1, E-Cars 2 and E-Cars 3) do not seem to have much of an impact on neither of the production systems. This is simply because the share of transportation cost and emissions in the overall production and supply chain cost and emissions is already very small. A variance in the electric share of a few percentages again does not seem to be of obvious consequence.

The relatively high impact of the carbon tax projections can partially be considered as result of the underlying simplifications. A higher carbon tax level only increases the cost without influencing decisions within the simulation model. Comparing DMUs 260, 332 and 404 which represent scenario 2 with a z-value of 4 subject to the same electricity mix and electric cars projections, the total cost of the production system is increased by 1.5% for a medium carbon tax level and by 3.3% for a high carbon tax level. Besides the costs, no other inputs to the DEA are affected. In reality it can be expected that higher carbon tax levels would add pressure to the implementation of new technologies at an earlier point and should therefore reduce CO2 emissions. This complexity has not been modelled but would be an interesting point for future research.

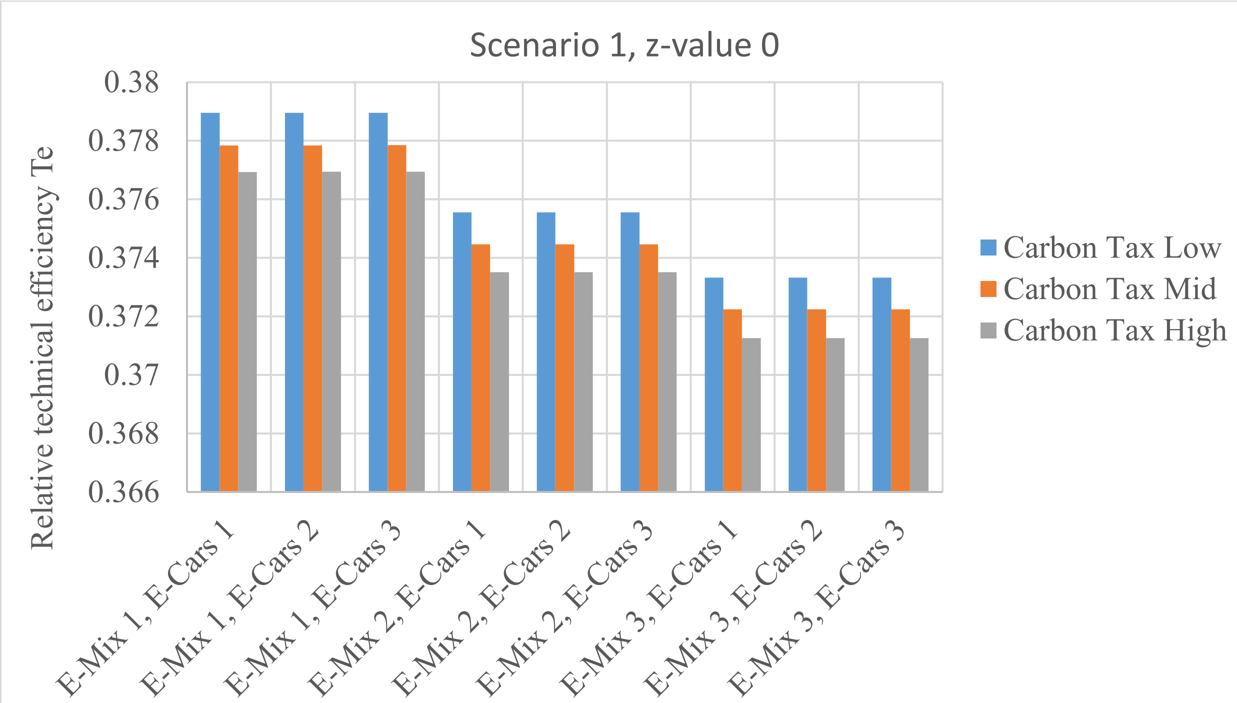


Figure 29: Impact of projected development scenarios on Te of scenario 1

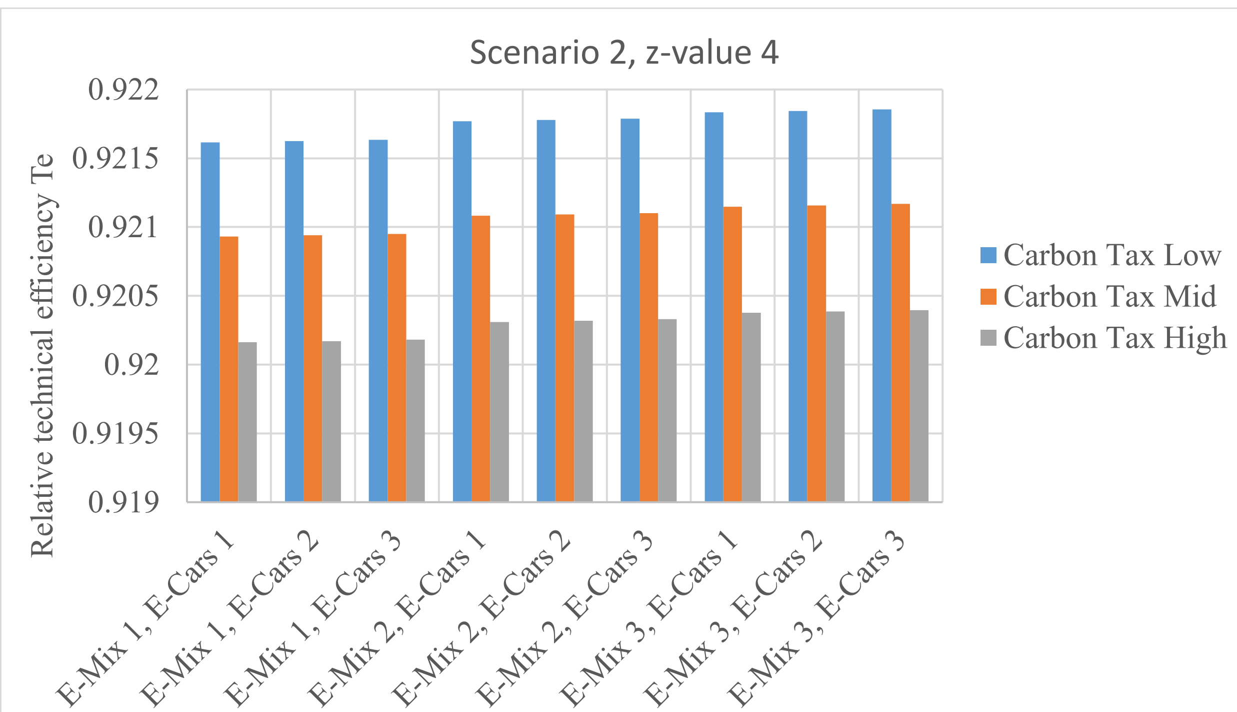


Figure 30: Impact of projected development scenarios on Te of scenario 2

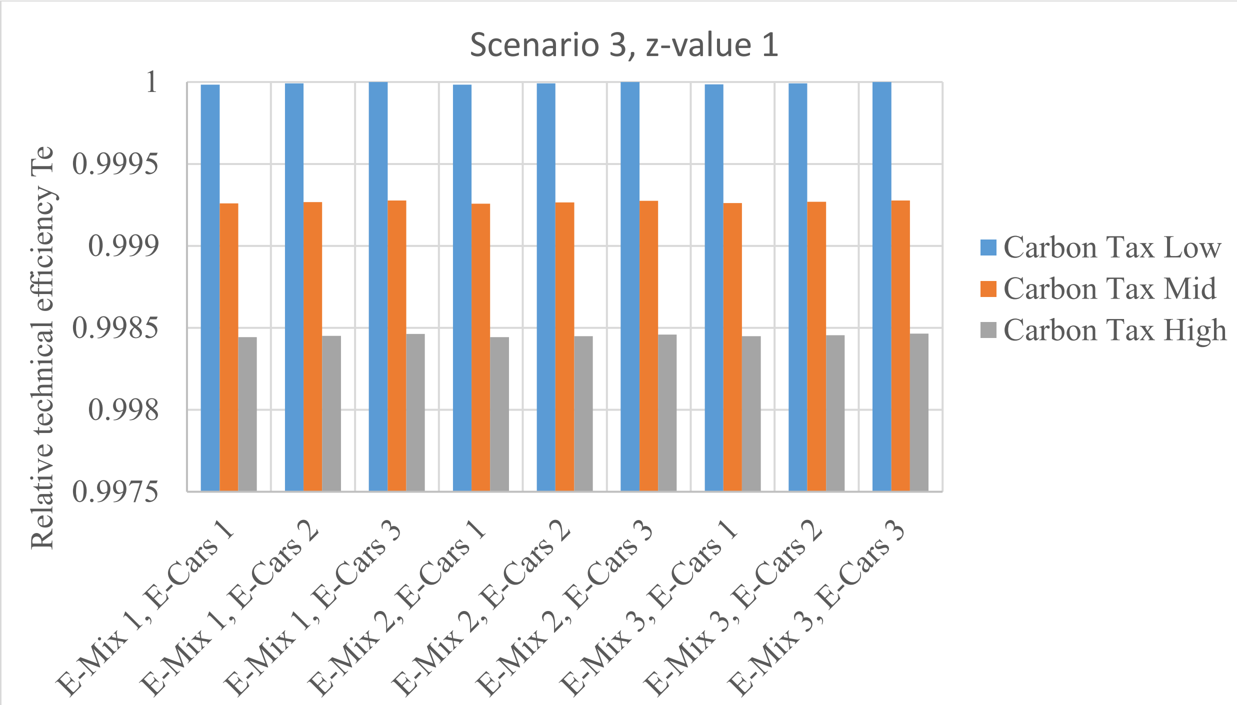


Figure 31: Impact of projected development scenarios on Te of scenario 3

3.7 Electricity mix projection scenarios

Figure 29, Figure 30 and Figure 31 show contrary developments of the relative technical efficiency scores for production scenarios 1 and 2 while only negligible changes can be observed for scenario 3. E-Mix 1 represents a projection with low oil and gas resource and technology developments and therefore higher shares of renewable energy sources. E-Mix 2 represents the reference case with mid-levels of energy from renewable sources and E-Mix 3 represents high oil and gas resource and technology developments and therefore, lower levels of energy from renewable sources. As the underlying relations of these projections are rather complex and also involve different developments of energy generation from coal and nuclear sources, the following analysis focusses on the development of the Climate Change [kg CO2-eq] indicator over time. Figure 32 illustrates the development of Climate Change [kg CO2-eq] emissions per MJ of electricity generation for the considered locations and projection scenarios E-Mix 1, E-Mix 2 and E-Mix 3. It shows the development for the Alabama location (blue), the US average (orange) and the unweighted average of the seven production locations of scenario 3 (green). It can be seen that although the E-Mix 1 scenario causes the least CO2-eq emissions on the long run, it needs until around 2030 to perform better than the E-Mix 2 scenario and even longer to create less emissions than the E-Mix 3 scenario. As production scenario 1 faces a strong increase of average demand after 2030 due to the shorter lifetime of the fuel nozzles and ageing aircraft fleets, it produces significantly higher amounts of parts during the period in which E-Mix 1 outperforms the other projections. As the average demand for production scenarios 2 and 3 is more stable over time, this effect does not occur for scenario 2. Production scenario 3 only shows little sensitivity towards changes in the electricity mix as it profits from a high number of production locations, in which the majority of electricity is generated from renewable sources already today (Quebec, Manitoba, Brazil). As the margin of average demand stays relatively stable over time for production scenario 3 as well, the changes of the relative technical efficiency scores can be neglected. Looking at the input measures of the DEA analysis, the CO2-eq output measure only happens to get worse for scenario 1 when the electricity mix changes from E-Mix 1 to E-Mix 2 and from E-Mix 2 to E-Mix 3. **Error! Reference source not found.** shows how the ormalized climate change indicator changes for selected DMUs representing scenarios 1, 2, 3 with z-values 0, 4, 1 and a low carbon tax and electric cars scenario. As can be seen in Table 23, all other output indicators behave the same across the scenarios. Thus, the climate change indicator turns the scale, i.e., causes scenarios 1 and 2 to react contrary towards the electricity mix projections.

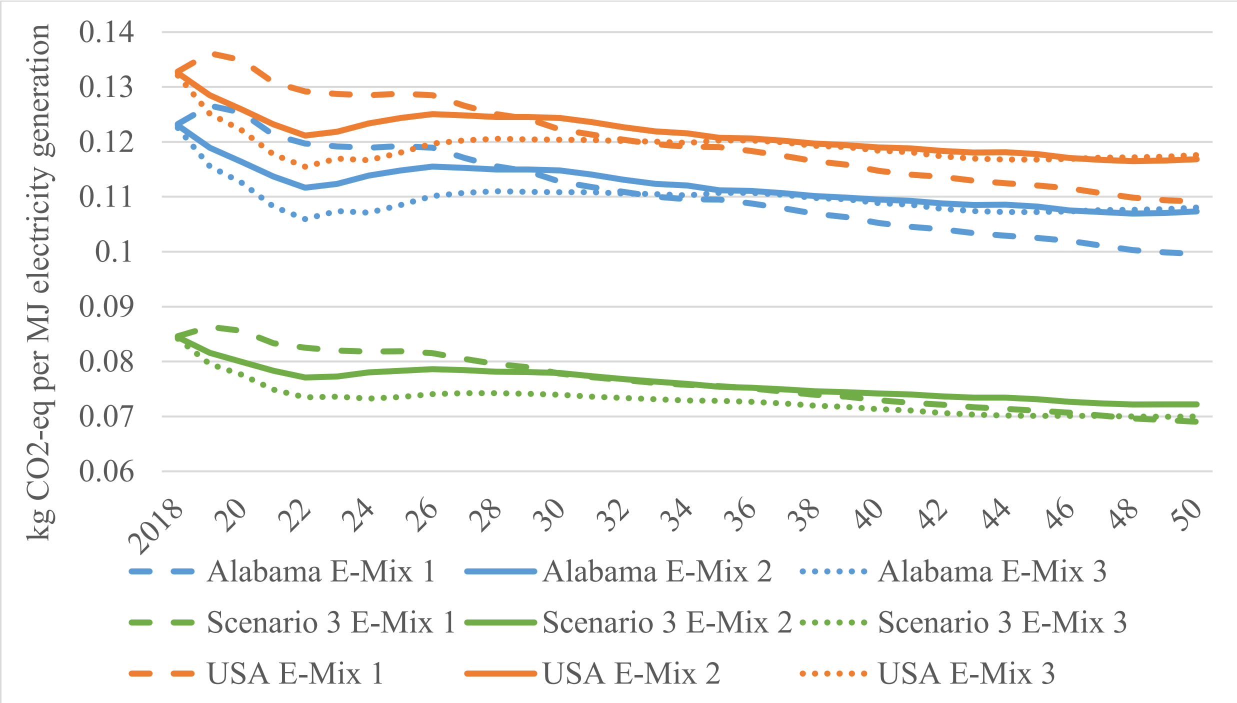


Figure 32: Climate Change [kg CO2-eq] per MJ electricity generation over time

	Reference DMU No.			Climate Change, kg CO2-eq measure [normalized]		
	E-Mix 1	**E-Mix 2**	**E-Mix 3**	**E-Mix 1**	**E-Mix 2**	**E-Mix 3**
Scenario 1	DMU #001	DMU #217	DMU #433	2.2654	2.2679	2.2697
Scenario 2	DMU #020	DMU #236	DMU #452	0.3549	0.3544	0.3541
Scenario 3	DMU #006	DMU #222	DMU #438	0.3431	0.343	0.3417

Table 22: Change of Climate Change indicator with changing electricity mixes

	Reference DMU No.			Indicator development with changing electricity mixes				
	E-Mix 1	E-Mix 2	E-Mix 3	Resource Availability	Climate Change	Human Health	Environmental Quality	Cost
Scenario 1	DMU #001	DMU #217	DMU #433	↑	↑	↑	↓	↓
Scenario 2	DMU #020	DMU #236	DMU #452	↑	↓	↑	↓	↓
Scenario 3	DMU #006	DMU #222	DMU #438	↑	↓	↑	↓	↓

Table 23: Change of input indicators with changing electricity mixes

3.8 Independent electricity solutions at the centralized manufacturing location

The importance of the site selection found and discussed in 3.6 and 0 raises the question what impact an energy mix from only renewable sources, i.e., a zero emissions mix would have on the performance of the centralized manufacturing location in scenario 2. This additional research question has been added to address questions, whether it could be beneficial to invest in and to promote independent electricity solutions. Companies of a certain size with a high electricity consumption like high volume additive manufacturers could consider building their own electricity supply solutions. This approach is assumed to be more beneficial in centralized locations due to high volume production and governmental subsidization that cannot be considered the same for all international locations. For production scenario 2, it has been tested how the relative technical efficiency changes, if the company would decide to invest into a geothermal power plant with entry into service in 2022. The scenario and related costs have been developed based on publicly available information of the U.S. Energy Information Administration. The "Levelized Cost of Electricity (LCOE)" per MWh includes capital costs, fuel costs, fixed and variable operations and maintenance costs, financing costs, and an assumed utilization rate for each plant type. (U.S. Energy Information Administration 2018b, U.S. Energy Information Administration 2018a) Figure 33 shows how the average relative technical efficiency scores of the new scenario 2-B arrange themselves above the ones of scenario 2, for some z-values almost reaching the scores of scenario 3.

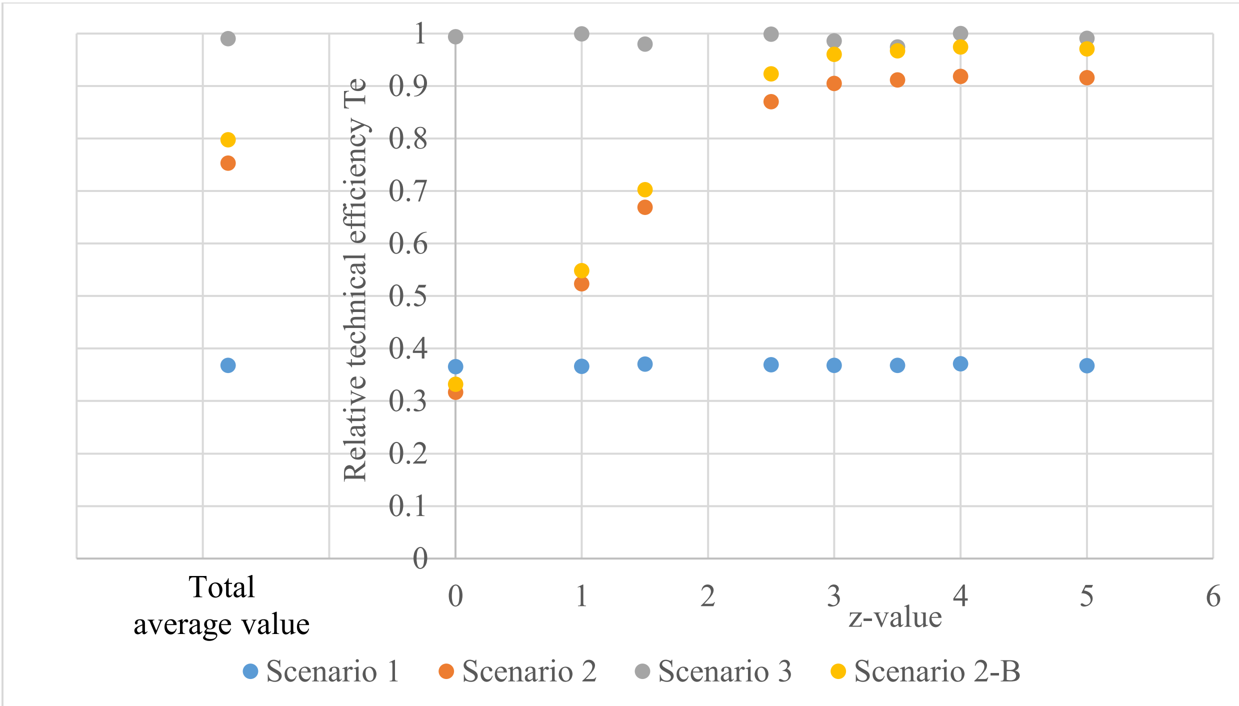


Figure 33: Efficiency score Te over z-value (average values) incl. "New plant scenario" 2-B

Figure 34 illustrates the impacts of electricity mix, electric truck and carbon tax projections on the new scenario 2-B for a z-value of four. Due to the new electric plant, the production within this scenario is completely independent of the electricity mix projections. The electricity mix projections only influence the transportation portion of the outputs and therefore have very little impact on the relative technical efficiency. This graph shows a side effect of the DEA analysis as now the growth of the electric truck market (E-Cars 1, 2, 3 projections) gains a higher importance for the overall results than in Figure 29, Figure 30 and Figure 31. This happens because they also need to be considered relative. After one previously more important input has been neglected, the remaining ones automatically increase their leverage. Moreover, it is important to mention that a higher share of electrically powered trucks increases the relative technical efficiency of the production system although the overall effect remains little.

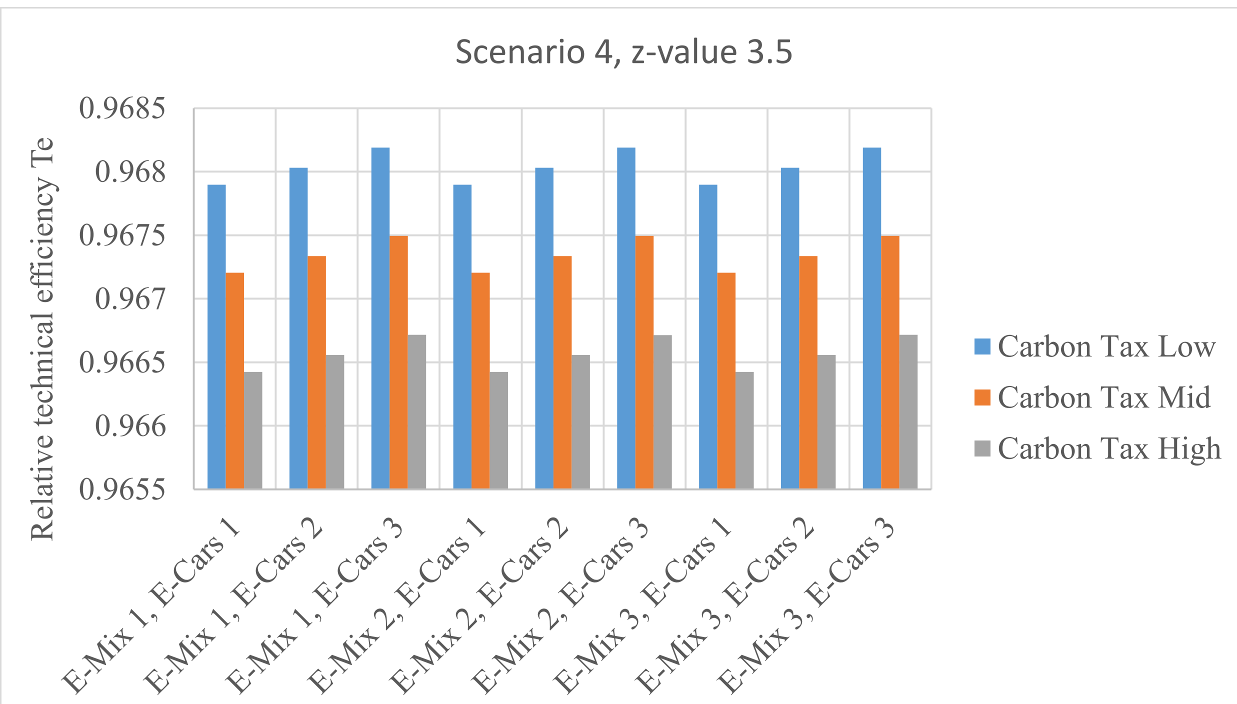


Figure 34: Impact of projection scenarios on "New plant scenario" 2-B

4. Conclusions and future work

4.1 Conclusion

The goal of this thesis was to decode Industry 4.0 and direct digital manufacturing (DDM), to identify a promising and representative industry example and to analyze its potentials for a de-centralization of production capabilities taking into account likewise, economic and sustainability criteria. An example of the additive manufactured GE Fuel nozzle has been found and used to build up three competitive production and supply chain systems. These systems have been simulated facing different sets of conditions over a time frame of 30 years. Output measures representing the economic, the sustainability and the supply chain performance have been recorded for a total of 648 input combinations or experiments. Based on these output measures a technical efficiency score has been established that has been used for benchmarking the three scenarios and their reaction to changing external conditions.

The data envelopment analysis methodology has been adopted and adjusted for assessing the efficiency of a number of systems or system alternatives relative to each other as well as a set of systems under different future scenario projections over their lifecycle. It makes it a flexible and easy to use tool for decision makers that enables them to quickly evaluate their alternatives not only under static conditions but also taking into account a variety of potential future developments. From another perspective, it can also be a helpful tool to support public policy makers in benchmarking new policy concepts providing feedback of competitiveness implications at an early stage of the political process.

This methodology has then been used to rank the 648 experiments according to their relative technical efficiency score. The technical efficiency score shows the best possible efficiency an experiment can reach relative to all other experiments and is analyzed to address the research questions by assessing the economic and ecologic implications of three supply chain operation systems representing conventional manufacturing, additive centralized manufacturing and additive de-centralized manufacturing.

It has been shown that the de-centralized production system reacted very flexible to fluctuations in demand and profited from reduced production and distribution lead times resulting in higher service and lower inventory levels. It reduces costs and the environmental impact as well as inventory risks, such as product obsolescence, as it is operating relatively lean and close to an on-demand production with small batch sizes and very little transportation efforts. Furthermore, it showed little sensitivity towards the different projections of the electricity mixes, which must be interpreted as a positive side effect of the distributed manufacturing locations. These distributed manufacturing locations coincidently have much higher shares of renewable energy than the US average and the centralized location in Alabama. As for the different electricity mix projections, it also showed little sensitivity towards the changes in safety stock (the z-value) and the different projection scenarios of the electric truck market. Overall operating very efficiently and robust against the simulated changes of superior conditions.

On the other hand, the centralized production system proved that it can keep up with the de-centralized production system under certain circumstances. It profits from lower per part cost and emissions due to economies of scale. It shows a higher sensitivity then the de-centralized production system towards the different electricity mix projections and the safety stock levels (the z-value). Provided that the right adjustments of the safety stocks are made and with some punctual investments, it reaches similar levels of the relative technical efficiency score as the de-centralized production system. This requires better long and short term planning and forecasting methods. Besides the safety stock other measures like shift planning or flexible capacity allocation could also increase the overall flexibility of the production system. Nevertheless these measures have not been considered within the scope of this research.

To conclude, using an existing industry example it has been shown that Industry 4.0 and Direct Digital Manufacturing have high potentials in reducing cost and environmental emissions within supply chain and production systems. Besides short lead times, on demand production, low inventory levels and little transportation efforts they also show a very robust behavior. It has further been shown that a centralized production can improve its efficiency by comparatively small measures and investments while still profiting from other factors such as economies of scale, simplified management of quality standards and employee skills as well as a better predictability of future workloads and capacity requirements. It is therefore expected that a company must see a significant competitive edge for their products resulting from direct digital manufacturing to accept the relatively high initial effort of changing its entire supply chain. Such a competitive edge can only be caused by market needs and could include examples like late product customization and high responsiveness requirements from the market or drastic changes of the self-conception of customers towards "prosumers" with highly individual needs. It is not expected that the benefits resulting from a de-centralized production and supply chain itself would be sufficient to justify such a big initial effort. However, with a market evolving towards a more de-centralized organization of work, it can be expected that the opportunities of Industry 4.0 and Direct Digital Manufacturing outweigh the risks considering both, the economic as well as the environmental performance.

4.2 Limitations

This study is benchmarking systems based on the simplification that they are up and running without considering any ramp-ups or capacity restrictions. It is the goal of this study to assess the potentials of direct digital manufacturing on the long run assuming that the ideas of Industry 4.0 would start changing current production paradigms and the trend towards more individual and flexible market requirements as well as higher digitalization and decentralization of the production process would intensify.

However, being at the initial stage of such a relatively young development also involves high risks and investments. Initial efforts are high and the direction of the trend can change rapidly driven by new inventions and unforeseen technology leaps.

Building up production capabilities in distributed locations increases the flexibility of the system a lot, but overall more machines and therefore higher investment cost are required. This can be compensated for by using the machines for other products, but it certainly increases the efforts such as capacity and maintenance planning, employee skill and quality management. Within a highly specialized field there is also the risk that machine or product interchangeability is not given or not given the same for all distributed locations with implications on the available capacities, machine utilization and exchange capacities in case of machine unavailability.

The industry example in this study has been based on energy mixes that are "greener" for the distributed production locations than for the centralized one in Auburn, Alabama. This highlights the importance of the location selection process. Depending on local conditions a future supply chain network will look much more complicated than in this simplified case. For some locations it could be beneficial to produce at one or several centralized locations while others have good conditions to produce on their own fulfilling their own demand or even the demand from other locations. Thus, it is expected that decision makers will need to consider each case individually and that companies would often find the optimum solution in a hybrid network.

The results have shown that based on the used simplifications an adequate assessment of the implications of carbon tax projections is not possible as the model only considers the additional cost resulting from this tax. For complexity reasons, this model does not consider the positive effect of implementing such a tax which is to promote technologies that would ultimately reduce CO2 emissions. As additional costs alone are never positive for a supply chain operations, this analysis concludes that higher carbon tax leads to weaker performance.

4.3 Future Work

Being at an early stage of Industry 4.0 developments, further work is expected to include new perceptions and study approaches of companies that attempt to organize their production and supply chains in a decentralized way. With more practical examples from the industry the level of detail will increase and questions will occur which might not be foreseeable today.

Furthermore, future work may include relaxations or other adjustments of constraints in data envelopment analysis (DEA) as well as the use of more advanced data envelopment models that would allow for a more detailed analysis of the relative technical efficiency score in between the time periods. This would provide policy makers and decision makers with better insights of planned transitions towards new technologies. Especially for the transition towards "greener electricity mixes" it has been shown that under certain circumstances the expected effect would not even occur after 30 years which should definitely play a role in the decision making process.

For an adequate assessment of carbon tax implications this model would need to be expanded to include at least one more set of projections forecasting the expected reduction of CO2 emissions depending on the particular carbon tax projection.

Appendices

Appendix 01

Airline	Aircraft Type	Fleet Numbers	Average age in yrs.	Statistical age distribution	Chi Square Test, corr. p-value	Kolmogorov-Smirnov Test, corr. p-value
American Airlines	A319	125	13.84	912 + 6.13e+003 * BETA(0.677, 0.417)	0.112819	< 0.005
	A320	57	16.51	2.85e+003 + 4.49e+003 * BETA(0, 0)	0.076726	< 0.005
	737	313	7.95	-0.001 + WEIB(2970, 1.09)	0.034302	< 0.005
Delta Airlines	A319	57	15.92	5.15e+003 + 1.61e+003 * BETA(1.21, 1.7)	0.004283	0.729
	A320	62	22.40	5.26e+003 + 4.78e+003 * BETA(0.978, 0.625)	0.085005	< 0.005
	A321	40	0.75	-0.001 + 694 * BETA(0.489, 0.76)	0.011871	0.451
	737	179	8.72	-0.001 + 7050 * BETA(0.471, 0.549)	0.066412	< 0.005
United Airlines	737	330	10.92	-0.001 + 7260 * BETA(0.875, 0.702)	0.016179	< 0.005
Southwest	737	720	10.40	UNIF(-0.001, 7.63e+003)	0.010886	< 0.005
Frontier	A319	18	12.62	TRIA(2.85e+003, 4.92e+003, 6.06e+003)	0.051813	> 0.15
	A320	44	4.04	-0.001 + WEIB(1010, 0.53)	0.014187	< 0.005
	A321	19	1.41	36 + 804 * BETA(1.08, 0.736)	0.103	> 0.15
Virgin America	A319	10	10.26	TRIA(3.36e+003, 3.61e+003, 4.27e+003)	0.058203	> 0.15
	A320	53	7.35	584 + 3.83e+003 * BETA(0.811, 0.67)	0.048678	< 0.005
	A321	7	0.26	-0.001 + EXPO(93.9)	0.106978	
Alaska	737	156	7.79	-0.001 + 6900 * BETA(0.735, 1.05)	0.012211	< 0.005
Allegiant Air	A319	37	12.53	3.94e+003 + 1.13e+003 * BETA(1.67, 1.32)	0.008504	0.673
	A320	48	10.94	73 + 7.45e+003 * BETA(0.588, 0.529)	0.045341	< 0.005
Sun Country Airlines	737	26	12.33	1.09e+003 + 2.24e+004 * BETA(0.565, 0.349)	0.024069	< 0.005
Air Transat	737	23	12.09	NORM(4.41e+003, 1.34e+003)	0.018455	< 0.005
Sunwing	737	37	7.03	292 + 4.78e+003 * BETA(1.3, 1.43)	0.020879	0.137

Airlines						
Westjet	737	121	8.84	UNIF(73, 6.1e+003)	0.012431	0.088

Appendix 02

	Centralized Manufacturing Systems, Conventional (CMS)	**Centralized Manufacturing Systems, Additive (CMS)**	**Distributed Manufacturing Systems, Additive (DMS)**
Maximum capacity (1)	Not considered	35,000	Not considered
Total machines (1)	Not considered	50	Not considered
Lot size (3)		12	1
Lead time (3)	14 days	10 days	7 days
Delivery time	1-3 days	1-3 days	0 days
Average power standby (2)		0.7 kW	0.7 kW
Minimum layer thickness (5)		20 µm	20 µm
Maximum layer thickness (5)		100 µm	100 µm
Layer thickness assumed (3)		40 µm	40 µm
Laser power utilization (4)		25%	25%
Maximum power laser (5)		1 kW	1 kW
Number of lasers (5)		4	1
Changeover (C/O) Time (3)		2h	2h
Process time per lot (4)		83.5 hours	6.33 hours
Total time incl. C/O Time per lot (4)		85.5 hours	8.33 hours
Process time per part (4)		7 hours	6.33 hours
Total time per part incl. C/O (4)		7.15 hours	8.33 hours
Energy required for part shaping per part (4)	0.8 kWh	8 kWh	9.32 kWh
Accumulated energy for required pre and post processing per part (1)	80.6 kWh	40 kWh	40 kWh

(1) (General Electric Company 2016a) (2) (Kellens, Mertens et al. 2017b) (3) These information has been estimated.

(4) These data has been calculated based on / verified against (1), (2), (3), (5). (5) (Concept Laser GmbH 2017)

Appendix 03

	z=0.0			z=1.0			z=1.5			z=2.5			z=3.0			z=3.5			z=4.0			z=5.0											
	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Supply Chain Configuration 1	Supply Chain Configuration 2	Supply Chain Configuration 3	Electricity mix projection low	Electricity mix projection mid	Electricity mix projection high	Carbon tax projection low	Carbon tax projection mid	Carbon tax projection high	Electric trucks share low	Electric trucks share mid	Electric trucks share high
DMU Number	001	002	003	004	005	006	007	008	009	010	011	012	013	014	015	016	017	018	019	020	021	022	023	024	x			x			x		
DMU Number	025	026	027	028	029	030	031	032	033	034	035	036	037	038	039	040	041	042	043	044	045	046	047	048	x			x				x	
DMU Number	049	050	051	052	053	054	055	056	057	058	059	060	061	062	063	064	065	066	067	068	069	070	071	072	x			x					x
DMU Number	073	074	075	076	077	078	079	080	081	082	083	084	085	086	087	088	089	090	091	092	093	094	095	096	x				x		x		
DMU Number	097	098	099	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120	x				x			x	
DMU Number	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	x				x				x
DMU Number	145	146	147	148	149	150	151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	x					x	x		
DMU Number	169	170	171	172	173	174	175	176	177	178	179	180	181	182	183	184	185	186	187	188	189	190	191	192	x					x		x	
DMU Number	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210	211	212	213	214	215	216	x					x			x
DMU Number	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240		x		x			x		
DMU Number	241	242	243	244	245	246	247	248	249	250	251	252	253	254	255	256	257	258	259	260	261	262	263	264		x		x				x	
DMU Number	265	266	267	268	269	270	271	272	273	274	275	276	277	278	279	280	281	282	283	284	285	286	287	288		x		x					x
DMU Number	289	290	291	292	293	294	295	296	297	298	299	300	301	302	303	304	305	306	307	308	309	310	311	312		x			x		x		
DMU Number	313	314	315	316	317	318	319	320	321	322	323	324	325	326	327	328	329	330	331	332	333	334	335	336		x			x			x	
DMU Number	337	338	339	340	341	342	343	344	345	346	347	348	349	350	351	352	353	354	355	356	357	358	359	360		x			x				x
DMU Number	361	362	363	364	365	366	367	368	369	370	371	372	373	374	375	376	377	378	379	380	381	382	383	384		x				x	x		
DMU Number	385	386	387	388	389	390	391	392	393	394	395	396	397	398	399	400	401	402	403	404	405	406	407	408		x				x		x	
DMU Number	409	410	411	412	413	414	415	416	417	418	419	420	421	422	423	424	425	426	427	428	429	430	431	432		x				x			x
DMU Number	433	434	435	436	437	438	439	440	441	442	443	444	445	446	447	448	449	450	451	452	453	454	455	456			x	x			x		
DMU Number	457	458	459	460	461	462	463	464	465	466	467	468	469	470	471	472	473	474	475	476	477	478	479	480			x	x				x	
DMU Number	481	482	483	484	485	486	487	488	489	490	491	492	493	494	495	496	497	498	499	500	501	502	503	504			x	x					x
DMU Number	505	506	507	508	509	510	511	512	513	514	515	516	517	518	519	520	521	522	523	524	525	526	527	528			x		x		x		
DMU Number	529	530	531	532	533	534	535	536	537	538	539	540	541	542	543	544	545	546	547	548	549	550	551	552			x		x			x	
DMU Number	553	554	555	556	557	558	559	560	561	562	563	564	565	566	567	568	569	570	571	572	573	574	575	576			x		x				x
DMU Number	577	578	579	580	581	582	583	584	585	586	587	588	589	590	591	592	593	594	595	596	597	598	599	600			x			x	x		
DMU Number	601	602	603	604	605	606	607	608	609	610	611	612	613	614	615	616	617	618	619	620	621	622	623	624			x			x		x	
DMU Number	625	626	627	628	629	630	631	632	633	634	635	636	637	638	639	640	641	642	643	644	645	646	647	648			x			x			x

Appendix 04

						Endpoints (Impacts per unit)			
						Resource Availability	**Climate Change**	**Human Health**	**Environmental Quality**
Factor Classification	**Factor Type**	**Inventory Element**	**Inventory Item**	**Location**	**Inventory Item Unit**	***MJ extra***	***kg CO2-eq***	***DALY***	***PDF*m2*yr***
Input	Activity (transportation)	Other Costs	Transport, aircraft, freight	United States	t-km	8.6359E+00	1.3042E+00	7.3577E-08	3.8551E-03
Input	Activity (transportation)	Other Costs	Truck transport, class 6, medium heavy-duty (MHD), diesel, short-haul, load factor 0.5	United States	t-km	1.9225E+00	2.9476E-01	5.3172E-08	8.6182E-04
Input	Activity (energy use)	Energy	Jet kerosene combustion in average aircraft	Global / Unspecified	L	2.0566E+01	3.1318E+00	3.0476E-07	9.1806E-03
Input	Activity (energy use)	Energy	Electricity use, average generation mix	100% Coal	MJ	1.39E-02	2.77E-01	7.81E-08	4.60E-04
Input	Activity (energy	Energy	Electricity use,	100% Oil	MJ	1.72E-01	3.09E-01	1.32E-07	2.27E-04

	use)		average generation mix						
Input	Activity (energy use)	Energy	Electricity use, average generation mix	100% Gas	MJ	5.73E-01	1.37E-01	1.15E-07	2.55E-04
Input	Activity (energy use)	Energy	Electricity use, average generation mix	100% Renewable	MJ	1.19E-02	6.22E-03	1.36E-07	3.45E-04
Input	Activity (energy use)	Energy	Electricity use, average generation mix	100% Renewable (zero emission)	MJ	7.99E-03	3.57E-03	5.35E-08	6.91E-04

Appendix 05

<u>The .mod file:</u>

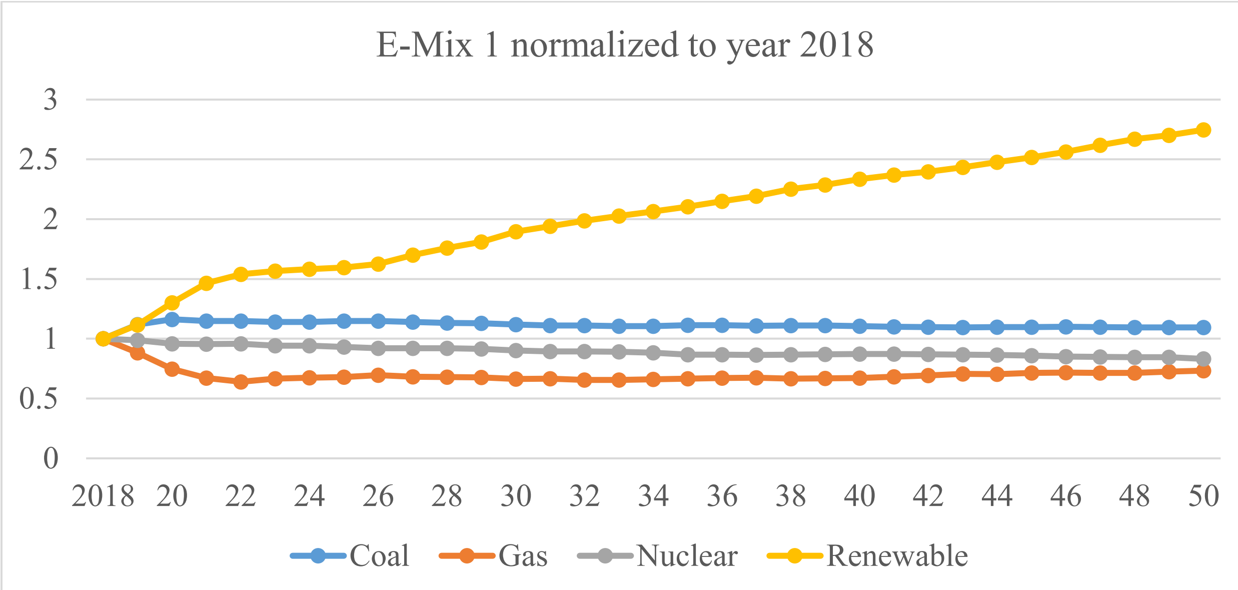
```
/*********************************************
 * OPL 12.7.1.0 Model
 * Author: Matthias Heppa
 * Creation Date: Aug 9, 2018 at 2:40:38 PM
 *********************************************/
int m =648;         // 648 DMUs
int n =2;           // 2 Outputs
int o =5;           // 10 Inputs

range M = 1..m;
range N = 1..n;
range O = 1..o;

float OUTPUT[M][N]= ...;
float INPUT[M][O]= ...;

dvar float+ U[N];
dvar float+ V[O];

dvar float+ EFF1[M];
dvar float+ EFF2;

int DMU = ...;

maximize sum(i in N) U[i]*OUTPUT[DMU][i];

subject to{
const01: sum(j in O) V[j]*INPUT[DMU][j]==1;
const02: forall (k in M) sum(i in N) U[i]*OUTPUT[k][i] - sum(j in O)V[j]*INPUT[k][j]
<= 0;
const03: forall (i in N) U[i]>=0.025;
const04: forall (j in O) V[j]>=0.025;
const05: U[1]==U[2];
const06: forall (k in M) EFF1[k]==sum(i in N) U[i]*OUTPUT[k][i];
EFF2==sum(j in O) V[j]*INPUT[DMU][j];
}

main {
thisOplModel.generate();
var model = thisOplModel;
var def = model.modelDefinition;
var data = model.dataElements;
var value1 = model.DMU;

var ofile = new IloOplOutputFile ("Output.txt");

while (value1<=648){
model = new IloOplModel (def,cplex);
data.DMU = value1;
model.addDataSource(data);
```

```
model.generate();
cplex.exportModel("model.lp")
if (cplex.solve() ) {
var curr = cplex.getObjValue();
var value2 = model.V[1];
var value3 = model.V[2];
var value4 = model.V[3];
var value5 = model.V[4];
var value6 = model.V[5];
var value12 = model.U[1];
var value13 = model.U[2];
ofile.writeln("DMU=       ", value1, " ", curr, "   ", value2, " ", value3, " ",
value4, "    ", value5, " ", value6, " ", value12, "", value13);
} else {
writeln("No Solution!");
break;
}
value1 = value1 + 1;

}
ofile.close();
}
```

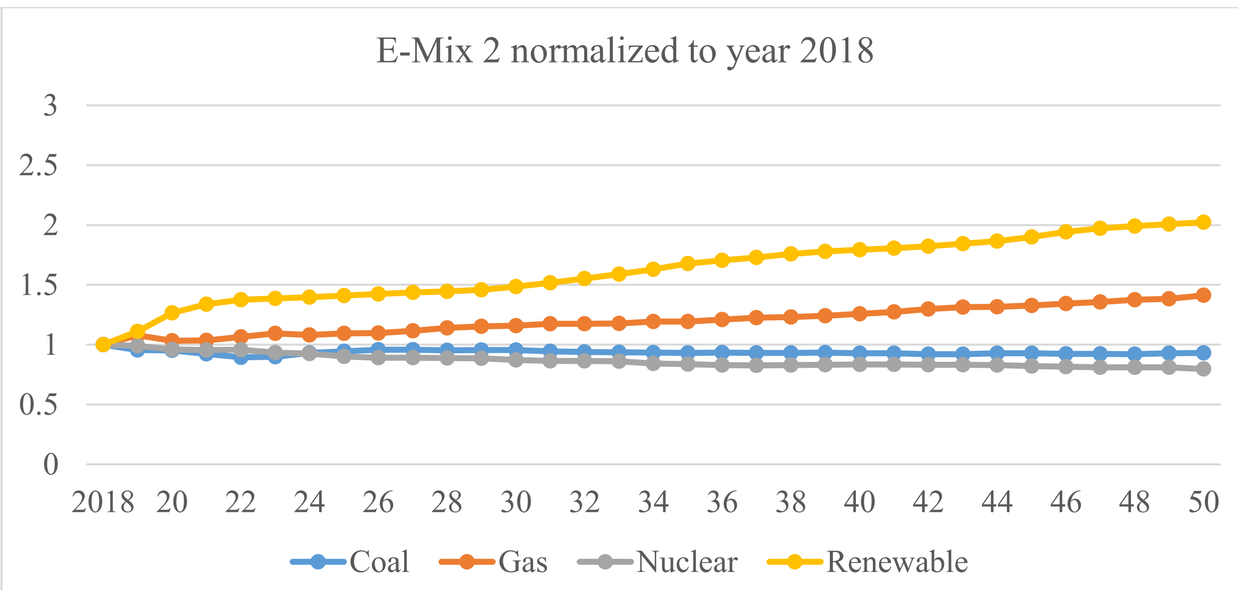
The .dat file:

```
SheetConnection sheet("DATA.xlsx");
INPUT from SheetRead(sheet,"data!D1:H648");
OUTPUT from SheetRead(sheet,"data!A1:B648");

DMU from SheetRead(sheet,"data!N1");
```

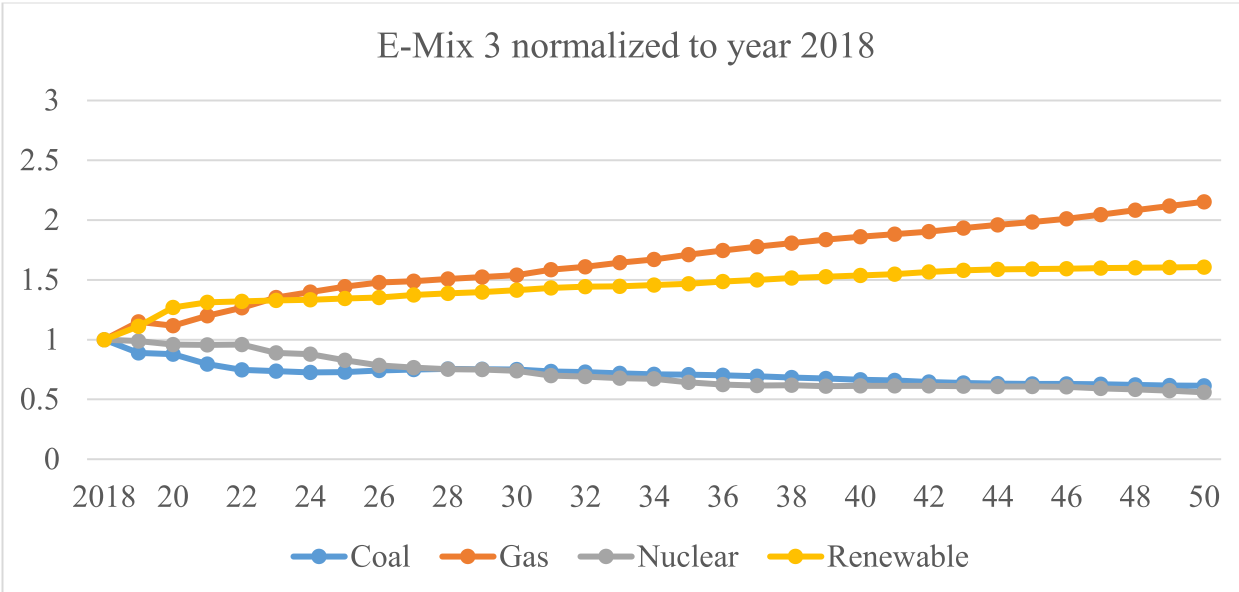
Appendix 06



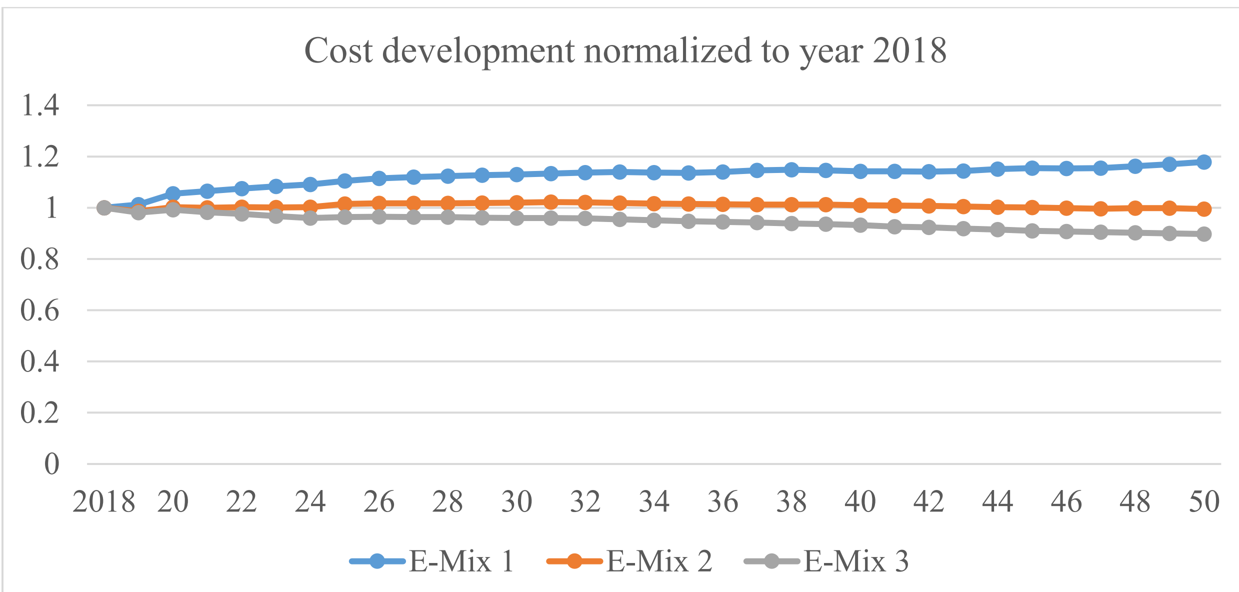
E-Mix 1 normalized to year 2018
3
2.5
2
1.5
1
0.5
0
2018 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
Coal
Gas
Nuclear
Renewable



E-Mix 2 normalized to year 2018
3
2.5
2
1.5
1
0.5
0
2018 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
Coal
Gas
Nuclear
Renewable



E-Mix 3 normalized to year 2018
3
2.5
2
1.5
1
0.5
0
2018 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
Coal
Gas
Nuclear
Renewable



Cost development normalized to year 2018
1.4
1.2
1
0.8
0.6
0.4
0.2
0
2018 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
E-Mix 1
E-Mix 2
E-Mix 3

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