Technology cost drivers for a potential transition to decentralized manufacturing

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Abstract

Popular dialogue around additive manufacturing (AM) often assumes that AM will cause a move from centralized to distributed manufacturing. However, distributed configurations can face additional hurdles to achieve economies of scale. We combine a Process-Based Cost Model and an optimization model to analyze the optimal location and number of manufacturing sites, and the tradeoffs between production, transportation and inventory costs. We use as a case study the commercial aviation maintenance market and a titanium jet engine bracket as an exemplar of a class of parts that are not flight-critical. We run our analysis for three different scenarios, one corresponding to the current state of the technology, and two which represent potential improvements in AM technology. Our results suggest that the cost-minimizing number of manufacturing locations does not vary significantly when taking into account a range of plausible improvements in the technology. In this case, distributed manufacturing is only favorable for a set of non-critical components that can be produced on the same equipment with minimal certification requirements and whose annual demand is in the tens of thousands. Distributed manufacturing is attractive at lower volumes for components that require no hot isostatic pressing.

1 Introduction

Additive manufacturing (AM) is a family of near net shape manufacturing processes where digitally created three-dimensional objects can be built up by depositing material in successive layers. Some of the potential advantages of AM over incumbent manufacturing technologies include creating optimized geometries, reducing material waste, and reducing lead time and therefore the need to keep inventory (Gibson et al., 2010; Harris, 2011; Horn and Harrysson, 2012).

Based on these claimed advantages, scholars and the popular press alike have argued that AM will bring manufacturing closer to markets and consumers (Ihl and Piller, 2016; Petrick and Simpson, 2013; The Economist, 2012). Others, however, have argued that the benefits of localization may be exaggerated, at least in this case, both in terms of which products may be customized (Sheffi, 2013) as well as the benefits and potential. This exaggeration may be especially true of metal AM, which faces constraints that polymer AM does not (Bonnín Roca et al., 2017a). Khajavi et al (2014), in assessing a polymer component for military aircraft, suggest that centralized production is preferred with the current state of the technology, but also argue that future developments could make distributed production more attractive. Under such conditions, producers could pool demand across different industries to more easily achieve economies of scale (Khajavi and Holmstrom, 2017).

Economic theory models the problem of factory location as one of finding a balance between the cost of producing a certain good, and the cost of the 'distance' to the market (Isard, 1951a, 1951b; Marshall, 1890; von Thünen, 1826). On one hand, firms are incentivized to locate close to areas with high market potential (Harris, 1954; Lowry, 1964). Proximity to the market reduces transportation costs and improves access to customers and production inputs (P. Krugman, 1991; Pred, 1966). On the other hand, those areas tend to have increased land (Marshall, 1890; von Thünen, 1826) and labor (Krugman, 1997) prices, which may have an important impact on the manufacturing cost. Thus, new entrants need to find a balance between positive externalities, and congestion costs due to agglomeration (Henderson, 1974). Improvements in transportation infrastructure may decrease transportation costs, allowing firms to produce in more remote areas (North, 1955). As the number of markets increases, firms face additional tradeoffs in volume and competition between serving the local or global markets (P. R. Krugman, 1991). In those cases, the total number of factories operating might be determined by economies of scale and scope, which are different for each industry and product (Chandler and Hikino, 1994; Lösch, 1954). Both the relative difficulty of achieving economies of scale, and the total production cost, can be affected by geographical differences in input prices (Fuchs and Kirchain, 2010).

Surveys among firm decision makers suggest that there is a wide variety of factors affecting firms' location decisions beyond those affecting economic productivity (Blair and Premus, 1987; Rees, 1986). In the case of high-technology manufacturing plants, the top three factors are usually access to labor, access to good transportation, and quality of life (Rees, 1986). In addition, firms may want to avoid regions with stronger union movements and higher taxation (Bartik, 1985). The scarcity of skilled labored might be partially overcome by locating close to the leading universities and researchers in the field (Zucker et al., 2002). Access to transportation can be gained by locating close to the major highways and airports (Karakaya and Canel, 1998). Quality of life encompasses often less-quantifiable factors such as the opportunities to enjoy cultural and recreational activities, living costs, or the quality of the surrounding environment, among others (Salvesen and Renski, 2003). In addition, entrepreneurs may show a strong preference to establish their firms close to their home town (Figueiredo et al., 2002).

The operations research literature seeks to optimize the design of supply chains, minimizing cost, maximizing profit, or minimizing time-to market across manufacturers, suppliers, distributors and retailers (Beamon, 1998; Melo et al., 2009). When the potential location of the facilities is known, discrete location problems are usually preferred over continuous algorithms, which are often used in macroeconomic studies (Melo et al., 2009). A particularly relevant application of discrete models is the uncapacitated facility location problem, where each of the locations presents a different location cost, and there is no upper limit to the production volume at each location (Fernández and Puerto, 2003; Mirchandani, 1990; ReVelle et al., 2008). The objective of those algorithms is primarily to minimize the cost of the entire supply chain (e.g. Barros et al., 1998; Marvin et al., 2013; Mina and Melachrinoudis, 1999). Nonetheless, the algorithms can be modified to include additional objectives such as balancing the capacity at each facility (Marín, 2011), maximizing the service area covered by the facilities (Church and ReVelle, 1974), minimizing 'dead' stock (Ishii et al., 1988), choose a production technology (Verter and Cemal Dincer, 1992) or even introducing environmental concerns (Wang et al., 2011). While many of these algorithms offer a deterministic solution, real-life uncertainty surrounding the demand levels and potential supply chain disruptions call for the introduction of robustness checks and sensitivity analyses (Correia and Gama, 2015; Snyder, 2006). For instance, while classical theory suggests that the centralization of inventory is optimal under deterministic conditions, decentralized inventory reduces cost variance under uncertainty (Schmitt et al., 2015). A limitation in the treatment of the uncertainty surrounding the production costs is that it is usually limited to the introduction of random parameters in the equations determining the costs (Louveaux, 1986; Sibdari and Pyke, 2014; Wang et al., 2012), which are disconnected from the real-life technical drivers of such costs, key drivers of most engineering cost estimation techniques (Laureijs et al., 2017; Niazi et al., 2005).

We combine a location-dependent Process-Based Cost Model (PBCM) (Field et al., 2007) of a metal AM (MAM) production process, with an uncapacitated facility location optimization model (Daskin, 2011), to analyze which configuration minimizes the total supply chain costs. The PBCM allows us to introduce a more thorough analysis of how uncertainty in the factors affecting MAM production costs changes the optimal solution, which is limited when following the traditional approaches in the operations research literature (Snyder, 2006). As an exemplar of a class of low-risk aircraft replacement parts we use the case of a titanium jet-engine bracket in the U.S. commercial aviation spare parts as a market. We model three scenarios: one corresponding to the current state of the technology, one which represents the potential improvements in performance, and a third one that assumes a dramatic fall in equipment costs. Our results suggest that, even after future improvements in equipment performance and a substantial fall in MAM equipment costs, centralized location will likely remain most cost-effective due to economies of scale, unless production volumes are high or there is a large reduction in the need for post-processing.

This study makes three key contributions. First, it combines three techniques that, to our knowledge, have not been used simultaneously before: the use of a process-based cost model to link design and production choices to cost; the inclusion of location-based factors (e.g., volume of demand, labor costs, and land costs); a mixed-integer linear program to perform a supply chain optimization. Second, it explores technology-specific details that the supply chain or operations management literature might abstract away (e.g., the cost and nature of post-processing; the potential for vast improvements in AM technology). Third, it directly addresses an assumption that decisionmakers sometime make about AM: that it will foster the localization of manufacturing. Support for AM is premised on the idea that decentralized AM will be good for society or bring manufacturing back to places that have lost them (EC, 2017; WEF, 2018). Our study tests this hypothesis against technical reality.

The paper is structured as follows. We start with general background information about the potential applications of additive manufacturing in the commercial aviation industry, and information about how regulation may affect the introduction of the technology. We then discuss the simulation and optimization models used in our analysis. We present our results, and we finish with a discussion about which circumstances may drive the decentralization of the manufacturing of spare parts in the aviation industry.

2 Industrial background: additive manufacturing in commercial aviation, and the regulation of spare parts

The aerospace industry is one of the main users of AM (Wohlers Associates, 2016). AM offers the reduction of material waste in high-value components; the optimization of geometries and lightweighting of components, which translates into important fuel savings for airlines; and the reduction of part count, through the combination of multiple components, which decreases inventory costs and may increase part durability (Frazier, 2014; Harris, 2011; Morris, 2014).

The first AM components are already flying. In 2015, the Federal Aviation Administration (FAA) approved the first replacement part made with AM, a cobalt-chrome case for engine inlet temperature sensors, manufactured by General Electric (GE) to retrofit engines for Boeing 777 aircraft (GE, 2015). GE also merged twenty components into one single piece to produce a new fuel nozzle for its “Leading Edge Aviation Propulsion” (LEAP) engine. GE reports that this integration reduced production costs by a 30%, decreased weight by 25%, and increased durability (GE, 2014; Morris, 2014). In 2017, a Boeing supplier started to manufacture the first AM structural components, made of titanium, approved for use in commercial aviation (Arnesen, 2017).

However, AM is a still-maturing technology with many sources of variability, and aviation is an industry with very stringent safety requirements. Hence, achieving a level of control over the AM manufacturing process, which is good enough for aviation standards and consistently produces components that can withstand cyclical loads, is one of the main barriers to the further adoption of the technology (Bonnín Roca et al., 2017b; Frazier, 2014). This variability is expected to decrease as the technology matures, and better process control and real-time monitoring systems are implemented in the next generation of equipment (Everton et al., 2016).

The regulatory process for spare parts is different than the process for components introduced in new designs. While new designs require the creation of extensive material databases and testing at different levels, which is very expensive and time-consuming, manufacturers of spare parts need only prove that the component they are producing is equivalent to the component approved as part of the aircraft design (FAA, 2009). The amount of testing and documentation required depends on the type and functionality of each component. FAA’s Advisory Circular 43-18 (2006) classifies components into three categories. Category 1 components are those whose failure could deter performance to the point of preventing safe flight and landing. A failure in Category 2 components still allows for safe flight and landing but would reduce the capability of the crew to face adverse operating conditions. Category 3 components are the least critical, and their failure affects neither the safety of the flight nor the aircraft's performance. The same advisory circular states that the fabrication of Category 3 components "will typically result in no involvement by AIR [Aircraft Certification Service] unless the Flight Standards Service aviation safety inspector requests assistance". Although it is a U.S. agency, the FAA is the preeminent regulator for civil aviation and its procedures are widely applicable.[2] As such, these regulatory constraints likely apply to most jurisdictions.

For Category 1 and 2 components, initial production runs at each manufacturing site require additional testing. This additional testing makes the distributed production of Category 1 and 2 components relatively unattractive. Hence, we will focus our analysis on Category 3 components. Once the applicant has been granted permission to produce components at a manufacturing site, the process to open new manufacturing plants would require much less paperwork and testing (Aviation Regulator, 2017). Therefore, we assume that there would not be large differences in the certification costs between centralized and distributed production.

Huang et al. (2016) estimate that 250-510kg of "auxiliary" metallic components in a narrow body aircraft that can be feasibly replaced by lighter, 3D printed equivalents. The components are identified as feasibly replaceable because they have low shape complexity, appropriate geometric volume, and low load. They are considered auxiliary because they are not structural and not functional (i.e., they do not perform functions during flight). As such, they coincide with what the FAA defines as Category 3 components. The heaviest such component Huang et al. consider weighs 1kg, and the lightest is 0.06kg. Assuming conservatively that all such components weigh 1kg, this suggests that there are at least 250-500 components per narrow body aircraft that could potentially be produced using AM.[3] There are nearly 7,000 commercial aircraft in operation in the United States (FAA, 2017),

[2] As Bonnín Roca et al. (2017b) note, "…there are international working groups and bilateral agreements to ensure that regulation and advisory materials written by other aviation authorities like the European Aviation Safety Agency are harmonized. In some cases, like Brazil, regulation and advisory materials are exact copies of those in the U.S. Interpretation will vary with the officers in each country. This said, we expect lessons learned from the FAA to be applicable to other regions like Canada, Europe, Japan and Brazil."

[3] Many of these components may be of the same type. For example, there are more than 100 seat belt buckles per aircraft. A such, the 250 components per aircraft might fall into far fewer part types.

which suggests that there could be 1.75-3.5 million such components on U.S. aircraft that could be feasibly produced using AM without undergoing the most burdensome certification processes. If we conservatively assume that 1% of these components needed to be replaced per year, the total market for such components for the U.S. domestic fleet alone would be 17,500-35,000 parts per year.

3 Methods

As discussed above, there are several such non-critical, non-structural parts. We use a titanium jet engine bracket as the canonical exemplar to explore how optimal supply chain configurations change as process and other parameters vary. The design of the bracket was made publicly available by GE in an online competition, with the purpose of minimizing the weight of an existing bracket while meeting its original functional specifications (Kellner, 2013). Laureijs et al (2017) used this design to demonstrate that AM is cost-competitive against the conventionally-manufactured design, thanks to a more than 80% weight reduction, from 2,033 grams down to only 372. The bracket is used during maintenance by airline personnel to hold the engine while it is being manipulated (Kellner, 2013). The component is an example of a Category 3 component, because a failure would not affect the safety of the flight or the performance of the aircraft.

The geographical scope of our supply chain analysis is the 48 contiguous states in the United States. To represent the demand, we chose the fifty busiest airports by total departures handled in the USA in 2016, published by the U.S. Bureau of Transportation Statistics. We excluded two in Hawaii and Puerto Rico which are not in the contiguous states, ending up with 48 airports. These 48 airports represent approximately 83% of the total enplanements in the USA (Bureau of Transportation Statistics, 2017). The 48 airports are located in 45 different counties. We assume that the demand for components at each airport is proportional to their share of passenger traffic.

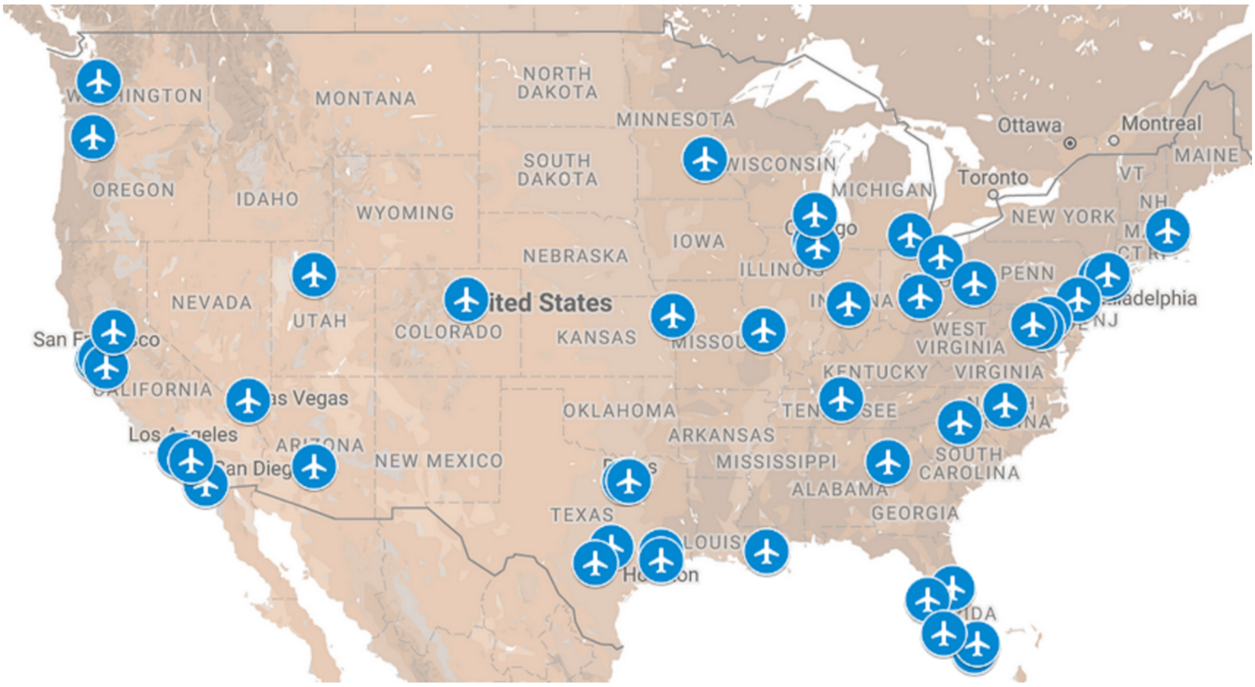


Figure 1 We study the supply and demand at 48 airports in the contiguous U.S.

Our analysis is divided into two steps. First, we build a location-dependent model for the production costs. The purpose of the production model is to generate a family of cost curves, which change according to the geographical variations in input prices; namely wages, energy prices, and land prices. Second, we build a cost-minimizing supply chain optimization model. The optimization model allows us to analyze the tradeoffs between production, transportation and inventory costs, for different production volumes.

Our null hypothesis is that policymakers who hope that additive manufacturing will automatically make localized, distributed manufacturing attractive are right. Our alternative hypothesis is that centralized manufacturing is likely to be economically preferable. This is because most AM components need several post-processing steps which increases the capital needed to open a new factory. We do our best to falsify this hypothesis by making assumptions that strongly favor the null hypothesis. As such, in the event of uncertainty surrounding certain cost components, our assumptions favor distributed production (e.g. by increasing transportation and inventory costs or lowering barriers to open a new production facility).

3.1 Process-Based Cost Model

To model production costs, we use Laureijs et al.'s (2017) Process-Based Cost Model (PBCM), specifically designed to simulate the production of MAM components. PBCM is a decision tool that analyzes the economics of novel manufacturing technologies and product designs before investing in them (Field et al., 2007); PBCM gives the flexibility to build 'what-if' scenarios to estimate how modifications to certain parameters may affect production costs. In PBCM, the production process is divided into its constituent steps. At each step, the model computes the inputs (material, capital, labor, building space, energy, etc.) required to achieve a certain annual production volume of good (usable) parts given the specified product design, operational, and financial parameters. To compute the total costs, we multiply the inputs required at each step by their price to find the total cost of "good" parts at the specified annual production volume.

Our analysis assumes one Direct Metal Laser Sintering (DMLS) system, referred to as DMLS1 in Laureijs et al (2017). Based on our interactions with industry, this is one of the most widely used systems in the manufacture of components for aerospace. We assume the following post-processing steps: heat treatment, wire EDM, Hot Isostatic Pressing (HIP) and Shot Peening. To make the cost model location-dependent, we changed input prices (wages, electricity prices and land prices) for each location, keeping the original production parameters published by Laureijs et al. fixed.

We obtained these region-dependent input prices for the PBCM from public sources. We obtained the 2016 average wages in the manufacturing sector from the Bureau of Labor Statistics (2017), at county level. We obtained the annual-average electricity prices, at the state level, from the Energy Information Administration (2017). Estimating land prices was challenging due to the high variances in prices across neighborhoods even within the same county, the location of airports in different counties than the city they serve (e.g. Washington, D.C.) and the lack of reliable data. At the same time, we expect errors in the estimation of land prices to have a small impact on our results, given the relatively low contribution of land prices to the final production cost. For instance, when producing 10,000 components per year in the baseline scenario (see Table 1 and below), the cost of land represents about 0.4% of the total production cost. This percentage is small when compared to labor, which at the same production volume represents about 7% of the cost. We estimated land prices at the county level by building a parabolic function to correlate the House Price Index (HPI), published at the county-level by the Federal Housing Finance Agency (Bogin et al., 2016), and median list housing prices, for 40 different cities, published on the real estate portal Zillow (see Appendix A).

Table 1 Summary of the production inputs changed across the different scenarios

Scenario	Baseline	20x build rate; no rejects	20x build rate + 1/10th machine cost; no rejects
Machine price [k$]	600	600	60
Batch size	2	4	4
AM Build time [h]	19.50	0.98	0.98
Total reject rate	~20%	~0%	~0%

Our “**Baseline**” scenario (Table 1) corresponds to the state of the technology in 2016. We constructed two other “what-if” scenarios. Our second (“20x build rate” in

Table 1) scenario accounts for improvements in reliability and performance which are likely to happen in the next decade. In this, we assumed a twenty-fold[4] improvement in speed, doubled the batch size, and assumed that reject rates were close to zero (ideal case). We assumed that these improvements would be delivered without an increase in machine cost, but that might not always be the case. Currently, the faster systems are those which use multiple lasers at the same time. Multiple laser systems are currently substantially more

[4] The speed of laser-based machines currently scales roughly linearly with the number of lasers, and the fastest machines are four times faster than the single-laser machines that we model. (see, for example, (SLM Solutions, 2017a)). There are, however, machines that jets of binders to produce parts that are sintered to consolidate them. These machines may be up to 100 times faster than current single-laser machines (Warwick, 2017).

expensive than single laser systems. Laureijs et al. (2017) assume that single laser systems cost between $500,000 and $800,000. In 2017, SLM Solutions GmbH (SLM Solutions, 2017b) announced the sale of 10 multiple-laser systems at a price of up to EUR1.2 million each ($1.5 million at the EUR-USD exchange rate as of March 2018). The introduction of robust real-time monitoring systems and more complex algorithms to optimize the build process could increase the price of the newest generation of machines. At the same time, learning effects and an increase in market size could lower costs. The third, extreme scenario ("20x build rate + 1/10th machine cost" in Table 1) assumes machines that are not only 20 times faster, but also that such fast machines cost one-tenth as much as current laser-based systems. One of the companies trying to commercialize such systems is Desktop Metal. However, Desktop Metal machines use the so-called Single Pass Jetting technology, which produces parts with poorer and more variable mechanical properties than does Direct Metal Laser Sintering (DMLS), which is the process we assume in our base case. Therefore, it remains to be seen under which conditions such low-cost systems could be used in industrial applications with stringent qualification procedures such as commercial aviation (Warwick, 2017). The initial price of Desktop Metal's machines is $49,900 plus tax (Petch, 2017), which is indeed roughly one-tenth of the price of the DMLS machine assumed in our base case. The last two of these scenarios also assume that rejection rates are reduced to zero.

We recognize that it is in fact unlikely that such large improvements in performance will be accompanied by a dramatic fall in costs. Indeed, it is also the case that a combination of high power and high speeds might result in a deterioration in properties such as porosity (Cunningham et al., 2017). Making the extreme assumption that the technology does improve as much as this is a reflection of our conservatism. As we note at the start of this section, our alternative hypothesis is that centralized manufacturing is likely to be economically preferable. We do our best to falsify this hypothesis by making assumptions that strongly favor the null hypothesis. Assuming that machines can be made much faster without increasing costs is a conservative, implausible assumption and therefore represents a strong test of our alternative hypothesis.

For each of the three scenarios, we simulated the production costs for 45 different counties (there are three counties which contain two large airports). The PBCM gives as an output the total cost for a given production volume. To obtain a relationship between the production cost and the production volume, we repeated the calculation in intervals of 100 units per year, between 1 and 10,000 units. We used these hundred data points to express the production cost as a linear function of the production volume, using ordinary least squares. The linear estimator had an R^2 of 99.9% in all cases and provides two parameters (a constant and a slope) which we will use in our optimization model. The parameters obtained from this linearization can be found in Appendix C.

3.2 Supply Chain Optimization Model

We model the supply chain of spare parts as an uncapacitated location optimization problem (Daskin, 2011). We choose a discrete optimization model because the location of the potential sites, which correspond to the major airports and maintenance hubs are known. We model the problem as uncapacitated because the typical production volumes in the aviation aftermarket are typically low (tens or hundreds per item) (Regattieri et al., 2005), and hence do not require the establishment of large manufacturing plants.

In our model, there are **i** potential manufacturing locations, and **j** demand nodes. Airline maintenance hubs are located at, or in the proximity of, major airports. We assume that AM equipment could be located at any of those major airports. Therefore, the number of potential manufacturing locations is the same as the number of demand nodes, which is the number of counties with a major airport (45). The total annual demand of components, D, is an input parameter to the model which allows us to analyze the effects of economies of scale on the optimal supply chain configuration. We assume that the demand at each airport is proportional to their passenger traffic, for each level of total demand D. The local demand at each airport, d_j, is computed by rounding up to the nearest integer the product of D and that airport's share of the passenger traffic.

The objective of our model is to minimize the total supply chain cost, which has three components: production costs C_p, transportation costs C_t, and inventory costs C_s.

$$minimize\ C = C_{production} + C_{transportation} + C_{inventory} = C_p + C_t + C_s \quad (1)$$

The decision variables of the model are q_ij and y_i. q_ij represents the quantity of components between factory i and the airport j. To improve the performance of the algorithm, q_ij has been scaled so that it has a value of 0 when there is no flow, and a value of 1 when the flow equals the total demand of parts D, which is a parameter of the problem. y_i is a binary decision variable equal to 1 when there is a factory operating at airport j, and 0 when there is no factory.

The model is subject to the following constraints: first, the demand at each airport must be met

$$D * \sum_i (q_{ij}) = d_j \ \forall\, j \quad (2)$$

And second, the quantity of components produced at a certain factory is only larger than zero if the solution of the optimization problem is for a factory to exist at location i (y_i =1).

$$\sum_j (q_{ij}) - y_i \leq 0 \ \forall\, i \quad (3)$$

Finally, the scaled component flows have a value between 0 and 1:

$$q_{ij} - 1 \ \leq 0 \ \forall\, i, j \quad (4)$$

$$q_{ij} \ \geq 0 \ \forall\, i, j \quad (5)$$

3.2.1 *Production costs*

Production costs are computed directly from the linearization of the PBCM, as a sum of the production costs at each potential location. For each county **i**, the linearized cost curve has a fixed cost component, c_pf_i, and a marginal cost, c_pm_i. When the solution of the optimization problem is for a factory to exist at location i (y_i =1), the fixed and variable components of the production cost are obtained from the output of the PBCM model at that location. Conversely, when the optimal solution is to have no factory at a particular location i (y_i =0), production costs are zero.

$$C_p = \sum_i y_i * c_{pf_i} + D \sum_i \sum_j c_{pm_i} * (q_{ij}) \tag{6}$$

3.2.2 *Transportation costs*

According to our conversations with maintenance personnel, spare parts are normally transported using expedited courier services such as FedEx or UPS. The price of the service is not linear with distance but is determined by 'zones'. For instance, according to UPS zone division, sending a package from San Francisco to Dallas (2,385 km) has the same price as sending it to Chicago (2,984 km). On top of the transportation, spare parts are usually transported in special containers to avoid any damage to high-value components, and the sender pays for additional insurance.

To be conservative, we decided to use a constant transportation price, which represents the maximum price a sender could pay to send a bracket from one factory to any airport in the USA. According to the UPS online freight calculator, the price of sending a $900 bracket from San Francisco to New York using the Next-Day Air service is about $1,500, assuming a package of 1kg or less. If the value of the bracket were only $300, the shipping price would only fall by $32. Therefore, we will use the same transportation price T = $1,500 as a parameter for all the three scenarios. Transportation costs are zero for those components manufactured at the same airport where they are demanded.

Transportation costs can be expressed as:

$$C_t = T * D * \sum_i \left(\sum_j q_{ij} - (q_{ii}) \right) \tag{7}$$

3.2.3 Inventory costs

To obtain better insights about how airlines manage their inventory, we reached out to the major U.S. airlines. We conducted semi-structured interview with two managers at a major U.S. airline, in charge of maintenance and supply chain operations. The interview was by telephone and lasted approximately one hour, during which we also tried to understand which niches constitute the low-hanging fruit for the introduction of AM in the aircraft spares market. We also conducted an hour-long in-person interview with a purchasing manager at a major European maintenance repair and overhaul firm. We cross-validated the information provided by the firms with an interview with an FAA official, who explained to us some of the regulatory restrictions which might arise when trying to introduce AM. That interview also lasted one hour and was conducted on the phone. They explained that there is a lot of variance in the lead time of components, depending on their criticality and the age of the aircraft (Supply Chain Manager, 2017). For instance, it may be easier to quickly obtain components for out-of-production aircraft and engines than for currently-produced aircraft. For in-production aircraft, most components are channeled to build new aircraft to clear the order backlog. This reduces the availability of spare parts for in-production aircraft. Lead times can be long: for non-critical components such as aircraft interiors, lead times are highly uncertain and may sometimes be as long as 45 or even 60 days (that is, 7-10 weeks).

In commercial aviation, replacement parts must often be supplied and installed while an aircraft is at the gate between consecutive flights. Using the FAA's data on flight arrivals and departures, we find that aircraft on U.S. domestic service spend a median of 63 minutes at the gate, and 70% of the flights stay 100 minutes or less at the airport (Figure 2). Therefore, we assume that the time it would take to produce and deliver a bracket in response to customer demand at another location is much longer than the lead time demanded by customers.

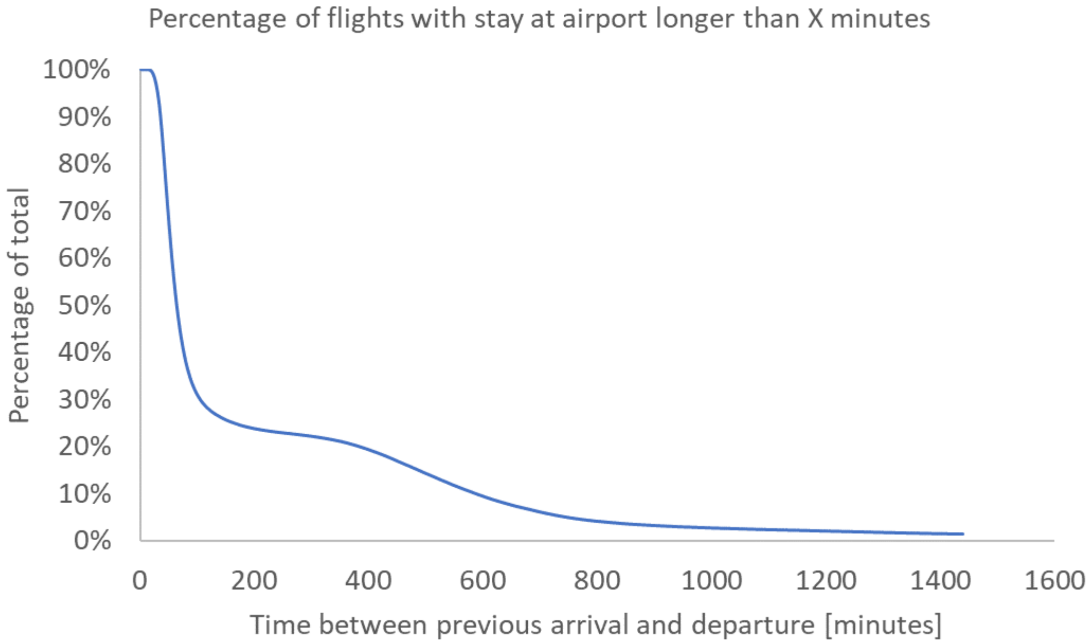


Figure 2: Percentage of flights which stay at the airport longer than a certain time. 70% of the flights stay 100 minutes or less at the airport, which is less than the time required to manufacture a component.

We assume that brackets are produced to demand at airports where manufacturing takes place ($y_i = 1$) and that the stock held at such airports is zero. Similarly, we assume that where there are no manufacturing facilities ($y_i = 0$), demand must be supplied from stock. To calculate the cost of carrying this stock, we estimate its level. The average number of brackets that must be held in stock at any airport is a function of the demand at that airport, the lead time, and the re-order policies (which in turn may be determined by minimum order quantities). Since the lead time and demand are both variable and uncertain, demand cannot always be met, and the average level of stock also depends on the service level (Eppen and Martin, 1988). While these data can be inferred from historical demand and purchases, doing so is doubly difficult in this case. One, the product we are analyzing is new: there are no historical data. Two, the demand for brackets is likely to change as aircraft age: the time series would be non-stationary. As such, we approach the problem parametrically (Van

Landeghem and Vanmaele, 2002). We assume that the amount of safety stock needed at those airports is proportional to the annual demand of components at each airport d_j, and that each airport carries a certain number of weeks (w) of inventory. We treat w as a parameter, and we vary it from one (1) to 20, although such variations do not affect our final conclusions, given that inventory costs are at least an order of magnitude lower than production and transportation costs. The annual cost of carrying inventory is the average stock level, multiplied by the price of the bracket p, and a factor r which encompasses overhead, damage and amortization costs.

$$C_s = \sum_j \left[d_j * \frac{w}{52}\right] p * r \tag{8}$$

We assumed a typical 25% profit margin in the aftermarket (Gallagher, 2005), which yields a price of approximately \$1,300 for the bracket in the scenario A, and \$700 for scenario B, and \$650 for scenario C. We used r = 25% for the capital costs of inventory (de Decker, 1998).

4 Results

Table 2 shows the number of manufacturing locations for each scenario and production volume. Table 2 shows the value of each of the cost components in the supply chain model, for each of the cases.

Table 2: Number of manufacturing locations for each scenario and production volume. The number of locations does not significantly change even taking into account potential improvements in MAM technology.

Parts/year	100	1,000	10,000	25,000	50,000	100,000
Baseline	1	1	1	4	14	26
20x build rate; no rejects	1	1	1	3	14	24
20x build rate + 1/10th machine cost; no rejects	1	1	1	4	14	27

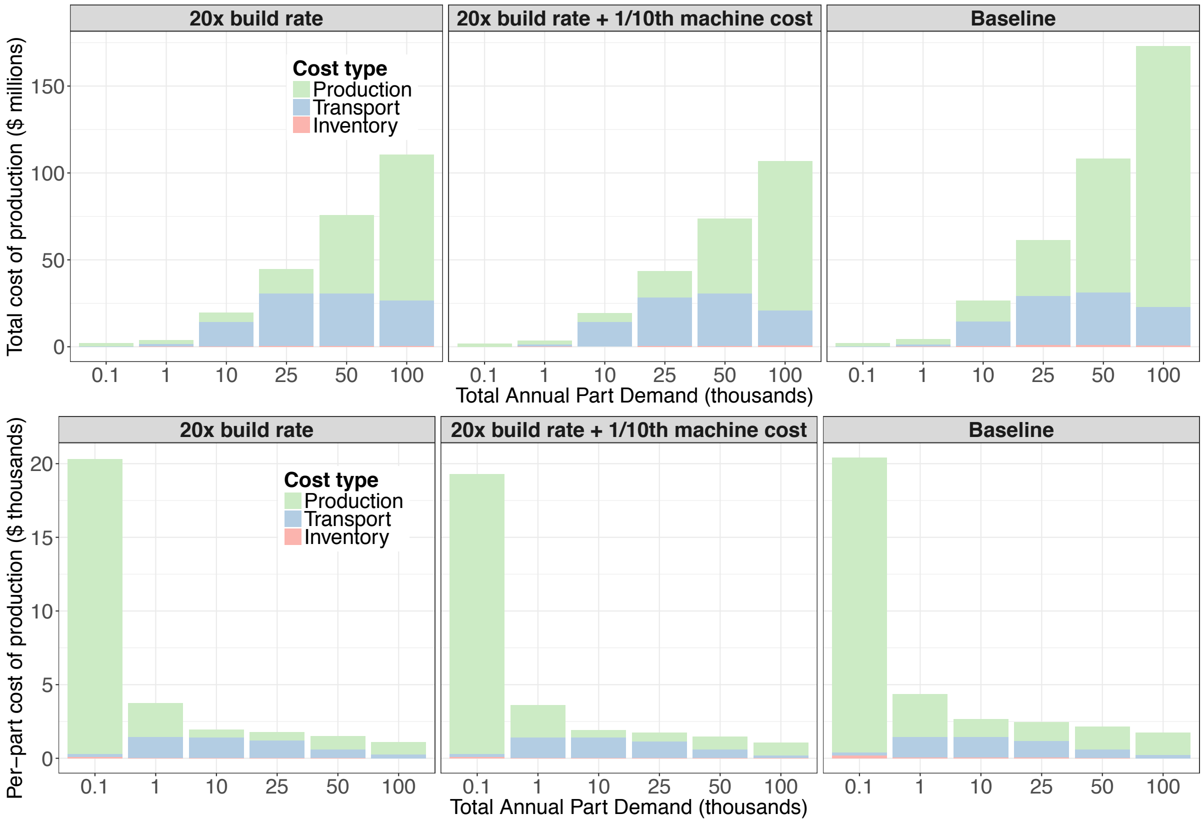
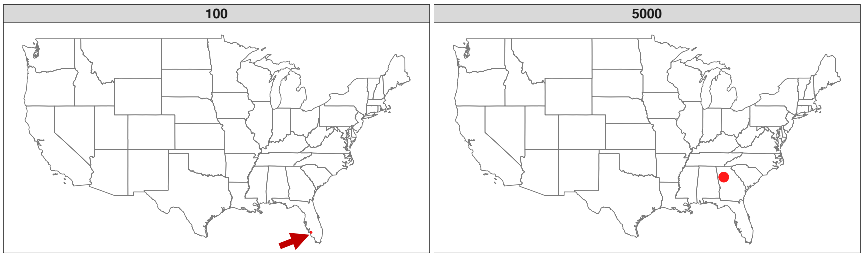


Figure 3: Components of (top) total cost and (bottom) cost per part for the optimal solution obtained using our mixed integer linear program. Note that per-product transport costs start to drop for volumes greater than 10,000 parts, as the optimal solution involves setting up multiple factories, which raises production costs but lowers transport costs.

We can also analyze how the chosen location varies as demand increases (Table 3). At low production volumes, the chosen regions are the those with the lowest production costs. As demand increases, the optimal location of the factory moves to the airports with the highest demand.

Table 3 Relationship between location and demand: as production volumes increase, optimal manufacturing location moves from the one with the lowest production cost to others with higher demand and greater proximity to other airports



Annual Production Volume	100	5000
Chosen Airport	Southwest Florida (RSW)	Atlanta (ATL)
Fixed cost [$M]	1.91	2.01
Marginal cost [$]	968	965
Share of demand [%]	0.61	7.31

To better understand the tradeoffs between production, transportation, and inventory costs, we decided to run additional cases at the frontier between one (1) and two (2) manufacturing locations (Table 4). This frontier is located between 18,000 and 19,000 components per year. We introduce a new constraint in the optimization model ($\sum_i y_i = \{1\}$) to force the total number of manufacturing locations, so that we can analyze the differences in cost between the optimal solution and a suboptimal solution with only one factory. We find that, to open a second factory, the savings in transportation and inventory costs need to add up to slightly more than $2 million, which corresponds to the "fixed costs" in the production cost functions shown in Figure 7.

Table 4 Components of total cost for optimal and forced solutions at a volume of ~18000 parts per year. We see that at ~19000 parts, the additional production costs associated with setting up and maintaining two factories are offset by the lower costs associated with eliminating the need to carry inventory at the second location.

Production volume (D)	**18,000**	**19,000**	**19,000**
No. of factories	1	1	2
Type of solution	Optimal	Forced	Optimal
Production [$M]	19	20	22
Transportation [$M]	25	26	24
Inventory [$M]	1.1	1.1	1.0
Total	**45.4**	**47.9**	**47.8**

We note that, at an annual production volume of 18000 parts, increasing transport costs from $1500 to $1550 per part changes the optimal solution from one to two factories. Figure 4 shows that a two-factory solution is viable at an annual volume of 10000 if transportation costs are assumed to be $3000. While we have assumed a constant transport cost, it is not difficult to imagine situations (e.g., remote airports) where such costs might be much higher. Our model can easily be modified to account for this fact by assigning different transport costs to different route pairs.

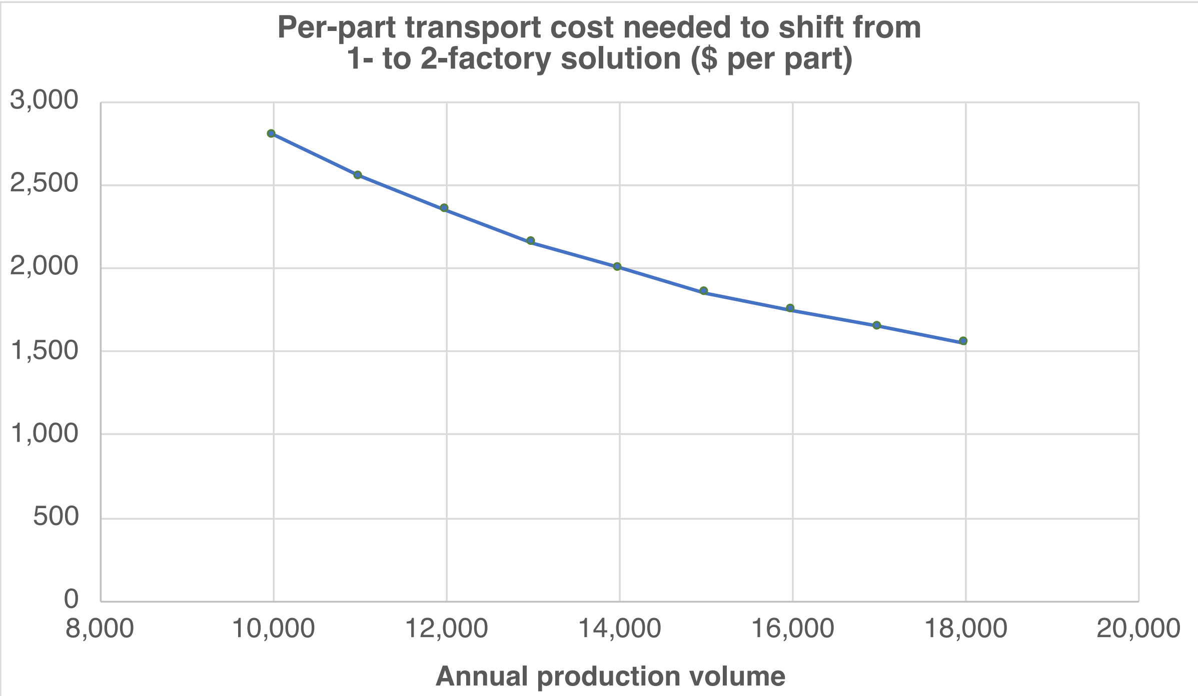


Figure 4: Transport costs needed to shift the optimal solution from one to two factories at different production volumes. A doubling of the assumed transport cost (to $3000) would make a two-factory solution viable at an annual volume of 10,000 parts.

It is possible that a firm may wish to have at least two supplying locations to make the supply chain robust. Our model allows us to estimate the cost of achieving this resilience (Figure 5).

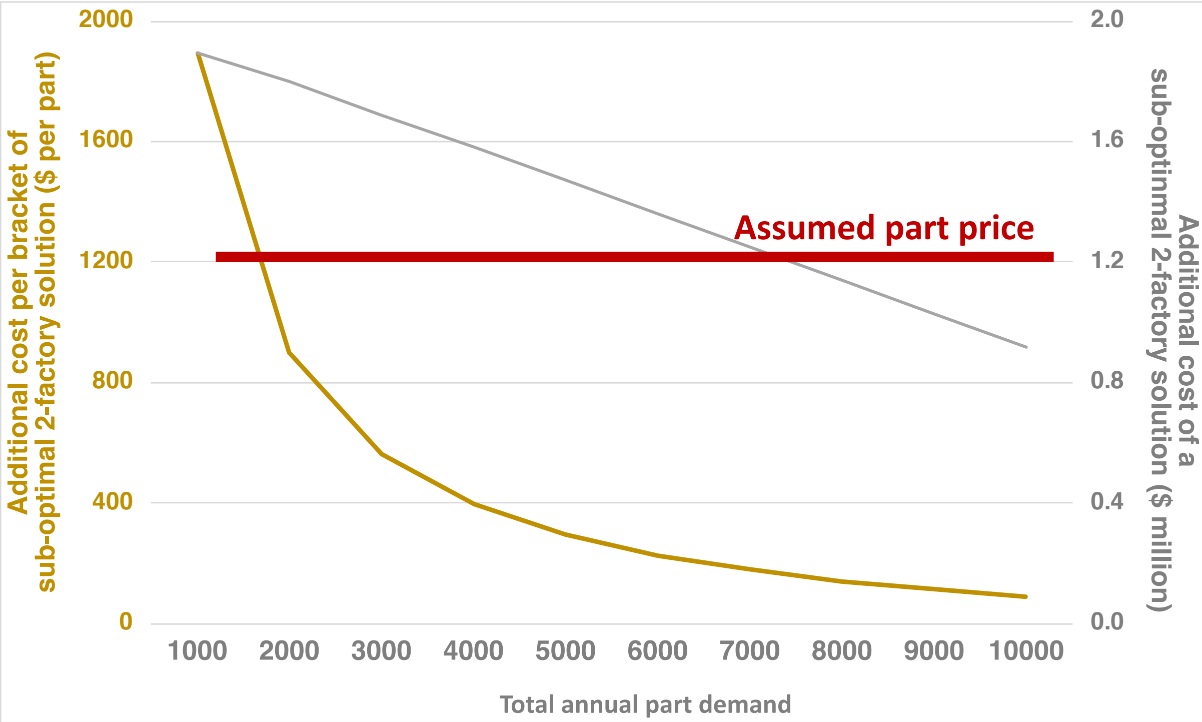


Figure 5: Additional cost per bracket (primary y axis on the left) and total additional cost (secondary axis on the right) of forcing a sub-optimal, two-factory solution.

For low volumes of total annual demand, this cost is $2 million in total and exceeds per part the price at which the part can be sold. The per-part premium falls rapidly as economies of scale start to apply, and the proportion of transport costs in the one-factory optimal solution starts to increase.

5 Discussion

From our results, we can extract two conclusions. First, that decentralization may only happen at volumes of tens of thousands of components per year or more. This suggests that the ideal situation of having low-volume, distributed production might not be economically optimal. Our analysis tries to show a 'best scenario for decentralization', and therefore the case for centralized production is likely stronger in real life cases. For instance, transportation costs could be lower when shipping over shorter distances, and we did not consider a case where several brackets could be shipped at the same time, which would substantially reduce the shipping cost. In addition, we did not consider the costs and the uncertainty surrounding the certification process of a new manufacturing facility, although it may be possible—in the future—to virtually certify individual parts by comparing their "digital twin" to the digital twins of a family of parts that are known to meet specifications (Knapp et al., 2017). Finally, we have not considered any constraints on the availability of skilled labor at certain locations, or the location of quality control equipment tailored to detect the defects which are unique to additively-manufactured parts.

Our second conclusion is that, under our assumptions, even significant improvements in the technology will not affect the optimal supply chain configuration. This contrasts with previous results, in the field of polymers, which suggested that the evolution of the technology could provoke a change in the most cost-effective supply chain configurations (e.g. Khajavi et al., 2014). We analyze the structure of the production costs to better understand why the optimal choice does not change.

To explain this observation, Figure 6 shows a comparison of the structure of the production cost of each bracket, between scenarios A and B. As technology evolves, machine costs represent a lower portion of the total costs because machines are faster and more reliable, and therefore fewer machines are needed to achieve the same production volume. If a single machine at one location can produce enough to meet demand at multiple locations, this increase in capacity weakens the case for having multiple locations. Among all the input prices, labor represents the most important one and becomes almost as expensive as the equipment. This could suggest that, as technology evolves, production might move to regions with lower wages, in line with traditional life cycle theory (Krugman, 1979; Vernon, 1966). It also suggests that designing machines that either do not require skilled labor to operate, or which can be operated remotely, would promote distributed manufacturing. This belies the hope that distributed manufacturing will generate local employment.

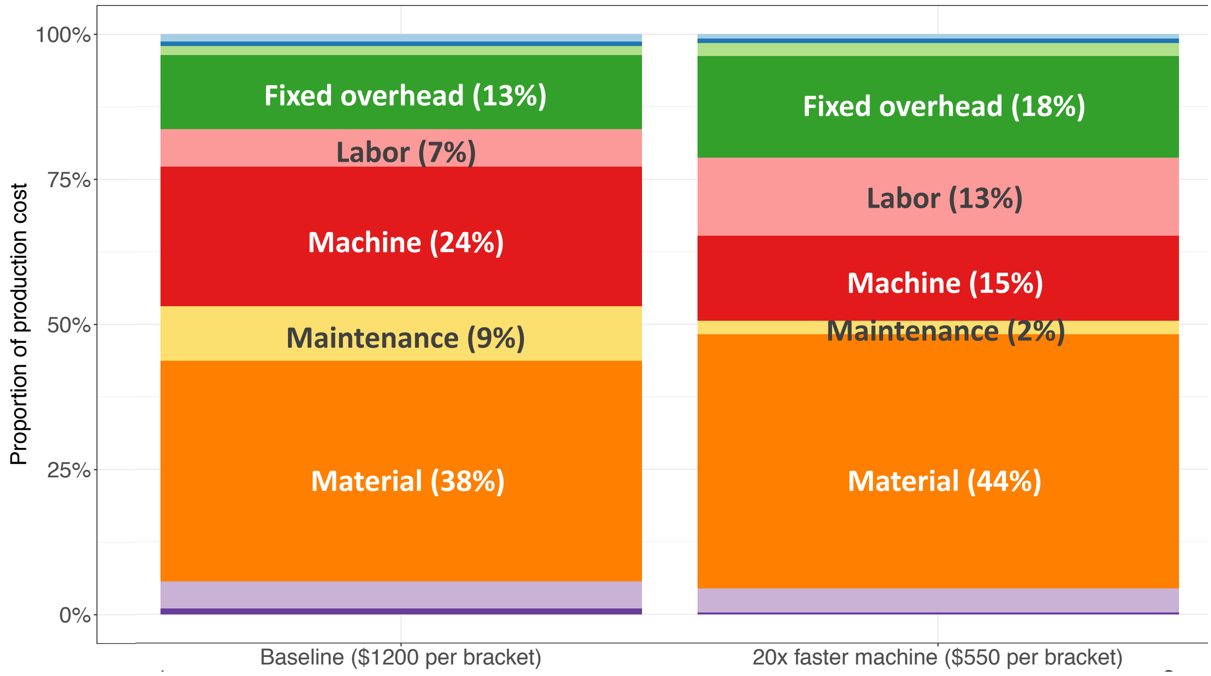


Figure 6 Comparison between the cost components for each bracket in scenarios A and B, assuming an annual production volume of 10,000 units, and a manufacturing location close the airport of Phoenix, AZ.

The PBCM makes it apparent that the economies of scale associated with the production of the bracket stem from post-processing, and in particular hot isostatic pressing. Figure 7 shows that the cost of producing brackets is dominated by the fixed cost (>$2 million), while the marginal cost of production is fairly small ($1000). Even large improvements in the cost and performance of additive manufacturing equipment do not substantially reduce the fixed costs associated with the bracket. We note that this result reflects a characteristic of the metal AM production process: the economics of other methods of manufacturing such as forging or CNC machining are unlikely to be immune to such a large change in the cost of the equipment, since they do not require such expensive post-processing. Eliminating hot-isostatic pressing and other post-processing steps dramatically reduces the fixed costs of production.

This observation also has consequences for the generalizability of our results. Our analysis is based on the design for our exemplar part - an engine bracket. Other parts may be smaller (or larger) or take a longer (shorter) time to manufacture due to greater (lesser) geometric complexity. However, so long as the parts are manufactured on the same equipment, and undergo post-processing on the same equipment, this will only change the marginal cost of producing them (i.e., the slopes of the lines in Figure 7), but not the fixed cost. For moderate volumes, this means that the total cost of manufacturing a part is driven largely by the cost of the equipment needed to manufacture it, and not by minor differences in the part's geometric characteristics. Since our model determines the optimal number of locations based on total cost, this suggests that we would obtain similar results for a range of different parts, so long as they were manufactured on similar equipment.

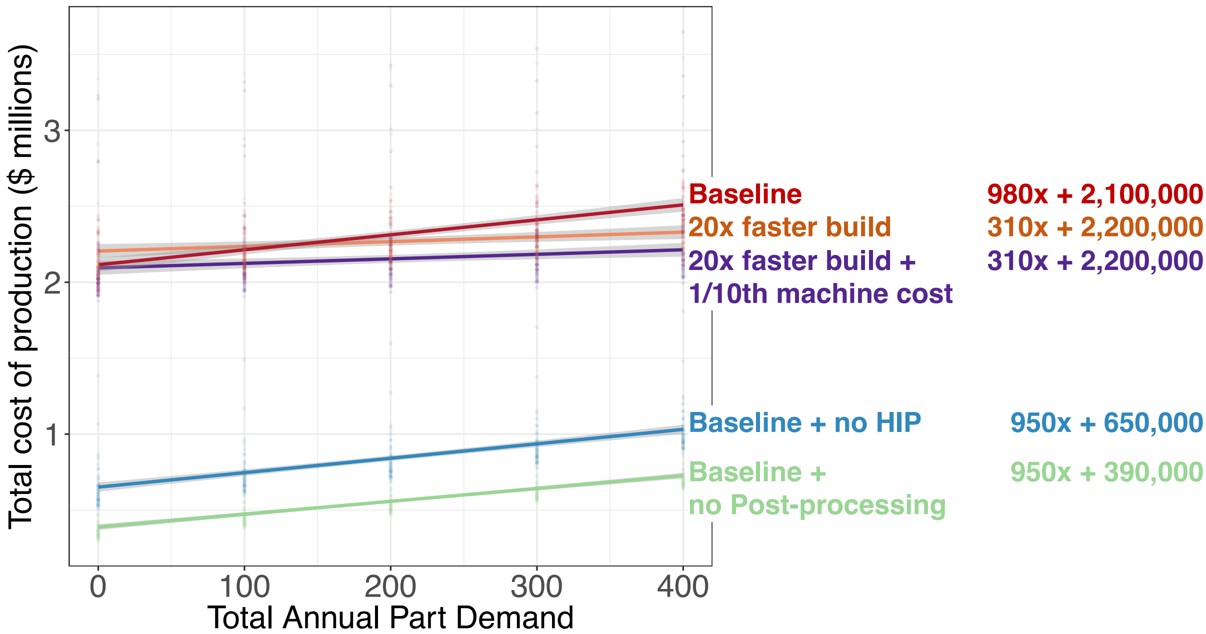


Figure 7: Total cost of production (y axis, in $ million) a given volume of parts (x axis).

For instance, at a production volume of 10,000 units, the cost of the HIP steps was still $149 per bracket, or about 12% of the unit cost, but at a production volume of 100,000 units per year, that cost was down to $35 per bracket, or about 3% of the unit cost. Hence, the economies of scale associated with the post-processing equipment is an important barrier to the decentralization of additive manufacturing. Centralized production would also help manufacturers to share their post-processing equipment with non-MAM components, reducing costs even further.

While MAM technology is relatively immature and has a lot of room for improvements in cost performance, most of the technology used for post-processing is mature and costs may not decrease substantially. The first vacuum induction furnaces date back to the 1920s, and nowadays are used in a wide variety of industrial applications (Mühlbauer, 2008). Hot Isostatic Pressing, which is the most expensive post-processing procedure, was invented in 1955 and fully developed as a production tool in the early 1970s (Hanes, 1979). Shot peening, a cold metal hardening process, was first demonstrated in 1927, and in the 1960s was already considered 'a controlled mechanical process' (Hawkinson, 1962). Current industrial trends to solve this issue fall into two categories. First, some manufacturers are trying to develop hybrid systems which combine additive and subtractive tools in the same machine (Flynn et al., 2016), which may eliminate the need for a separate machine to perform post-AM subtractive operations (e.g., milling or grinding down to achieve required tolerances or surface finish). However, hybrid systems do not perform heat and/or pressure treatments which might be needed to ensure the consistency in the mechanical properties of the component, especially fatigue resistance, so material and component choices might be limited (Flynn et al., 2016). Second, some manufacturers are trying to develop integrated systems where the entire production process happens, from beginning to end, including also heat treatments, inside the same machine (TCT, 2015). These integrated systems have the advantage of reducing labor costs and setup times, but also limit the possibility of sharing the post-processing equipment with other production lines. Further work would need to assess the exact tradeoffs taking place in such integration.

It is possible that AM processes will improve up to the point at which certain components can be used "green"; that is, without post-processing. Figure 8 shows that distributed production becomes the optimal choice at much lower levels of total annual demand if no post-processing is needed. It is also possible that the fixed cost associated with post-processing, especially hot isostatic pressing, may be eliminated by outsourcing these processes to nearby machine shops. Green parts could be sent to these shops for hot isostatic pressing and returned to airline maintenance facilities either for further processing or for sale.

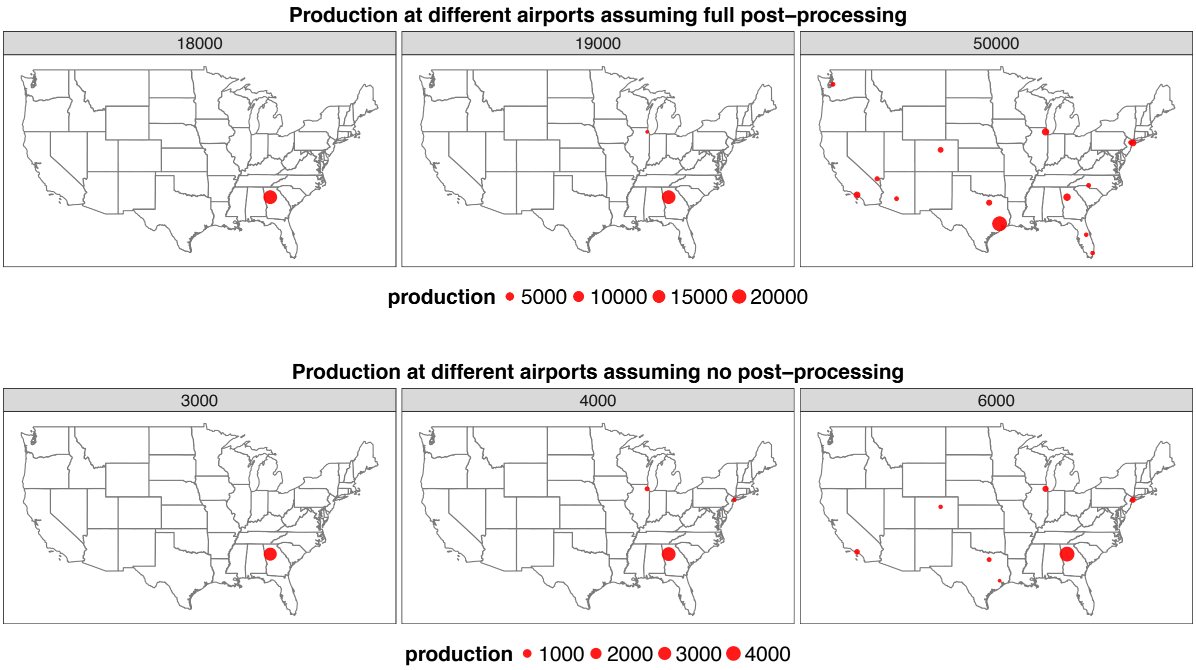


Figure 8: Locations selected for manufacturing as total annual demand increases, assuming (top) full post-processing, and (bottom) no post-processing. Distributed manufacturing is attractive at a much lower total annual demand if no post-processing is needed.

To probe the robustness of our results, we consider how changes in geometry might affect them. A change in geometry (e.g., component size) is likely to affect our results through a change in build times (Pradel et al., 2018). We compare the bracket we analyzed, and whose production characteristics are described in Laureijs et al (2017), to other aerospace components (Table 5). In addition to a number of brackets with dimensions similar to our example part, Huang et al. (2016) consider a seatbelt buckle, whose dimensions we then estimated. We also considered two aerospace components, (a hinge and a hook) whose dimensions were revealed to us in confidence by collaborators on another project. We then estimated the build times of these components using a formula that relates machine settings and part dimensions to build time.[5]

Table 5: Dimensions and build times for various parts. We note that the engine bracket we modeled has a relatively long build time, relative to the estimated build times of other components

	X	Y	Z	Build time
	mm	mm	mm	hours
Seat buckle	50	70	20	3.6
Bracket	170	89	60	19.2
Hinge	450	20	3	0.6
Hook	190	100	5	2.2

We then ran a scenario in our PBCM and optimization models, where there was no post processing and where build time was assumed to be four times as long as in the base case (i.e. 76 hours per part). This is an extreme test since a part large enough to take that long to manufacture would likely fill the build chamber of many metal AM machines and because such a long build time defeats the original goal of rapidly supplying parts in response to demand. We find that, with this longer build time, it is optimal to have multiple factories at a total annual volume of 3100 parts, compared to 3200 parts for the build time assumed in the baseline (i.e., 19 hours per part). This suggests that the optimal solution is insensitive to part geometry, and our results would likely apply to the types of parts described in Table 5. It also suggests that—if the need for post processing could be eliminated or reduced by a longer build time (e.g., by using lower power and lower speed)—both sides of that trade-off would favor distributed manufacturing. Table 5 also shows that the engine bracket we modeled has a relatively long build time and favors a distributed solution. This suggests that other components that might be good candidates for production via additive manufacturing

[5] We estimate build times using a heuristic formula given us by Luke Scime, a PhD student in Prof Jack Beuth's lab in the Mechanical Engineering Department at Carnegie Mellon University. It is estimated as
Build Time = (z-height / layer thickness) * [layer area/(hatch spacing * velocity) + layer spread speed]
We assume that layer thickness is 20 microns, (hatch-spacing*velocity) is 1165mm^2/second, and layer spread speed is 10seconds per layer. All other variables are derived from the dimensions shown in Table 5.

generally have shorter built times and the case for the distributed manufacturing for such components might be somewhat—but not substantially—weaker than for our canonical example.

While the analysis in this paper is based on an airplane component, Section 5 outlines a series of sensitivity analyses that show how our results might be translated to other components and industries. Table 6 summarizes how these sensitivity analyses allow our results to be applied in other contexts.

Table 6: Summary of how changes to different parameters in our case study would modify the results of the analysis

Dimension of generalization	Discussion about the effect on the results
Different components	While we run a process-based cost model that was originally developed for an engine bracket, we note that the principal way in which the geometry of the part is reflected in the model is through build time and the mass of material used. Changing the build time would change the number of AM machines needed, and the marginal cost of producing each component. However, at any one location, adding an AM machine might cost a few hundred thousand dollars, whereas adding a new production location and therefore a new HIP-ing machine might cost a few million. So long as hot isostatic pressing is needed, the total cost is dominated by the cost of the equipment needed for it; so, there are strong economies of scale, regardless of the size and nature of the component
Material and material cost	Materials are an important driver of marginal cost of production. However, the total cost—which determines the optimal supply chain configuration—is driven by the fixed costs of equipment. As such, a different material would not dramatically alter our conclusions.
Stringency of quality requirements and regulatory stance	Our results generalize to regulatory environments where no direct oversight of the manufacturing facility is needed by the regulator, and the same equipment can be shared across different applications We also demonstrate the consequences of changes in quality requirements: if parts can be used "green" (i.e., without HIP-ping), then the economics of distributed manufacturing are more attractive. We show that if HIP-ping were not needed, it would be easier to justify distributed manufacturing.
Improvements in machine technology / cost-effectiveness	We model potential improvements in machine performance (Scenario 2), and a substantial decrease of machine costs (Scenario 3). Our results suggest that performance improvements have a smaller effect than reduction in capital requirements, and that the solution of the problem is dominated by the costs of post-processing equipment, which are already mature and not expected to fall substantially.
Motivation and context for distributed manufacturing	Our paper studies the case of distributed manufacturing for aircraft repair, where the motivation for rapid repairs in scattered locations is obvious. However, other industries also recognize the benefits of distributed manufacturing. For example, an automobile model or family of models may stay in production for a few years but stay in service for decades and need to be serviced or repaired in a much more widely dispersed set of locations than aircraft need to be. One way of providing service is to accept the need to carry an enormous parts inventory. However, many auto firms now see the benefit of eliminating much of this inventory and relying instead on additive manufacturing.

Our work has important implications for policymakers. Currently, countries around the world are investing hundreds of millions of taxpayers' dollars in the development of national capabilities in additive manufacturing, with the objective of bringing production closer to the customer and creating local jobs (European Commission, 2014). However, our results suggest that such regionalization may not occur in industries where volumes are low, and/or where products have stringent specifications. Therefore, governments should analyze the potential of MAM in those industrial sectors where they actually hold a comparative advantage or focus on non-critical consumer products which may indeed benefit from the emergence of low-cost machinery.

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Appendices

Appendix A: Selected airports

Table 7 Airports considered in our analysis. Number of enplaned passengers from Bureau of Transportation Statistics

Airport	IATA 3-Letter Code	2016 Total Enplaned Passengers	Share of Demand
Hartsfield-Jackson Atlanta International	ATL	46,738,828	7.31%
Los Angeles International	LAX	36,739,546	5.75%
Chicago O'Hare International	ORD	34,807,000	5.44%
Dallas/Fort Worth International	DFW	28,892,344	4.52%
John F. Kennedy International	JFK	26,763,037	4.19%
Denver International	DEN	26,282,242	4.11%
San Francisco International	SFO	23,689,957	3.71%
McCarran International	LAS	21,245,433	3.32%
Seattle/Tacoma International	SEA	20,180,429	3.16%
Charlotte Douglas International	CLT	20,003,812	3.13%
Phoenix Sky Harbor International	PHX	19,558,474	3.06%
Miami International	MIA	19,056,337	2.98%
Orlando International	MCO	18,641,627	2.92%
George Bush Intercontinental/Houston	IAH	18,402,879	2.88%
Newark Liberty International	EWR	18,189,705	2.84%
Minneapolis-St Paul International	MSP	16,827,248	2.63%
Logan International	BOS	16,384,706	2.56%
Detroit Metro Wayne County	DTW	15,565,642	2.43%
LaGuardia	LGA	13,559,959	2.12%
Philadelphia International	PHL	13,534,364	2.12%
Fort Lauderdale-Hollywood International	FLL	13,002,486	2.03%
Baltimore/Washington International Thurgood Marshall	BWI	11,543,328	1.81%
Ronald Reagan Washington National	DCA	10,571,032	1.65%
Chicago Midway International	MDW	10,432,344	1.63%
Salt Lake City International	SLC	10,285,694	1.61%
Washington Dulles International	IAD	9,749,989	1.52%
San Diego International	SAN	9,639,689	1.51%
Tampa International	TPA	8,522,772	1.33%
Portland International	PDX	8,343,693	1.30%
Dallas Love Field	DAL	7,223,271	1.13%
Lambert-St. Louis International	STL	6,419,698	1.00%
Nashville International	BNA	6,000,123	0.94%
William P Hobby	HOU	5,929,329	0.93%
Austin - Bergstrom International	AUS	5,712,783	0.89%
Metropolitan Oakland International	OAK	5,560,309	0.87%

Louis Armstrong New Orleans International	MSY	5,219,411	0.82%
Kansas City International	MCI	5,086,194	0.80%
Raleigh-Durham International	RDU	4,975,665	0.78%
Norman Y. Mineta San Jose International	SJC	4,918,935	0.77%
John Wayne Airport-Orange County	SNA	4,843,051	0.76%
Sacramento International	SMF	4,631,116	0.72%
Indianapolis International	IND	3,938,248	0.62%
San Antonio International	SAT	3,908,897	0.61%
Southwest Florida International	RSW	3,890,676	0.61%
Cleveland-Hopkins International	CLE	3,800,535	0.59%
Pittsburgh International	PIT	3,707,037	0.58%
Port Columbus International	CMH	3,320,485	0.52%
General Mitchell International	MKE	3,144,797	0.49%

Appendix B: Input data used in the PBCM

Table 8 Data used to obtain a correlation between the House Price Index and land prices.

State	City	Housing Price Index	Median list price from Zillow [$/sq ft]
Alabama	Montgomery	244.45	67
Arizona	Phoenix	567.53	153
Arkansas	Little Rock	416.31	100
California	Sacramento	800.97	206
Colorado	Denver	1083.75	346
Connecticut	Hartford	494.76	95
Delaware	Dover	266.61	106
Florida	Tallahassee	437.35	119
Georgia	Atlanta	551.35	229
Idaho	Boise	562.37	158
Indiana	Indianapolis	395.29	84
Iowa	Des Moines	422.99	115
Kansas	Topeka	327.85	80
Kentucky	Frankfort	222.65	103
Louisiana	Baton Rouge	425.52	130
Maine	Augusta	212.51	93
Maryland	Annapolis	687.43	261
Massachusetts	Boston	1039.82	650
Minnesota	Saint Paul	524.98	181
Mississippi	Jackson	291.84	72
Missouri	Jefferson City	264.4	96
Montana	Helena	520.52	153

Nebraska	Lincoln	436.59	150
New Hampshire	Concord	335.78	145
New Jersey	Trenton	625.11	47
New Mexico	Santa Fe	683.82	234
New York	Albany	477.32	114
North Carolina	Raleigh	521.72	144
Ohio	Columbus	432.79	104
Oklahoma	Oklahoma City	439.06	100
Oregon	Salem	651.16	155
Pennsylvania	Harrisburg	407.26	44
Rhode Island	Providence	620.13	165
South Carolina	Columbia	385.14	84
Tennessee	Nashville	686.04	184
Texas	Austin	815.76	216
Utah	Salt Lake City	698.96	268
Washington	Olympia	652.52	163
Wisconsin	Madison	584.15	179
Wyoming	Cheyenne	572.68	160
Quadratic estimator: Land price = $0.0006x^2 - 0.266x + 122.13$ $R^2 = 0.7166$			

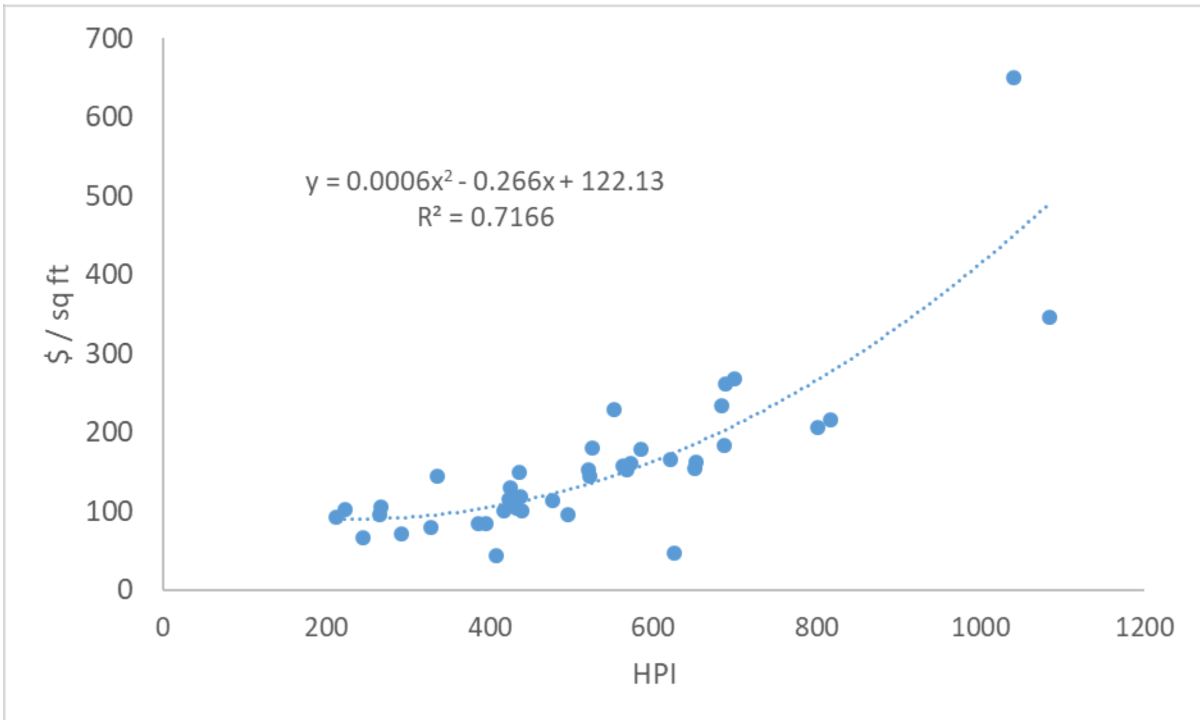

Table 9 Input prices used in the PBCM

	Inputs		
Airport(s)	Electricity Price [c$/kWh]	Wages [$/h]	Land Price [$/m2]
PHX	6.26	35.13	1,770
SFO	12.17	66.55	15,170
OAK	12.17	45.13	11,320
SJC	12.17	92.95	17,490
SMF	12.17	32.10	3,160
LAX	12.17	32.18	7,720
SNA	12.17	34.95	7,470
SAN	12.17	39.45	5,740
DEN	7.4	26.93	5,800
TPA	8.22	26.80	1,610
RSW	8.22	23.33	1,300
MCO	8.22	32.65	1,780
MIA	8.22	24.43	2,450
FLL	8.22	26.30	1,320
ATL	5.87	31.15	1,000
ORD, MDW	6.67	31.25	1,480
IND	6.86	37.25	1,190
MSY	5.41	32.18	1,990
BWI	8.53	52.35	2,400
BOS	13.54	39.38	5,320
DTW	7.02	34.25	1,190
MSP	7.02	35.60	1,930
MCI	6.44	25.80	1,160
STL	6.44	25.88	1,420
LAS	6.75	25.95	1,380
EWR	10.64	28.20	3,630
JFK, LGA	6.31	24.03	5,040
CLT	6.51	33.13	1,650
RDU	6.51	54.23	1,580
CMH	7.02	28.30	1,290
CLE	7.02	29.28	1,070
PDX	5.97	26.38	5,950
PIT	7.2	30.60	1,350
PHL	7.2	38.75	1,490
BNA	6.17	28.35	2,390
SAT	5.59	27.50	1,320
AUS	5.59	45.48	3,280
DFW	5.59	36.40	1,330
DAL	5.59	36.80	1,460
IAH,HOU	5.59	29.10	1,410
SLC	6.17	29.90	2,470
IAD	6.95	45.83	1,950

DCA	6.95	28.68	3,240
SEA	4.35	40.38	7,400
MKE	7.58	31.70	1,240

Appendix C: Output of the PBCM, used as an input for the optimization algorithm

Table 10 Parameters obtained after the linearization of the production cost curves

	LinearizedCostCurve ScenarioA		LinearizedCostCurve ScenarioB		LinearizedCostCurve ScenarioC	
Airport(s)	Constant[$]	Slope[$/unit]	Constant[$]	Slope[$/unit]	Constant[$]	Slope[$/ unit]
PHX	2,080,472	972	2,168,635	308	2,057,658	295
SFO	2,791,424	1,075	2,909,221	330	2,798,244	317
OAK	2,414,361	1,043	2,517,753	323	2,406,777	311
SJC	3,206,847	1,104	3,339,727	337	3,228,750	324
SMF	2,066,740	995	2,154,962	317	2,043,986	304
LAX	2,160,432	1,017	2,253,709	319	2,142,732	306
SNA	2,194,005	1,018	2,288,321	319	2,177,344	307
SAN	2,221,557	1,013	2,316,100	320	2,205,124	307
DEN	2,048,056	989	2,136,758	309	2,025,781	297
TPA	1,961,197	972	2,045,223	309	1,934,246	296
RSW	1,906,410	968	1,988,445	308	1,877,469	295
MCO	2,046,095	977	2,133,076	310	2,022,099	298
MIA	1,945,025	974	2,028,842	309	1,917,866	296
FLL	1,948,342	970	2,031,812	309	1,920,835	296
ATL	2,009,346	965	2,094,776	306	1,983,799	293
ORD,MDW	2,020,472	969	2,106,470	308	1,995,494	295
IND	2,098,361	973	2,186,892	309	2,075,915	296
MSY	2,043,871	968	2,130,887	306	2,019,910	293
BWI	2,333,518	994	2,430,529	316	2,319,553	303
BOS	2,212,074	1,015	2,306,115	322	2,195,138	309
DTW	2,056,535	971	2,143,641	309	2,032,665	296
MSP	2,090,409	976	2,178,971	309	2,067,994	297
MCI	1,938,018	964	2,021,083	306	1,910,107	293
STL	1,944,317	965	2,027,703	306	1,916,726	293
LAS	1,944,645	966	2,028,025	306	1,917,048	294
EWR	2,021,890	990	2,108,792	314	1,997,815	301
JFK,LGA	1,992,289	980	2,078,794	307	1,967,817	294
CLT	2,050,094	971	2,137,172	308	2,026,196	295
RDU	2,342,967	985	2,439,979	313	2,329,003	300
CMH	1,975,436	968	2,059,822	307	1,948,845	295
CLE	1,984,714	967	2,069,328	308	1,958,351	295
PDX	2,043,508	985	2,132,129	307	2,021,153	294
PIT	2,008,819	970	2,094,365	308	1,983,388	295
PHL	2,125,277	976	2,214,841	310	2,103,865	297
BNA	1,998,598	970	2,084,231	306	1,973,254	294
SAT	1,965,046	963	2,049,104	305	1,938,128	292
AUS	2,255,466	984	2,350,205	310	2,239,229	297
DFW	2,089,330	969	2,177,619	307	2,066,643	294
DAL	2,097,527	970	2,186,149	307	2,075,172	294

IAH,HOU	1,989,215	964	2,074,133	305	1,963,157	293
SLC	2,021,814	972	2,108,269	307	1,997,292	294
IAD	2,233,420	982	2,326,856	312	2,215,880	299
DCA	2,020,356	977	2,107,069	308	1,996,093	295
SEA	2,268,243	996	2,365,116	309	2,254,140	296
MKE	2,022,043	972	2,107,993	309	1,997,017	296