Automatic cost estimation of aerospace composites components based on retrieved knowledge from historic process data

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The growing interest in composites structures triggered a development in composites manufacturing technologies and methods up to the present day, whose momentum is certain to be carried into the future. Particularly, in the aerospace industry, composites have become the predominantly used material given its many advantages over traditional metallic materials. However, because of the sector´s economic competitiveness, manufacturers have to better deal with cost requirements.

This research describes the capture and reuse of rich historic process data, over multiple aircraft programs, to develop an approach capable of generating good cost estimations of new components in a preliminary design stage. The collected samples populate a series of tecno-economic relations, developed to estimate manufacturing process parameters and requirements, based on a set of components' geometric properties. In turn, these methods are integrated into a process-based cost model, that translates the generated process information into the final manufacturing cost assessment. Additionally, the traditional deterministic approach to cost modelling is replaced in favour of developed stochastic methods that inherit process uncertainties. By doing so, a broader view of expected costs is provided, which reflects existing process variabilities.

Results obtained in this approach indicate close agreement with the manufacturer cost assessments (MAPE=16.4%, NRMSE=5.1%), validating the applicability of the developed cost tool in estimating projects' manufacturing costs. Ultimately, the tool provides a solution to the lack of readily available cost assessments prior to process industrialization and may help designers to overcome the challenge of evaluating design and process decision consequences on final product cost.

Index Terms—**Composites, PBCM, Aeronautics, Cost Modelling**

1 INTRODUCTION

Since the 1990s [1] Carbon Fiber Reinforced Polymers (CFRP), have been gaining increased interest from aerospace manufacturers. The switch from predominately aluminium to predominantly composite structures enables lighter and more fatigue resistance components to be obtained, promoting reductions in aircraft fuel consumption and maintenance costs. With this growing appeal, improvements have been made not only in developing materials with better mechanical properties but also in the technologies and methods that process and shape these materials into working structures [1]. Reliability and consistency of composites manufacturing processes have historically been of key importance, as an efficient use of these expensive materials can single-handedly improve production returns and ensure the economic competitiveness of the manufacturer. In many regards, this has only become possible with the recent automation of layup processes such as Automated Tape Laying (ATL) and Automated Fibre Placement (AFP), that significantly increased the rate and consistency to which the material is placed when compared to the more traditional method of manual layup [2]. However, with newer and different technologies arises new technical challenges, to which engineers must adapt their designs (Design for Manufacturing), while at the same time trying to make conscious decisions in order to achieve management imposed cost targets (Design to Cost). Pressured by the economic competitiveness that must be achieved, a lot of effort is put into the early stages of product development since a major part of the program costs are decided during this phase [3] and, once production takes place, excessive manufacturing costs are often irreversible [4]. Therefore, it is of the utmost importance to provide tools that allow designers and cost engineers to perform meaningful, yet reasonably fast cost assessments during design and process iterations, in order to evaluate its economic viability, and ensure project profitability.

Many studies offer different approaches and solutions to the cost assessment problem [5], concluding that costs can be modelled and integrated into the engineering design process, becoming a key design variable. Within this study, we focus on developing multiple methods that capture a series of manufacturing cost drivers based on component geometric attributes, which are embedded into an existing process-based cost model (PBCM) [6]. The goal is to further improve its existing capabilities while at the same time addressing some of the limitations currently upheld by not only this but most of the current cost modelling techniques:

- The inability to perform accurate cost estimations at a conceptual design phase due to the limited data that is available [7].
- Time consuming and labour intensive tasks; A significant amount of data often needs to be manually imported and the knowledge and expertise to perform these calculations is typically not available to the designer, but rather to the cost engineers [8].
- Process uncertainty and variability, which is often disregarded from the cost estimation, despite its impact on overall manufacturing costs.

Ultimately, the goal of this work is to address these shortcomings, and provide an analytical tool that can help engineers to better understand - during the design process and early

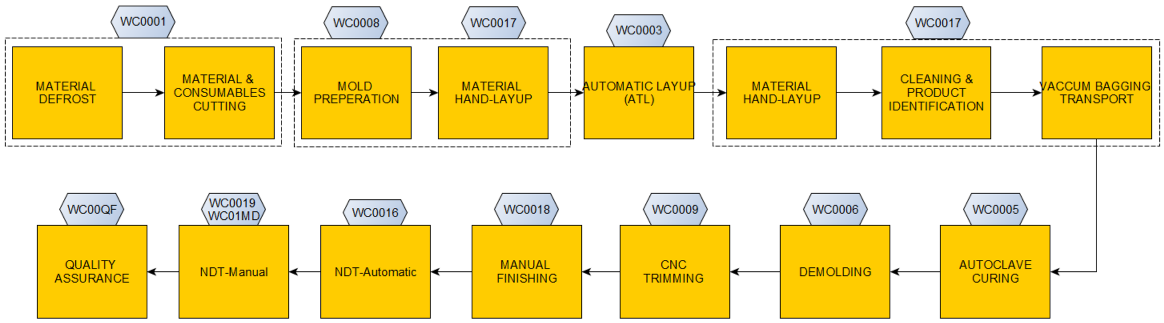


Fig. 1: Composite part manufacturing process flowchart.

stages of process industrialization - possible manufacturing costs, in order do weight on the economic viability of changes to the manufacturing process in a more streamlined way.

2 Data and Methods

Understanding the dynamics of the manufacturing processes allows for the underlining of the relevant cost origins, and ensures the correct development of suitable cost assessment methods that determine the final component cost. Typically, composite layup manufacturing processes (Fig. 1) start with the removal of the pre-impregnated composite fibers materials – hence the name prepreg – from the freezers where they are stored to avoid material deterioration.

After a 24-hour period of material stabilization at room temperature, the materials are cut by automated equipment into the required shape and sizes for the intended component. Afterwards, the mold is cleaned and prepared for the manual application of the previously cut materials along the appropriate orientations and positions. This initial deposition is followed by the vacuum bagging of the mold surface, in order to remove voids and consolidate the layers. Next, comes the automatic layup of material, that can be performed either by ATL or AFP, depending on the component's geometry. Planar surfaces are predominantly laminated using ATL while more complex and curved geometries require the improved deposition control and flexibility of AFP. Once this process is finished there is a minor manual layup of materials, the laminate is vacuum bagged, and taken into the autoclave where the prepreg materials are cured by undergoing a heat and pressure cycle. The part is then demolded and trimmed to its final shape using CNC equipment, followed by some light manual finishes to remove any residual burs. The last step of any process is non-destructive ultrasound testing (NDT), where the surface of the part is scanned and analysed to detect any non-conformity that could compromise its structural integrity, such as voids, wrinkles or delaminations.

Depending on the component, there could be additional operational blocks, where activities are performed in tandem to the main manufacturing flow. These parallel operations are typically associated with more complex manufacturing methods that feature reinforcements integration, such as stringers, trough co-curing processes. In turn, these processes require a wider range of supporting technologies, in particular Hot-Drape Forming (HDF), that preforms flat laminates into the initial U profiles which are later transformed into the final T shape stringer. HDF can also be used in the manufacturing of Spar structures, by preforming an initial flat stack of prepreg onto the Spar mold surface.

2.1 Data Collection

In this study, the collected data samples encompass 14 different components with varying manufacturing methods and technologies, that aggregate nearly seven-hundred successfully manufactured parts. Process data for this sample include:

- Cycle time samples, accounting for the time an operator takes between setup and finish of a single operation.
- Operational inefficiencies or non-conformities, divided into four different categories: Scrap, Repair, Rework, and Use as is, in decreasing order of severity.
- Components' material quantities and materials unit price.
- Acquisition costs of industrial equipment and manufacturing tools, such as molds, jigs, and fixtures, etc.

Process data has been directly extracted from the software database history of the manufacturer, and a summary of its contents are shown in Table 1. Regarding the collected samples, outliers resultant from incorrect measurements or software discrepancies were identified and filtered, based on empirical knowledge from both engineers and process operators.

Additionally, part data was also retrieved, taking into account the geometric characteristics of each component such as Area, Volume, Perimeter, Length, Width, etc.

Part complexity is known to have a significant impact on layup technologies efficiency and manufacturability [9], thus a set of complexity metrics were introduced and extracted from each part. To determine these complexity metrics, a MATLAB script was implemented that captures the information from the component's 2D sketches from two different views and assigns a complexity metric for part contour (C_{xy}), and overall curvature (C_{xz}). These metrics are defined using measures of Lempel-Ziv complexity and its value grows as the length of the sequence of information and its irregularity increases. In this case, the variations in angles between the countour normal and the horizontal reference of neighboring points[10]. In addition to the aforementioned complexities, a third metric

Table 1. Gathered process data summary table. (Absolute number of non-conformities (†) and parts produced has been omitted to respect confidentiality)

Aircraft	Part Description	Tag	Main Technologies	Amount Produced of Total Sample	Cycle Time Data Samples	Non-conformities Data Samples
A	Skin 1	P_1	ATL	21.6%	1688	†
A	Skin 2	P_2	ATL	21.1%	1648	†
A	Skin 3	P_3	ATL	23.3%	1664	†
A	Skin 4	P_4	ATL	22.2%	1653	†
B	Skin 1	P_5	ATL	0.7%	43	†
B	Skin 2	P_6	ATL	1.2%	52	†
B	Spar 1	P_7	AFP	3.6%	201	†
B	Spar 2	P_8	AFP	2.9%	130	†
C	Spar 1	P_9	ATL+AFP+HDF	1.0%	116	†
C	Spar 2	P_{10}	ATL+AFP+HDF	0.7%	100	†
C	Skin 1	P_{11}	ATL+HDF	0.4%	108	†
C	Skin 2	P_{12}	ATL+HDF	0.4%	78	†
C	Skin 3	P_{13}	ATL+AFP+HDF	0.4%	55	†
C	Skin 4	P_{14}	ATL+AFP+HDF	0.3%	53	†
Total				>680	7589	†

is introduced, taking into account part consolidation, such as stringers, defined as:

$$C_{int} = 1 + N_{sp}\frac{A_{sp}}{A_{pp}} \quad (1)$$

where N_{sp} represents the number of additional secondary parts to be integrated into the primary part, and A_{sp} and A_{pp} , the surface areas of the secondary and primary parts, respectively.

2.2 Modelling Cycle Time as Stochastic Variable

Composite manufacturing processes are highly automated in critical tasks such as material lay-up and trimming with computer numerical control (CNC) equipment, but there is still a significant contribution from manual sources of labour, as even these machines need some level of human interaction. While the automated processes themselves perform at reproducible speeds, operators do not, influencing operations cycle times and consequently final component cost. This assumption is clearly observed in the collected cycle time samples, which not only display considerable time variations between different parts and operations but also among similar parts performing the same type of operation. Consequently, this variability between identical parts has clear implications on its final costs, and reinforces the need to include its effects on the current cost modelling method.

One such way is by modelling each work center variabilities accordingly to an appropriate probability distribution. Triangular distributions were chosen to model these variations, given the simplicity in its architecture, and affinity for modelling historic data in a manufacturing setting. To build the distribution, a minimum value (a), a most likely value (c), and maximum value (b) are necessary. With the current sample size, close to 400 parameters where determined, representing the minimum and maximum cycle times of each component manufacturing steps. To minimize bias in the chosen parameters, the decision making was supported by the empirical knowledge of factory workers and engineers, for each individual process step and component. The most likely value is determined based on the minimum, maximum, and median of each work center samples, according to (2).

$$c = \begin{cases} \frac{b-2(b-m)^2}{b-a}, & \text{if } m < \frac{a+b}{2} \\ \frac{a+2(a-m)^2}{b-a}, & \text{otherwise} \end{cases} \quad (2)$$

Given all three parameters, it is then possible, through Equation 3, to compute each work center triangular inverse cumulative distribution function (INVCDF).

$$F^{-1}(u) = \begin{cases} a + \sqrt{(b-a)(c-a)}, & 0 < u < \frac{c-a}{b-a} \\ b - \sqrt{(b-a)(b-c)(1-u)}, & \frac{c-a}{b-a} < u < 1 \end{cases} \quad (3)$$

The INVCDF (3) enables the generation of synthetic cycle times within the gathered samples bounds, by randomly assigning a value u between [0,1], and thus replicate the historical patterns across the multiple work centers.

However, this process relies on the availability of process data, and thus, it would not be possible to generate cycle times for new components, falling outside of the current discrete points of information. It can be argued that a new component with a larger surface area should result in increased cycle times during the ATL layup process - but by how much? The hypothesis that, depending on the type of operation, there is one or multiple component properties that clearly influence cycle times deserves to be investigated.

The challenge lies in identifying the component properties that hold a stronger relationship with each process step cycle times. Ultimately, if the hypothesis is validated, it will enable the estimation of the triangular distribution parameters to model the new distributions. For that end, regression analysis was used, allowing for the identification of the geometric properties that demonstrated stronger statistical correlation with cycle times. The process of finding the set of component geometric properties that better describes each work center cycle time is done by generating 100 synthetic cycle times - from the initially determined distributions - for each component whose manufacturing tasks are performed in that respective work center. These generated cycle times form the dependent variables working set, while the independent variables are their respective properties namely: component's surface area in contact with the mold surface (A), perimeter (P), volume

(V), and complexity metrics (C_{XY}, C_{XZ}, and C_{INT}). Surface area, perimeter, and volume are studied both separately and in combinations of two, while the different complexities were paired in combinations with the latter. In total, the search is performed across 15 different models, for each work center within the studied industrial environment.

Table 2 summarizes the independent variables found to best describe the cycle times variations within each work center, for the current components sample. With this new found knowledge, a final set of linear regressions were built for each of the n-th work center, describing its distribution parameters - minimum (4) , most likely (6), and maximum values (5).

$$a^n = \alpha_0^n + \alpha_1^n x_1^n + \alpha_2^n x_2^n \tag{4}$$

$$b^n = \beta_0^n + \beta_1^n x_1^n + \beta_2^n x_2^n \tag{5}$$

$$c^n = \theta_0^n + \theta_1^n x_1^n + \theta_2^n x_2^n \tag{6}$$

Table 2. Work centers best describing geometric properties and fittings results. Pc=Pearson-Coefficient

Work Center (n)	Sample Size	Indep. Variables x_1^n	x_2^n	Goodness-of-fit Pc	R^2
WC0001	1400	V	C_X	0.43	0.18
WC0002	1100	A	C_{INT}	0.93	0.87
WC0003	600	A	C_{XZ}	0.74	0.55
WC0004	400	V	C_{XZ}	0.32	0.1
WC0008	900	A	V	0.72	0.53
WC0017	1400	A	C_{INT}	0.91	0.84
WC0006	900	V	C_{INT}	0.52	0.27
WC0009	1400	P	C_{INT}	0.83	0.69
WC0016	1400	A	C_{XY}	0.88	0.77
WC0018	1400	P	C_{INT}	0.9	0.82
WC0019	1400	P	C_{INT}	0.83	0.69
WC00QF	1400	P	C_{INT}	0.66	0.43
WC01MD	1000	V	C_{XY}	0.68	0.46
WC00QA	600	A	C_{XY}	0.97	0.94

By doing so, it enables the determination of cycle times distributions that inherit the process time variabilities, given the component geometric properties. A benefit of the approach of fitting the distribution parameters is to estimate the cycle times variability for new parts avoiding any manual input, based on human expertise. The approach allows to obtain an expected distribution of cycle times based only on the parts' geometric properties and complexity metrics, and on past variability of similar parts. From the estimated parameters, the INVCDF can be determined, and cycle times within a particular work center can be estimated for any desired component, as represented in Fig. 2.

2.3 Modelling Non-Conformities

As previously mentioned, there are four different types of non-conformities: Scrap, Repair, Rework, and Use as Is. From any activity performed across the different manufacturing steps, there is a chance for any of these to occur; some more likely than others.

Undoubtedly, non-conformities impact process performance, which leads to increased manufacturing costs and delays. Estimating their occurrences prior to process implementation would provide valuable insights into its possible cost impacts.

In probability theory, binomial distributions are categorized as discrete probability functions of a random variable X, and measure the number of successes (k) in a sequence of n independent experiments [11]. This could translate to the number of each type of non-conformity (X) to occur, in a sequence of n production runs (production volume). In short, binomial distributions can be used to answer the following question : Given the current efficacy $(1-p)$ of the activities completed in this step, how many non-conformities of each type will there be, for a certain amount of parts being produced (n)?.

For the intended purposes, the probability of success (p) of each non-conformity, at any given work center, needs to be known. These probabilities were determined as the ratios between the number of each non-conformities occurrences, and the total number of operations performed at each work center. Knowing the rate of success of each non-conformity, the binomial inverse cumulative distribution function (BINVCDF) can be used (7), enabling the determination of the minimum number of expected non-conformities to occur (k) of each type, for a given production volume (n). The confidence level (u) can be adjusted; Higher confidence levels translate into more occurrences, which lead to more conservative results.

$$u \leq \sum_{i=0}^{n} \frac{n!}{i!(n-1)!} p^i (1-p)^{n-i}, \quad \begin{array}{c} n \in \mathbb{N} \\ p \in [0,1] \\ u \in [0,1] \\ i=0,1,2,\ldots,k \end{array} \tag{7}$$

The resulting cost impacts for the number of estimated occurrences are accounted by the appropriate cost relations implemented in the cost model, described in the following sections.

2.4 Modelling Tooling Acquisition Costs and Material Quantities

Different components have different requirements in terms of tooling and materials used. So, in order to be able to estimate their cost, it is necessary to determine which tools and materials are going to be used and in what quantities.

Thus, following a similar approach as to what was done with cycle times, the available component's geometric properties were correlated with the tooling and materials data, in order to create regression models able to estimate tooling costs and materials quantities based on a new part's geometry.

Due to the heterogeneity between materials in the components sample, three different groups were created. Group 2 consists of spar type parts while Group 1 & 3 address similar types of components: standalone skins and co-cured stringer reinforced skins, respectively. The latter requires an additional material to be used that promotes the bonding between the two surfaces, but also displays different weightings in material types distribution, hence the separation of the two. For each material type inside each group, a simple linear regression was modelled, between the material quantities and the components' surface area, which demonstrated the best correlation results, among all the available properties (Table 3).

Tooling cost estimates follow a similar approach, by fitting its acquisition costs with the components' surface area

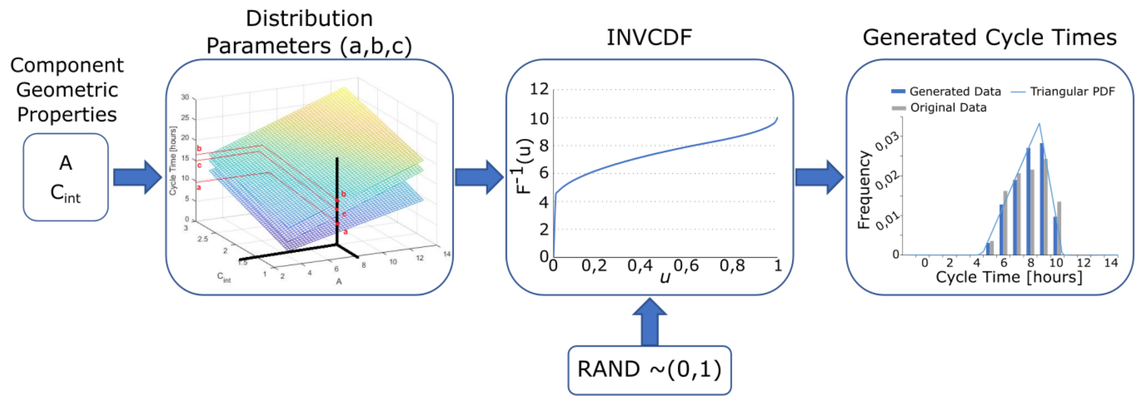


Fig. 2: Manufacturing steps cycle time generation scheme.

Table 3. Material quantities regression coefficients and goodness-of-fit summary. A=Unidirectional Carbon Fiber Prepreg Tape; B=Carbon Fiber Prepreg; C=Glass Fiber Prepreg; D= Copper Mesh; E=Epoxy Resin Film

Group	Material	β_0	β_1	Goodness Pc	of fit R^2	p-value
1	A	-60,78	36,45	0,99	0,98	0,0002
	B	-13,93	3,90	0,99	0,98	0,0001
	C	20,18	-1,21	0,91	0,83	0,0112
	D	5,66	0,31	0,34	0,11	0,5160
2	A	-8,88	37,54	0,74	0,55	0,0365
	B	1,16	1,93	0,90	0,82	0,0020
	C	1,53	0,41	0,12	0,01	0,7795
3	A	-22,48	24,04	0,99	0,98	0,0001
	B	-4,62	4,55	1,00	1,00	8,08E-07
	C	0,29	0,31	0,99	0,98	0,0002
	D	0,28	1,27	0,75	0,56	0,0891
	E	-1,64	1,66	0,86	0,74	0,0288

(Table 4). These are further segmented into two different categories: Main Mold Cost and Extra Tooling Cost. In some processes the material is directly laminated onto the mold surface, thus requiring a single mold; designated as the main mold. On the other hand, manufacturing processes that require additional steps, as in the case of spars and skins with co-cured stringers, usually need extra tools such as jigs and fixtures, that ensure the correct positioning and alignment between the two parts prior to curing. In such cases, these extra tooling costs are determined separately, but later added onto the main mold costs and comprise the bulk of tooling acquisition costs associated with the manufacturing process.

Table 4. Tooling acquisition cost regression coefficients and goodness-of-fit summary

	β_0	β_1	Pc	Goodness of fit R^2	p-value
Main Mold	33045	65285	0,963	0,928	2,1E-09
Extra Tooling	84433	29769	0,977	0,955	2,9E-05

The proposed regression offer good references on expected materials quantities and tooling acquisition costs, for the purposes of cost estimation. Moreover, it allows for future estimates to be made regarding new components, whose geometric properties that fit within the observed properties bounds.

2.5 The Cost Model

In its simplest form, process-based cost modelling proposes that manufacturing processes can be modelled as a series of interdependent steps, where costs are a function of technical factors, such as materials consumed and cycle time. At the same time, it incorporates operational inefficiencies that are detrimental to achieve a production volume on a certain time horizon, which also increases the amount of resources required to do so. PBCM's can also be used as a simulation tool to evaluate new manufacturing processes, by feeding the model with the required information, either from literature, or interpolations from available historical data.

In this study, we follow a similar approach and build upon a PBCM from a previous work [6]. Most of the cost relations proposed by the aforementioned work remain the same, albeit some changes regarding the allocation of equipment (8), material (11), and scrap costs (12) calculation.

$$Alloc_i = \frac{Treq_i}{Uptime_i} \tag{8}$$

$$Treq_i = CT_i \times NP_i \tag{9}$$

$$\begin{aligned} Uptime_i = {} & Days\ per\ year \times 24 - (Idle \\ & + Unplanned\ Breakdowns + Paid\ Breaks \\ & + Unpaid\ Breaks + On\ Shift\ Maintenance) \end{aligned} \tag{10}$$

Where total time required ($Treq_i$) is the time period necessary to achieve a target production volume (NP_i), knowing each individual part cycle time (CT_i), for a specific ith process step. Machine allocation ($Alloc_i$), is determined as the specific consumption of machine uptime ($Uptime_i$) in process step i, similarly to activity-based costing (ABC).

Material costs are calculated based on their price per unit of area ($Cost_{sqm\ i,j}$) and each respective quantity ($Mat_{quant\ i,j}$), for each of the j materials, at each ith process steps.

$$Mat_{cost\ i} = \sum_{j=1}^{n} Cost_{sqm\ i,j} \times Mat_{quant\ i,j} \tag{11}$$

$$
\begin{aligned}
Scrap_{cost\ i} = \sum_{j=1}^{n} (Mat_{quant\ i,j} \times \rho_j) \times Cost_{kg\ i} \\
\times NP_i \times (TechScrap + scrp_i + rw_i \\
\times rwscrp_i + rep_i \times repscrp_i)
\end{aligned} \tag{12}
$$

Costs arising from technical inefficiencies along the process steps ($Scrap_{cost\ i}$), are a combination of technical scrap ($TechScrap$) originated in both manual and automatic layup processes, and non-conformities such as scraps ($scrp_i$), reworks (rw_i) and repairs (rep_i) that may occur throughout the multiple manufacturing steps. The latter are introduced as ratios between the number of estimated occurrences, discussed in subsection 2.3, and the production volume (NP_i). $rwscrp_i$ and $repscrp_i$, represent the percentage of parts that fail to meet quality criteria after being reworked or repaired, respectively, determined based on the evidence from gathered data.

The cost model is encoded onto a large EXCEL spreadsheet, where a series of cost relations translate the technical requirements into manufacturing costs and its sources along every process step. The cost sources are separated into variable and fixed costs, each with a set of different cost items. Variable costs account for Materials, Energy, Labour and Scrap, whereas fixed costs appraise machine, tooling, building, and fixed overhead costs.

The developed methods that determine the manufacturing process data such as, material quantities, tooling investments, cycle times, and non-quality occurrence are integrated into the cost model. These intermediate estimates that result from the methods are fed into each process step cost relations, where they are translated into their respective cost items, resulting in the final component cost assessment (Fig. 3).

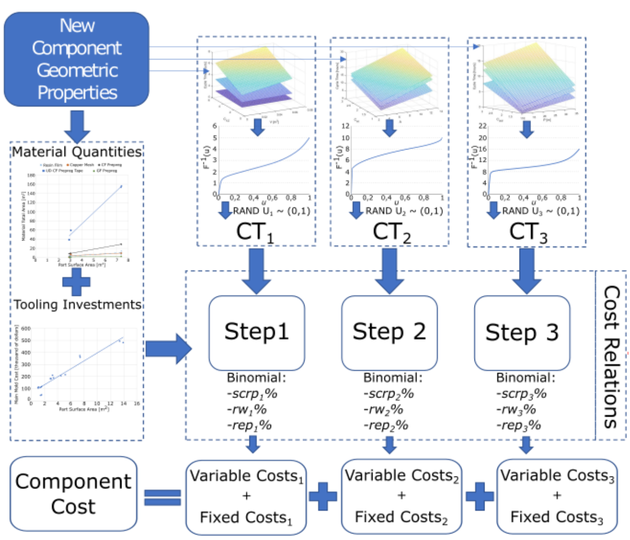


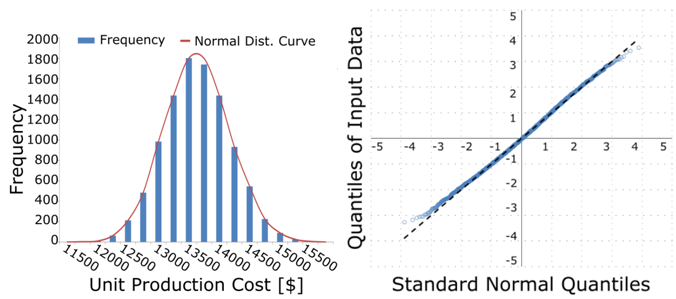
Fig. 3: PBCM component cost calculation flowchart.

Additionally, because each step cycle time is generated from an expected distribution, it is possible to perform a Monte Carlo simulation in order to study the influence of time variability on manufacturing costs.

By estimating most of the process information from a limited set of part geometric properties, the model reduces the amount of inputs that, otherwise, would have to be manually introduced. At the same time it automatically generates the necessary inputs for the cost estimations, based on past performance, free from potential biases. Furthermore, given the simplicity in the required inputs, it is expected that even at the early stages of design, this information is already fully available, thus allowing for cost estimation to be made at that point.

3 Results

The proposed cost model was used to analyse costs for each of the different components within the studied sample. As a result of each analysis, a cost distribution is obtained through a Monte Carlo simulation, making use of the stochastic nature of cycle times which introduces the manufacturing process variabilities (Fig. 4a). It is interesting to note that, despite the cycle times at each work center being modelled according to a triangular distribution, the component final costs follow a normal distribution. This is a well-known consequence of the



(a) (b)

Fig. 4: (a) P_4 Component Final Costs Histogram of 10,000 simulations. At each run, every manufacturing step cycle time is picked at random inside its respective time distribution. (b) Q-Q plot of final component costs sample.

central limit theorem (CLT), stating that when independent samples from any distribution are added, their sum approximates a normal distribution, even if the original samples themselves are not normally distributed. This assumption can be further supported by the Q-Q plots of the output data from the Monte Carlo simulation (Fig. 4b), where it is possible to observe that most of the points follow the ideal line of the normal distribution.

The range of costs resulting from the simulation, consequence of the different processes cycle time variabilities provides a realistic notion of final cost variability. In this way, we move away from the more traditional and deterministic approach to cost estimation, where a single cost is provided and any cost differences that are likely to occur are neither contemplated of taken into account in the early project decisions. Despite this fact, when comparing multiple design iterations, having a single result can be more straightforward. For that reason, the distribution's average cost is adopted as the reference cost metric.

Production volume can also be taken into account on the analysis, allowing for considerations to be taken regarding optimal production volumes to be explored, considering the

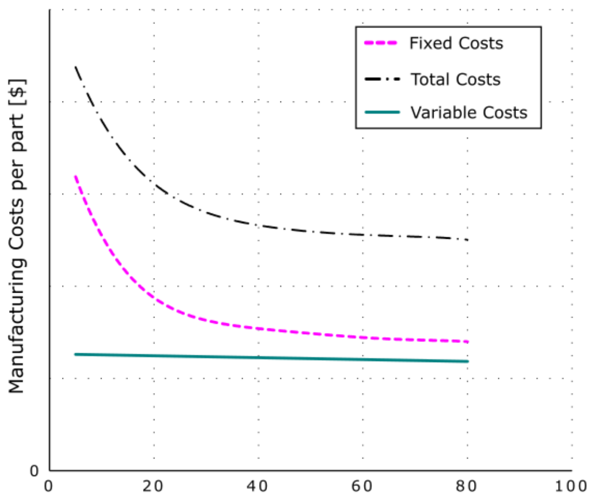


Fig. 5: Unit production cost with increasing annual production volume for component P_4. (Cost values have been omitted to respect confidentiality.)

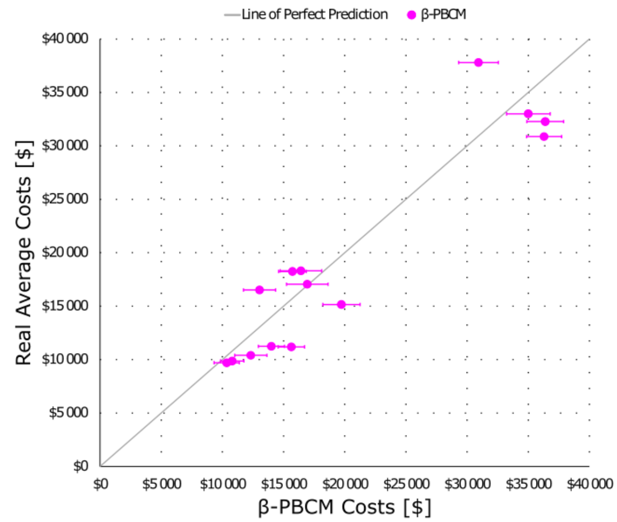


Fig. 6: Final model (β-PBCM) results comparison with the real manufacturing costs.

effects of economy of scale. Typically, with the increase of production volume, there is a bigger diffusion of fixed costs, hence the observed reduction in component final costs (Fig. 5).

On the other hand, variable costs do not benefit from the same effect, as their costs – mostly associated with materials, labour, and energy – rise proportionally with the increase of production volume, remaining constant per unit produced. In this approach, component manufacturing costs are broken

Table 5. Components' cost sources distribution summary. (Values have been omitted to respect confidentiality.)

Part Tag	Material Cost	Scrap Cost	Labour Cost	Energy Cost	Machine Cost	Tooling Cost	Fixed Overhead Cost	Building Cost
P_1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_{10}	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_{11}	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_{12}	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_{13}	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
P_{14}	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

down into its different sources, such as machine, material, energy etc. (Table 5). This same segmentation is done at a process step level, enabling a deeper analysis into processes cost origins and its drivers.

Machine and material costs represent the bulk of costs in most of the processes. Interestingly, the greater the components' area, the greater its relative material cost contribution to overall costs.

Regarding the available data set, final component cost results obtained from the developed model demonstrate a good agreement with the manufacturer costing values (real costs), with a mean absolute percentage error (MAPE)=16.4% and normalized root mean square error (NRMSE)=5.1% (Fig. 6).

3.1 Verification

The accuracy of the obtained results is dependent on two conditions: The ability of the model's cost relations in translating process data into costs. And the precision of the intermediate estimations of cycle times, material quantities and tooling costs that feed its information to the former. In this setting, errors in the intermediate quantities estimations inevitably steer the final cost result — either into a more or less accurate one — depending on the magnitude of each quantity individual error. Even if the former does occur, it adds no additional merit to the model itself.

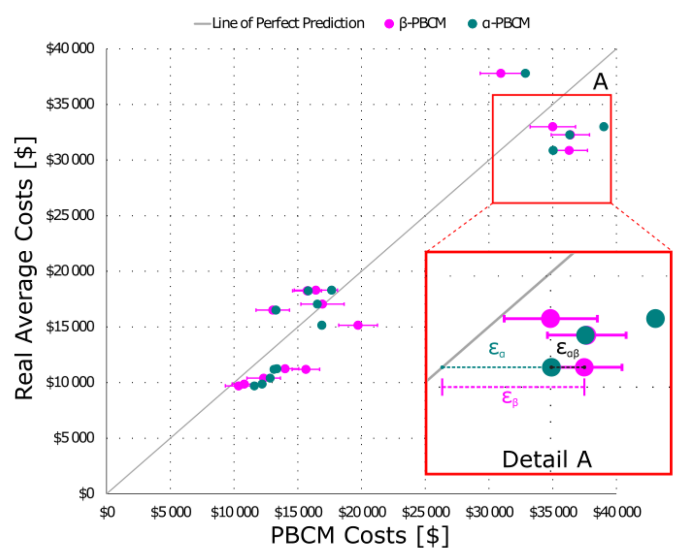


Fig. 7: PBCM average costs VS. Real Average Costs. α-PBCM costs are calculated using real process data. β-PBCM costs are calculated based on process data obtained from the employed regression methods; ϵ_{α}=Lack of Agreement of between α-PBCM and real costs; ϵ_{β}=Lack of Agreement between β-PBCM and real costs; $\epsilon_{\alpha\beta}$= Difference of agreement between α & β -PBCM results

Certainly, due to possible intermediate estimation discrepancies between estimated and true cycle times, material quantities, and tooling costs, deviations are expected. Performing the cost simulations leaving out the estimation of these intermediate quantities, but instead, using real data as inputs (α-PBCM), there is an overall improvement of results - approximately 9% (Fig. 7). This result demonstrates that the level of discrepancies of the developed intermediate estimates is acceptable, encouraging model approval.

One should note that this validation is in its essence a fitting validation. And in that sense, it can be argued that the descriptive power of the developed model is validated. Certainly, this does not guarantee its estimation (predictive) power. However, as far as new components, whose costs are to be estimated, are similar enough to the ones used in this research, it can be expected that the model estimations have enough merit to be used to support decision making at any given project stage.

3.2 PBCM as a Decision-Making Tool

Besides being utilized to estimate manufacturing costs, PBCMs can also be used as a test-bench and enable the fine-tune of process variables, with the intent to study its influence in production costs. In doing so, the most economical manufacturing routes can be determined. However, with hundreds of different variables, some more controllable than others, it becomes difficult to target those that may provide meaningful results or significantly influence manufacturing costs. With this in mind, the scope of this analyses involves three different scenarios, where mainly cycle time, materials costs and material quantities are the main cost items driving decisions. The scenarios are as follow:

- Scenario A: Considers the drop in the market price of the materials used, and consequently a component cost reduction. This reduction in material price can be linked to future improvements in material manufacturing processes, which can potentially reduce its costs [12][13].
- Scenario B: Explores possible technological progress on composite manufacturing technologies, enabling higher rates of deposition and therefore smaller cycle times during automatic layup steps [14]. Improvements to layup times can also be achieved by optimizing the machine layup paths and reducing unnecessary stoppages [15].
- Scenario C: Takes into account possible reductions to overall material usage in the manufacturing of the component. This could be achieved in two ways: One, where materials mechanical properties improve overtime, and the same mechanical integrity can be achieved with fewer material quantities [16]. Or, by optimizing components designs, and thus reduce materials usage [17].

Out of the three scenarios results presented in Fig. 8, Scenario C proves to be the most efficient at reducing cost, achieving a 1.72% reduction per 5% decrement of its respective quantities. This result is not entirely surprising, as Scenario C is comparable to a combination of Scenario A and B with reductions of 1.49% and 0.54%, respectively. Through these examples, it is clearly shown that material reductions

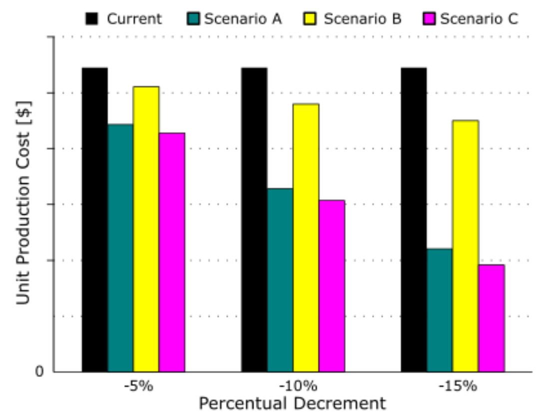


Fig. 8: Unit production cost reduction according to different scenarios for component P_4. (Cost values have been omitted to respect confidentiality).

outperform material deposition time reductions, when trying to reduce production costs. This is also linked to the fact that material costs represent one of the major contributions to overall costs, so, logically, any action to reduce its costs would yield increased gains when compared to other cost drivers.

This same approach can be followed to compare the manufacturing costs of using different technologies to manufacture the same component. Fig. 9, shows an example which explores the manufacturing costs of a component using ATL or AFP. Results show some significant differences, which are mostly attributed to the increased equipment and material cost of AFP, when compared to ATL. In this particular example, for AFP to be as economically viable as ATL, a reduction of 26% in both layup time and material quantities would be required, which is unlikely to be achieved. Typically, the layup technology is selected based on component constraints that might prevent one or the other from being used. However, in cases where there is freedom of choice, both options should be considered in order to evaluate its potential costs and determine the most economically efficient.

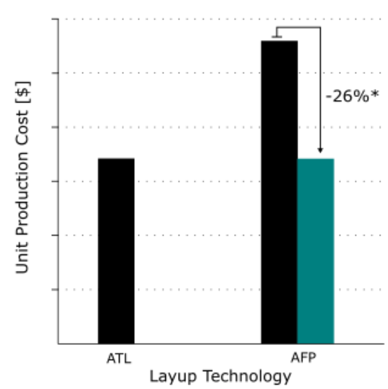


Fig. 9: Unit production cost of component P_4 using ATL or AFP as layup technology.*AFP's layup cycle time and material quantity reduction to achieve similar cost to ATL. (Cost values have been omitted to respect confidentiality).

Manufacturers continuously look into its processes, trying

Table 6. Unit production cost reduction response to each work centers' maximum and most likely cycle times reduction

Part TAG	WC0001	WC0002	WC0003	WC0004	WC0006	WC0008	WC0009	WC0016	WC0017	WC0018	WC0019	WC00QF	WC00QA	WC01MD
P_1	0,4%	1,8%	*	0%	0%	0%	1,8%	0,5%	0,7%	0,7%	0,6%	0,3%	0,7%	*
P_2	0%	1,9%	*	0,1%	0,1%	0,1%	1,6%	0,5%	0,4%	0,1%	0,6%	0,2%	0,1%	*
P_3	0,1%	1,4%	*	0,1%	0,1%	0,1%	1,5%	0,8%	0,3%	0,1%	0,6%	0,1%	0,3%	*
P_4	0%	1,5%	*	0,1%	0,1%	0,1%	1,7%	0,5%	0,2%	0,2%	0,6%	0,1%	0,4%	*
P_5	0%	1,3%	*	0,1%	0,1%	0%	0,9%	0,7%	0,2%	0,1%	0,3%	0,1%	0,2%	*
P_6	0%	1,2%	*	0,1%	0,1%	0%	1,2%	0,8%	0,2%	0,1%	0,4%	0%	0,4%	*
P_7	0%	*	4,8%	0%	0%	0%	0,9%	0,7%	0,1%	0%	0,1%	0%	*	0,1%
P_8	0%	*	5,0%	0%	0,1%	0,1%	0,9%	0,8%	0,1%	0%	0,1%	0%	*	0,0%
P_9	0%	0,2%	1,8%	0,2%	0,1%	0,0%	1,5%	1,9%	0,1%	0,1%	0%	0%	*	0,0%
P_{10}	0,1%	0,5%	2,1%	0%	0,1%	0,1%	1,4%	2,0%	0,3%	0%	0%	0,1%	*	0,1%
P_{11}	0%	0%	*	0,1%	0,1%	0%	3,4%	0,9%	0,1%	0,1%	1,6%	0,3%	*	0,1%
P_{12}	0,1%	0%	*	0,1%	0,1%	0%	2,9%	0,7%	0,3%	0,2%	1,3%	0,2%	*	0,1%
P_{13}	0%	1,8%	0,4%	0%	0,1%	0%	2,0%	0,5%	0%	0,1%	0,4%	0,2%	*	0,1%
P_{14}	0,2%	*	2,5%	0,1%	0,0%	0%	1,6%	0,6%	0,1%	0,1%	0,7%	0%	*	0,2%
Average	**0,1%**	**1,1%**	**2,8%**	**0,1%**	**0,1%**	**0,0%**	**1,7%**	**0,8%**	**0,2%**	**0,1%**	**0,5%**	**0,1%**	**0,4%**	**0,1%**

to come up with other solutions that could boost performance while reducing costs, and thus increase its cost efficiency and competitiveness. PBCM can be used to great advantage when trying to achieve such goals. It is possible, to reliably and effortlessly simulate the reduction of manufacturing steps cycle time, and record any consequent cost change. In this process, it becomes more transparent the precise manufacturing steps where these reductions have a greater effect, and where process improvement efforts should be channeled, in order to achieve them.

Table 6 shows the results of reducing each component manufacturing step distribution's maximum and most likely cycle time by 15%, as represented in Fig. 10.

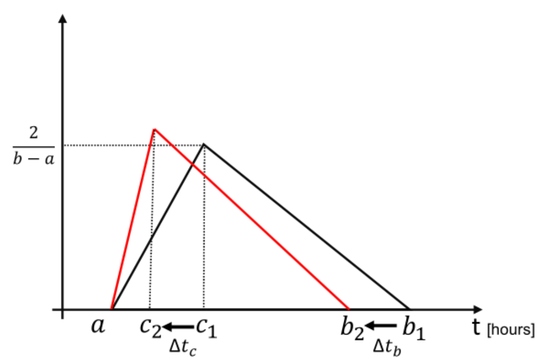


Fig. 10: Triangular Distribution's Maximum and most likely cycle times reduction; set to 85% of current values.

In doing so, each process step that contributes the most to the overall decrease in product cost, due to the reduction of its operations cycle time is highlighted. The results display an increased benefit in highly automated steps, where high equipment investments lead to greater operational costs. Thus, increases or decreases to cycle times will massively influence final component costs.

Improving these highly automated steps can be highly rewarding, but at the same time they can prove to be challenging, as there is usually very little to change. Contrarily, less critical and manual tasks, usually performed as intermediate steps of the manufacturing process, not involving the use of major equipment, have a very small to gain in reducing its cycle time. In its essence, the greater the operating costs of the process step, the more rewarding it can be to reduce final component costs, owning to improvements that lead to lower cycle times.

This evaluation could be coupled with the information in Table 5, which enhances the capability of underlining each process major cost sources.

Similar studies could be conducted in order to understand how different manufacturing parameters influence components' costs, besides cycle time and material quantities. Being able to perform these tests, at any given project stage, further cements the usefulness of having a tool that can accurately represent cost changes owning to process parameters variations. Ultimately, the developed model allows for thoughtful and readily available decisions to be made regarding manufacturing processes, mindful of their impacts on costs.

4 Conclusions and Future Work

In the current manufacturing paradigm, the control of manufacturing costs should begin at the product and process design stages. When manufacturing operations are already taking place, actions for cost reduction have normally a narrower impact and/or involve high investments, which are too expensive [4] [5]. Therefore, engineering costing within aircraft design, and certainly in many other areas, should play a more significant role inside the multidisciplinary design teams, to more effectively balance trade-offs between cost and performance. This work was set out to develop a tool based on Process-Based Cost Models (PBCMs) to facilitate and provide a manufacturing cost assessment, based on a limited amount of inputs, easily obtained even at the early stages of design. For a particular industrial environment and aeronautics components made of composites, this was done taking advantage of a significant amount of rich historical data to generate techno-economic regressions that materialize powerful knowledge, which can then feed the core of the PBCM tool.

Across many different manufacturing industries, process variability is often encountered, influencing operations cycle time and therefore the component's final cost. Trying to emulate its effects in the developed cost model, the common deterministic approach to cost modelling was abandoned, and instead, a stochastic method was introduced. It was shown that the modelled variabilities can significantly impact the components' final cost, and provide a broader view of expected costs, that may surpass deterministic cost targets. Additionally, by introducing cost variability into the cost estimation process, additional awareness is raised on the need for close process monitoring and allows for the identification of process steps whose improvements can deliver positive results in terms of final cost reduction. Outside of the cost estimation process, the modelled variabilities can also be used for process planning purposes. Using part-specific data as the basis for cycle time determination proved to be efficient in the current cost estimation scheme, although, in the future, the method could be further refined in several ways by (1) adding additional part properties (independent variables) to the time regressions or (2) adopting non-linear fittings or machine learning methods. Either in the current of future states, these methods would benefit from the maturity of some of the current processes, whose data randomness and uncertainty from the limited number of production runs hinders the accuracy of the developed methods.

Non-conformities are estimated based on a method that assumes that their occurrence is random and independent from one another. For the intended purposes of cost estimation, this is an effective and reasonable approach, but these events are usually dominated by the principle of causality – a cause that triggers an event. Given the abundance and detail of the available data, future studies should be performed that explore the possible cause-and-effect mechanisms in non-quality occurrences, providing valuable information to its causes and how to better prevent them, so that its effects are less noticeable on future costs.

It was also found that tooling costs were surprisingly well correlated with part surface area, and a simple linear regression was used to describe its costs based on the parts' surface area. A similar approach was followed to determine the manufacturing process material quantities, but the method was not as suited as it was with tooling costs, given the clustering of different part types. The heterogeneity between the different parts, results in different material demands that stem from the type of component in itself, rather than some quantitative part property such as its area. For that reason, future methods should be able to combine qualitative and quantitative data to distinguish the different types of components and consequently determine each of its required material quantities.

From the cost analysis of the studied sample, the results show the bigger the part, the higher the material percentage cost represents in the total manufacturing costs, followed by machine costs. In processes involving multiple parts integrations, labour, and tooling costs become more significant, given the increased manufacturing steps required and additional tools to ensure the correct alignment of parts.

The results from this study support the initial hypothesis that manufacturing cost can be automatically estimated based on simple geometric characteristics available in the very front end of the design and process planning. It should be noted however, that the predictive power of the current method is not fully validated, and further testing with parts outside of the learning sample would be required. Still, given the method's descriptive power, it can be expected acceptable predictive results on components' costs, whose properties are within the bounds of the studied samples. The achieved estimation errors of the manufacturing costs are substantially low (MAPE=16.4%;NRMSE=5.1%), and a clear step forward to support engineering decision making before production is initiated, or to launch cost reduction initiatives in current processes. Additionally, with further development, the cost estimation could be embedded as a CAD tool and become a design parameter during parts' design stages. In the future, the scope of this analysis may be broadened to include assembly costs and thus enable the economic evaluation of one of composites main advantages that is part consolidation.

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