



Economic assessment for additive manufacturing of automotive end-use parts through digital light processing (DLP)

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ABSTRACT

Within the last years, digital light processing (DLP) became a viable solution for the manufacturing of end-use parts in various industries among other additive manufacturing (AM) processes. As the number of applications realized in a rapid manufacturing (RM) approach grows, it is necessary to understand the process economics better when moving from laboratory and prototyping applications into the cost-sensitive production scale. This paper presents a production-centered economic assessment of DLP production in the early product development process, based on Continuous Liquid Interphase Printing (CLIP). It is applied to an automotive exterior part case study to reveal expected process economics and estimate part prime cost for different printer sizes and automation concepts. A subsequent sensitivity analysis assesses the influence of relevant cost drivers and identifies opportunities for further cost savings when producing end-use parts with DLP. Results may help machine OEMs and application developers in cost optimization and decision making in RM.

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Introduction

The manufacturing sector for polymeric automotive parts and components is dominated by well-explored and widely used manufacturing technologies such as injection molding, insert molding and back molding [1]. However, additive manufacturing (AM) is considered as an emerging and conceivably disrupting technology for polymer processing [2,3]. Its relevance for the production of end-use parts is expected to increase within the next years [4]. Due to significant improvements, AM materials and processes are now found to be partially fulfilling automotive part requirements [5]. As a consequence, AM is not only used for rapid prototyping but also applied for rapid manufacturing (RM) [6] and cost of end-use parts manufactured with AM become an important factor to identify positive business cases for this manufacturing technology. Addressing these trends, this paper presents an approach for cost assessment of end-use parts printed with digital light processing (DLP). The approach is centered around the

Continuous Liquid Interphase Process (CLIP) technology which can be assigned to the DLP process family.

Introduction to DLP: the example of CLIP

In general, DLP systems are based on a vat photopolymerization process, working with a light mask projector [7]. This principle is derived from the method of dynamic mask projection, which was originally enabled by a digital micro-mirror device from Texas Instruments [8]. These technologies build a part in a layer-wise approach by selective curing of a liquid photosensitive resin when exposed to an UV-light mask [8,9]. CLIP recently emerged among these technologies and delivered high production speed paired with multiple programmable resins to form end-use parts [10]. Its working principle is illustrated in Fig. 1.

At the beginning of a print, the build platform or carrier is submerged in the resin reservoir. An oxygen-permeable and optically transparent window creates a dead zone, a thin layer of oxygen, between its surface and the photopolymer resin. From beneath, a digital light processor irradiates a defined cross-section layer of the three-dimensional object into the liquid and solidifies the exposed sections of photopolymer resin. During the build process the build platform continuously moves upwards while

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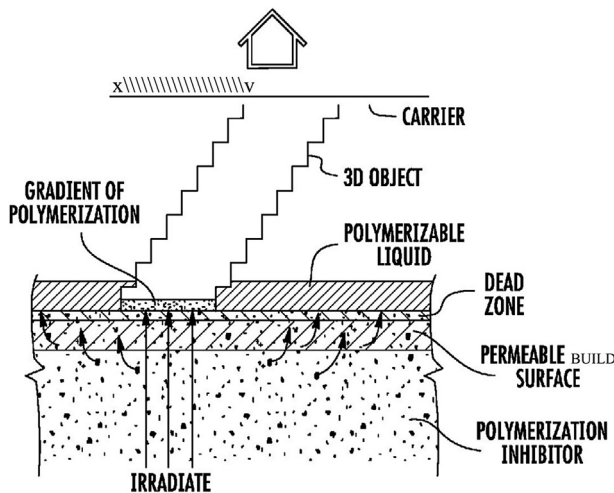


Fig. 1. Illustration of the working principle of the CLIP technology [11].

maintaining a thin gradient of polymerization between the previously cured layer and the dead zone. The oxygen layer prevents the cured resin from sticking to the reservoir. Through this continuous process, a three-dimensional object is formed. Upon print finish, the part and its support structures can be removed from the build platform. After removal of excess resin, the part is additionally cured in a heating chamber to enhance the mechanical and thermal properties [11].

Current trends and industry needs for end-use part production with DLP

The CLIP technology recently realized multiple end-use part applications in the automotive, sports equipment and apparel industries using rigid epoxy-based and soft elastic polyurethane-based materials. Table 1 presents some of these published applications.

As presented, most applications are driven by customization purposes, often in combination with a specific design for additive manufacturing (DfAM). In the automotive sector, cost-effective small series production is also an important driving force [12–14]. Applications in sports and apparel are influenced by the customer's desires or increase the functional value of the application through geometries that are tailored to the customer's body dimensions. For example, this process enhances the impact absorption of football helmet cushions, comfort of bicycle saddles or performance of running shoes [15–17]. These recent developments of end-use products in the DLP domain triggered market entry of new printer manufacturers with open-material systems [19,20] in collaboration with material suppliers to increase the spectrum of materials for DLP and enable new applications [21–23]. As the

systems aim to leave the domain of rapid prototyping, manufacturers present solutions to automatize the processes further. These solutions include automated loading and unloading of DLP machines by robots [24] or integrating multiple post-processing steps in a single unit [19].

With respect to all these emerging trends and growing possibilities, potential end-users need more profound understanding of cost-efficiency in series production with DLP. In general, the economics of AM influence the applicability of the technology for end-use part manufacturing as cost sensitivity of the user significantly increases when moving from rapid prototyping to rapid manufacturing. As a consequence, users need versatile cost evaluation tools which support them with detailed and specific information in the early product development process by providing:

- Detailed cost breakdowns
- Assessment of production system alternatives (e.g., different printer sizes)
- Evaluation of influence of operation concepts (e.g., partial automation)
- Sensitivity analysis regarding important cost drivers
- Extensibility and integrability in further product development (e.g., production line simulation)

Generated insights equip engineers and decision makers with important information regarding whether DLP in general can be considered a competitive manufacturing approach. Taken together, also further decision making regarding, e.g., a favorable location of production or following a make or buy approach is possible.

By reviewing and adapting existing cost modeling approaches for AM, this paper develops a cost assessment framework for DLP, which targets economic technology evaluation in the early product development process. It addresses the mentioned areas of decision support and is subsequently applied to a case study for early economic evaluation of DLP production of an automotive series part.

The applicability of existing cost modeling techniques and first approaches to quantify economics of AM processes, especially with regard to DLP, are addressed in the following section.

Cost modeling techniques and derivation of research need

Available cost modeling techniques

Today, a broad spectrum of available cost modeling techniques exists. These comprise analogical techniques, parametric techniques and analytical techniques [25–27]. To address the respective techniques' major advantages, drawbacks as well as their scope of application in the context of (AM) product development, they are assessed one by one in the following paragraphs.

Table 1
Overview of recently published end-use part applications of the CLIP technology.

Industry	Application	Material class	Driver	Ref.
Automotive	Personalized side scuttles	EPX	Customization	[12]
	Brake bracket	EPX	Small series	[13]
	Air duct split	EPX	Small series	[14]
	Fuel tank cap	EPX	Small series	[14]
Apparel & Sports	Running shoe midsoles	EPU	DfAM	[15]
	Bicycle saddle padding	EPU	DfAM	[16]
	Football helmet cushion	EPU	DfAM	[17]
	Eyewear frame cushions	EPU	DfAM	[18]

Analogical techniques

Analogical methods are using a certain codification for parts, frequently a morpho-dimensional codification, which relates to a typical solution for each codification (e.g., a manufacturing process, typical cost range) [28]. They are characterized by adjusting the cost of a similar product relative to differences between it and the target product [25]. This approach is one of the most successful approaches in the early design stage [29], where it profits from advantages like its fast application, clear relation of causes and effects and possible accuracy [27]. However, it requires expert knowledge for the definition of adjustment factors, identification of appropriate analog parts and build-up of the substantial and detailed database [27]. As a consequence, first implementation of this technique usually implies a high investment, which poses a high barrier especially for smaller-sized enterprises [28].

Parametric techniques

By bringing parameters of a part into a mathematical correlation with expected costs via statistical analysis, parametric cost estimation techniques enable cost prediction within part families [27]. Consequently, these methods are only feasible when two conditions are met: First, the product must be a member of a closely related product family. Secondly, this family must have many members with already established cost for provision of historical data [29]. Given this data exists, parametric techniques are suited for cost estimation in the early design stage [27]. However, while they are fairly easy to perform and do not require expert knowledge for their application, they often function like a 'black box', making it difficult for the user to understand elements of the manufacture, identify cause-and-effect relationships or justify the results. Moreover, if the context of production is altered, the estimation must be repeated and results need to be justified again [27,28].

Analytical techniques

In analytical cost estimation techniques, all work steps with their costs for material, work, infrastructure, etc. are added up to the product's cost in a bottom-up approach. This procedure requires deep understanding of the process, its interactions and part design details [27]. Degree of detail and a clear cause-and-effect relationship are major advantages of this technique [25]. Furthermore, it is able to provide insight into cost contributors and cost drivers. Also, miscalculation of single elements does not necessarily compromise the entire estimation [27]. While it is practically adaptable to changing workshop contexts [28], a new estimate must be built up for each alternative scenario, resulting in significant effort. [27]. Due to this data-intensive approach, it is rather suited for later stages of the product development process. However, when no historic data is available (e.g., for new technologies or products), this technique is the only cost modeling approach applicable [27].

Use in the product development process

As already partially addressed, the different cost estimation techniques demand varying degrees of available data and formalization of the product and manufacturing process. Thus, their individual position and contribution in the product development process differs as illustrated in Fig. 2.

Resulting from the statements in "Introduction" section, the targeted area for support through the proposed cost modeling approach is highlighted. It spans from the late product definition phase to the beginning of the production phase with main emphasis on the early (pre-)development phase. Here, first data concerning the product's geometry, requirements and qualified processes is available, enabling process-specific analytical cost

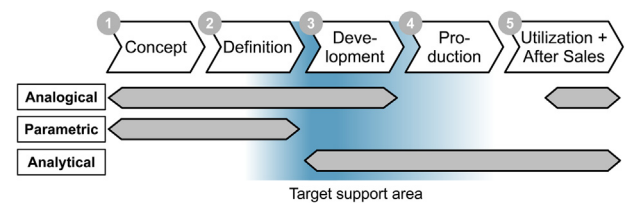


Fig. 2. Use of cost estimation techniques in the product development process and target support area for this concept [adapted from [28]].

evaluation through, e.g., an activity-based costing approach [27,30]. With regard to all available cost modeling alternatives, two main aspects need to be considered: First, with a low presence of AM in end-use part manufacturing, techniques relying on historic data like analogical or parametric modeling are less favorable due to low data availability. Secondly, analytical cost modeling not only represents the only technically feasible method in these circumstances, but also offers support and opportunities for extension (e.g., through integration into production-oriented discrete event simulation [31]) in the following steps of product development. In a more detailed investigation, existing analytical cost models for AM end-use parts produced in a rapid manufacturing approach are discussed in the next section.

Analytic cost modeling in context of rapid manufacturing

Several researchers dealt with AM cost identification in the past, as showed by Costabile et al. [32]. Thus, the literature review focuses on the key elements of the following analysis. This comprises the use of AM in a rapid manufacturing context, coverage of DLP processes, production with single geometries, varying printer size and cost driver analysis. In terms of rapid manufacturing, Hopkinson and Dickens tested production volume of parts including a cost model to compare part cost of different AM technologies like selective laser sintering (SLS), fused deposition modeling (FDM) and stereolithography (SLA) with injection molding. Their model determines the break-even point between the technologies and injection molding [33]. Ruffo et al. improved this model by integrating further cost factors like administrative and overhead cost for identification of scaling effects [34]. Based on the work of Ruffo, Charalambis et al. developed a first cost model for DLP using a specifically designed precision printer without regard to rapid manufacturing. Although this generic cost model is not restricted to DLP technologies, specific assumptions of parameters and limitations are derived from photopolymerization processes and thus need adjustment when applied to other AM technologies. The developed model sums up the cost for pre-processing efforts, material, build process, post-processing activities and overhead allocations [35]. Cunningham et al. and Schröder et al. extended cost analysis regarding cost driver influence. They conducted a sensitivity analysis (SA) on stereolithography (SLA), selective laser sintering (SLS), fused deposition modeling (FDM), selective laser melting (SLM), electron beam melting (EBM) and wire and arc additive manufacturing (WAAM) to uncover special economic effects or rank the cost drivers by their impact on the underlying cost models [36,37]. Yang and Li introduced a cost model with consecutive sensitivity analysis for production with mixed geometries using mask image projection stereolithography, which shares certain process similarities with DLP [38]. A brief overview of the different models' coverage of single geometry production (SGP), DLP and SA is presented in Table 2.

All approaches have in common, that they are based on a bottom-up analytical cost modeling approach, underlining the findings in "Use in the product development process" section.

Table 2

Overview of model coverage in identified cost modeling approaches.

Reference	SGP	SA	DLP
Hopkinson and Dickens [33]	•		
Ruffo et al. [34]	•		
Charalambis et al. [35]	•		•
Schröder et al. [36]	•	•	
Cunningham et al. [37]	•	•	
Yang and Li [38]		•	•

Research need

With regard to the findings in “Introduction” and “Cost modeling techniques and derivation of research need” sections, the need for a DLP cost assessment framework can be identified, which covers a rapid manufacturing context with a single geometry production approach and support of sensitivity analysis for cost driver evaluation. From a practical standpoint, producing end-use parts with DLP implies efficient and optimized build processes. It is questionable if a mixed geometry approach will be adopted for series manufacturing. Furthermore, the use of larger, more productive DLP systems is usually preferred over the use of small systems. Thus, the effect of printer platform size within the DLP technology family needs to be considered when selecting the right platform for series production. Especially in series manufacturing, users need to identify opportunities for further cost savings and back decisions, e.g., regarding whether to make or buy. Ideally, the assessment approach supports in the early development phases and provides an opportunity for further extension towards the production phase. This comprises, for example, a possible integration into dynamic simulation of production systems, which can be done when first production layouts are existent and availability and precision of data is very high.

Addressing these needs in research and industrial practice, the following introduces an assessment framework based on a static cost model for prime cost estimation in a DLP end-use part manufacturing environment during the early product development phase. Its activity-based approach aims to provide detailed cost insights (e.g., through application of cost driver sensitivity analysis) and offers the possibility for further extension or integration. Subsequent application to an automotive exterior part case study reveals differences in part cost on different platform sizes, potentials for cost savings through automation and influence of selected cost drivers in a subsequent sensitivity analysis.

Methodology

Overview of method and implementation

For better understanding, the fundamental framework for cost assessment is shown in Fig. 3, providing an overview about its elements, tools and deployment.

On the input level (1), build geometry data and machine parameters need to be gathered using the machine interfaces and/or a nesting software like Materialise MAGICS. Depending on the amount of already available data and the needed accuracy, the time span for this step varies. For example, if print experiments are required to collect data, which cannot be directly derived from historic evaluations or digital print job planning, it extends from minutes to several hours. The evaluation level (2) comprises the activity-based cost model and sensitivity analysis module, which are implemented in python scripts. This enables processing of large

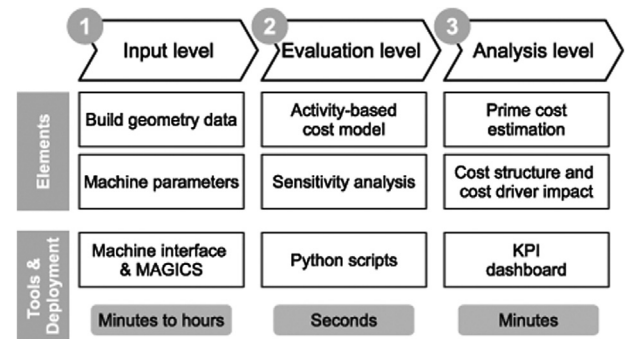


Fig. 3. Underlying methodological framework for cost assessment.

data amounts, e.g., coming from multiple parallel evaluations, and ensures repeatability of the evaluation in a very short time span. In this step, the scripts carry out the evaluation and cost modeling according to the parameters specified by geometry, print experiments and estimations. The analysis level (3) gives insight into the estimated prime cost for the respective part's production, the underlying cost structure and cost driver impact. For fast and comprehensive visual analysis of the key performance indicators (KPIs), the analysis can be coupled to a python-based KPI dashboard. Based on the results, different system configurations, cost driver impacts and potentials for further improvement of cost performance can be evaluated. The central elements defining the cost model and sensitivity analysis are described in the following, before the framework is applied to a case study in “Application to a case study” section.

Reference process chain and system boundary

The reference process chain for the assessment is depicted in Fig. 4. With three major steps, pre-processing, processing and post-processing, the system boundary covers all directly print-related activities to manufacture a blank part. Following finishing steps (e.g., subsequent surface treatments like painting) are not covered.

Pre-processing encompasses the activity sequence of nesting, data transfer to the machines, resin dispense and loading of the printer platform into the machines. The latter two manual activities can be automated through robot handling. During processing, the print is executed and subsequent unloading of the build platform is either done manually or automatically. Post-processing involves washing of the green parts, removal of support structures, cleaning of the build platform for subsequent jobs and thermal curing of the green parts.

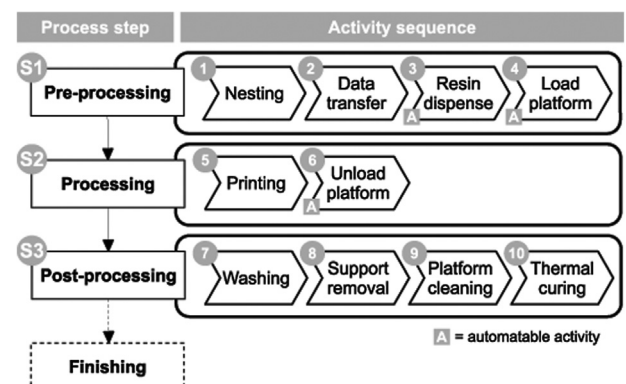


Fig. 4. Process steps and activity sequence for the considered process chain.

Cost structure

For the definition of the cost model, the underlying cost structure and way of cost calculation is assessed. To determine the prime cost per part, a calculation based on machine hour rates and differentiated overheads is applied. In general, the prime cost can be broken down into production cost and sales and administration (S&A) overheads, as illustrated in Fig. 5. Production cost are determined by material cost, summarizing the cost of production materials and their overheads, and manufacturing cost, comprising labor cost and manufacturing overheads.

A detailed view on the manufacturing cost in Fig. 5 is provided in Fig. 6. In manufacturing overheads, the depreciation and lease cost, calculatory interests, room and energy cost as well as maintenance cost constitute the machine cost. Together with labor cost and remaining overheads, machine cost are a central cost component of manufacturing cost.

This cost structure builds the base for the definition of the cost model in “Cost model” section.

Cost model

Using elements of the models presented in “Cost modeling techniques and derivation of research need” section and the cost structure introduced in “Cost structure” section as a baseline, the cost model defines cost-estimating relationships (CERs) for the parameters. For a complete overview of all involved parameters, calculations and resulting CERs, comprehensive tables are provided at the end of this article in Appendix A. Following the idea of production at an ideal AM part supplier facility, the part production is assumed to run 24 h in three shifts. This implies that apart from printers, also the shared pre- and post-processing equipment like washers, resin dispensers and ovens for post-processing is highly utilized and job distribution is done accordingly. The cost model is designed to analyze effects of partially automated production. Concepts involve a robot for loading and unloading operations of printers and part washer as well as automated resin dispensing during pre-processing. These automated tasks can be triggered to manual execution to evaluate potential cost savings through automation.

As illustrated in Fig. 7, prime cost are composed of four major cost blocks. These blocks contain CERs for labor cost, material cost, machine cost and overhead respectively S&A cost. The color coding of these components is also found in the subsequent cost analysis charts in Fig. 9 in “Calculated prime cost per part” section.

Manufacturing cost result from machine hour and labor rates in combination with the respective process and machine times. Material cost depends on resin cost, the geometrical properties of the part, its support and excess material which is not solidified during a print. Together, material cost, machine cost and labor cost form the manufacturing cost. Applying standard overhead rates for

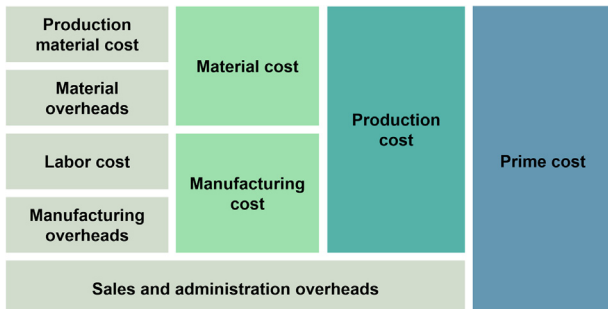


Fig. 5. Components of prime cost [adapted from Horsch [39]].

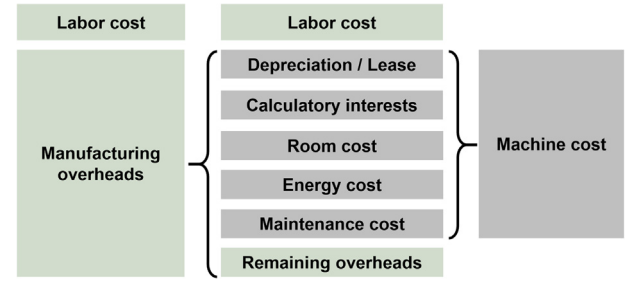


Fig. 6. Machine cost as a component of manufacturing cost [adapted from Plinke [40]].

polymer processing facilities as overhead and S&A cost, prime cost per part can be calculated assuming a yield factor. As a profit margin is not applied, the prime cost cannot be treated as an estimated net offer price.

In favor of readability, the next paragraphs only introduce central CERs of the model. A detailed summary of all involved calculations is provided in the appendix.

Material cost

As presented by Ruffo et al. [34] for the case of laser sintering, direct cost in AM are affected by the material cost, the part volume and wasted material. This also applies to the DLP technology, where the final material usage is composed of the part itself, support structures and excess resin covering the build's surface before washing. Usage of two-component resins leads to additional waste because of fast solidification, which prevents it from being re-used in a second print cycle. Translated into a CER, the material cost per part C_{Mat} can be expressed as follows.

$$C_{Mat} = \frac{(V_B + V_S + V_E) \cdot c_{Mat}}{N_{P,B}}$$

V_B describes the part build volume, V_S the amount of support volume per build and V_E comprises unsolidified excess material lost through adhesion and beginning age hardening. These volumes are multiplied with the specific resin cost c_{Mat} divided by the number of parts fabricated in a single build $N_{P,B}$. The amount of waste material is measured through weighing in the print experiment.

Manufacturing cost

As part of the manufacturing cost, labor cost per part C_L are affected by manual processing activities multiplied with the labor rate c_L . The time for resin dispensing t_D , the cumulative time for loading and unloading of the printer, part washer and post-treatment oven as handling time t_H as well as the time for manual equipment cleaning t_C can be assigned to the number of parts per build $N_{P,B}$. De-supporting takes the time t_{DS} and is accounted for each part individually. Equipment cleaning after a shift is represented through t_{SC} and distributed over the number of parts manufactured during a shift $N_{P,S}$.

$$C_L = \left(\frac{b \cdot (t_D + t_H) + t_C}{N_{P,B}} + t_{DS} + \frac{t_{SC}}{N_{P,S}} \right) \cdot c_L$$

As the model investigates the effects of automation on the part production cost, the parameters t_D and t_H are set to zero when the model is run.

$$b = \begin{cases} 1, & \text{for manual processes} \\ 0, & \text{for automated processes} \end{cases}$$

This assumes automation of dispensing and loading activities through continuous dispensing and robot utilization for handling

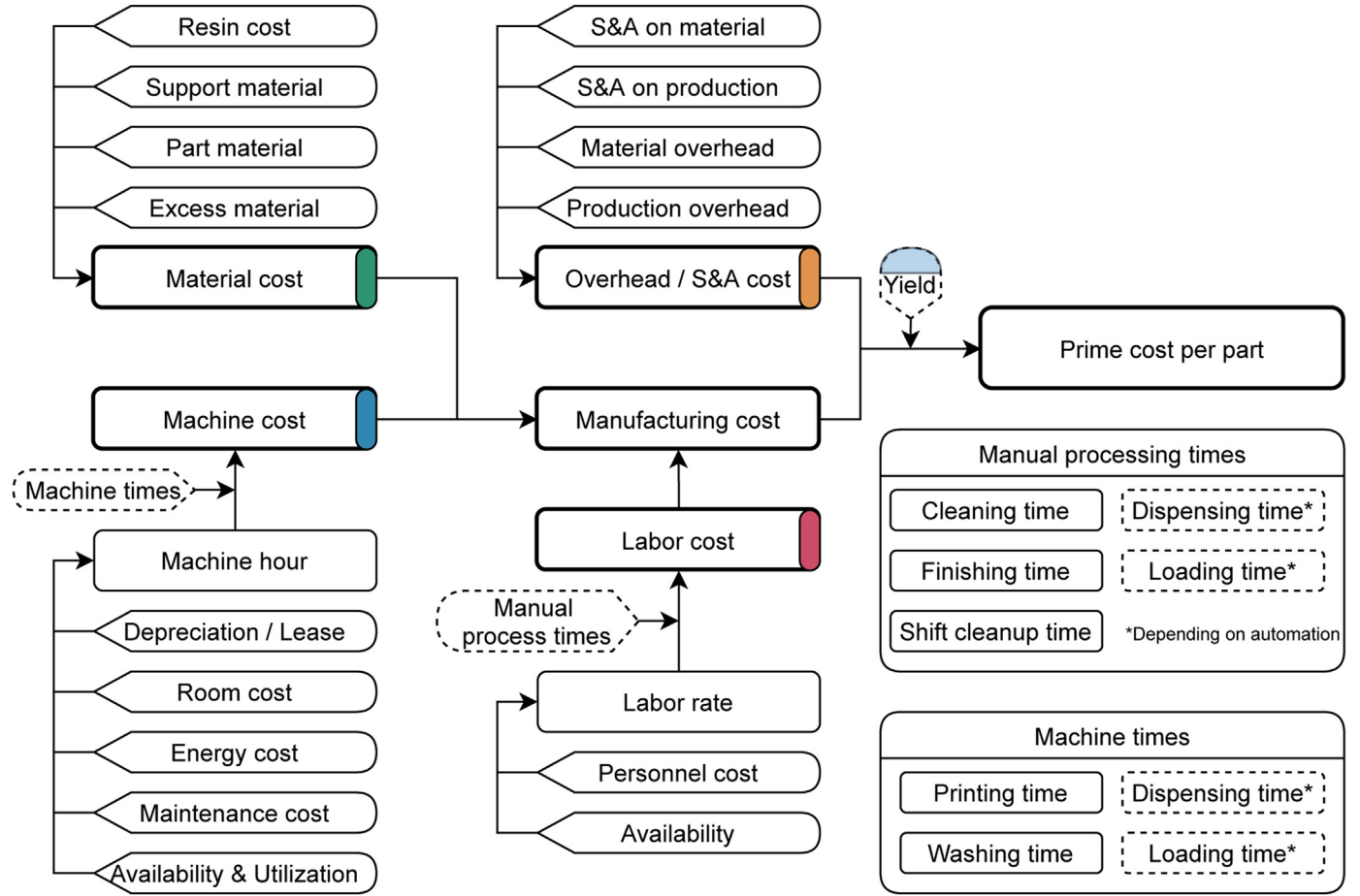


Fig. 7. Flowchart illustrating the components and parameters of the activity-based DLP cost model.

operations. These activities are then accounted for with machine times.

For allocation of the machine cost to the manufacturing cost, the cost per machine hour for the different used equipment needs to be calculated. This follows a common pattern for each equipment besides the curing oven.

$$c_{Mac,i} = c_{E,i} + \frac{c_{R,i} + c_{DL,i}}{t_{A,i} \cdot k_{U,i}}$$

Machine hours of the respective equipment (indexed with i) $c_{Mac,i}$ are characterized through the hourly equipment energy cost $c_{E,i}$, room cost $c_{R,i}$ and depreciation respectively lease cost $c_{DL,i}$. These figures are divided by the time of machine availability $t_{A,i}$ and utilization rate $k_{U,i}$. The different machine cost $c_{Mac,i}$ are then calculated by multiplying the respective equipment's machine hour rate $c_{Mac,i}$ with the associated processing times t_i (e.g., printing time t_p , washing time t_w) and can be broken down to single parts via the number of parts on a build platform $N_{p,B}$.

$$C_{Mac,i} = \frac{c_{Mac,i} \cdot t_i}{N_{p,B}}$$

Cost for the curing oven are attributed to a day's part output $N_{p,D}$, as it is assumed that oven capacity is selected according to the installed printing volume and curing time takes over 12 h. The cost for automation equipment and the simulated production environment of the L1 printer, which is not available at the facility, have been estimated based on publicly available data and expert guesses

or extrapolation of the equipment cost in the production environment of the M1 and M2 printer.

Overhead, yield and S&A cost

Overhead and sales and administration cost are estimated by applying standard overhead rates to the production cost. The selected values shown in Table 3 reflect experts' assumptions for a small to medium-sized polymer processing facility. The yield assumption is derived from operation experience with optimized DLP builds.

Sensitivity analysis

To investigate the influence of selected cost drivers on the proposed cost model's output, a sensitivity analysis is conducted. The selected parameters of the cost model are varied in their input to detect their effect on the model output and reveal potentials for further cost savings when using DLP in a rapid manufacturing

Table 3
Rates applied for overhead, S&A cost and yield.

Parameter	Rate in %
Material overhead	4
Production overhead	15
S&A on material	5
S&A on production	5
Yield	95

environment. The selection of parameters of interest can be oriented on the following three aspects:

- Significant contribution of the parameter to the prime cost.
- Technical parameters, which are influenceable by user and operation concept.
- Parameters, which are likely to be negotiable at resource purchase.

As frequently not all technical parameters are freely accessible on AM machines, the selection depends on the utilized equipment. For example, machines can limit the variation of print speed in the user interface for machine protection or quality reasons. Also, for the course of this work, parameters associated with the part orientation or geometry are excluded but have an influence on prime cost. However, this case study assumes a qualified build job and explores the cost drivers based on a fixed geometrical layout. Identified parameters and their effects will be presented after analysis of the prime cost structure.

Application to a case study

Print setup for the case study

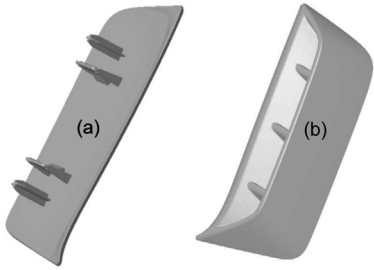
The following paragraphs describe the evaluation of a case study using the proposed assessment framework. After selection of the print properties for different machines sizes, the print is executed on two printers. Results from this experimental print help to improve the accuracy of the cost modeling and sensitivity analysis. The obtained results are discussed after the presentation of the print setup.

Part and print properties

The case study is centered on an automotive exterior trim part with a low production volume. Properties and shape of the part are described in Table 4. For this print, the material of choice is Carbon's EPX 82 [41], which has been used in multiple automotive interior and exterior applications [12–14].

As the part features critical surfaces on side (b) which are exposed to the customer's view, the part needs to be printed at an angle to maintain a single-sided support attached solely to side (a). The process chain of printing and post-processing depends on the

Table 4
Shape and properties of the case study exterior part.

Part back (a) and front (b) view		
		
Bounding box X (supported)	[mm]	51
Bounding box Y (supported)	[mm]	70
Bounding box Z (supported)	[mm]	118
Part volume	[cm ³]	21.61
Support volume	[cm ³]	13.23

selected base material. For EPX 82, Table 5 summarizes the resulting processing steps, duration and necessary equipment.

After the print duration (t_p) of 304 min, the build platform is washed in the part washer and dunked in IPA (t_w) for 16 min. After support removal, the green part is thermally cured in an industrial oven for 750 min (t_{TC}).

Nesting results

Support generation was done using the Carbon printer interface with its support generation feature and manual support adjustments to clear critical surfaces. The resulting supported single-part STL file was used to nest the same supported part on all considered printer platforms. Because of the isotropic build quality of DLP systems, the nesting of parts was optimized towards the highest platform utilization without maintaining a standardized orientation. This contributes to economical print optimization and lower cost per part.

Referring to the different printers' specifications, the print jobs were nested using Materialise MAGICS. Table 6 summarizes the nesting results for the physically present M1 and M2 printers and the estimation for the L1 platform based on publicly available data. The realized part number per print varies between 2 parts for the small M1 platform and 24 parts for the L1 platform.

Cost model parameter gathering

For check of printability and gathering parameters like process step timings and resin loss, the print jobs have been executed on a Carbon M1 and M2 printer using EPX 82 resin. Tracked times for processing steps influenced the parameter selection in the cost model and sensitivity analysis. Fig. 8 shows the parts on the M2's build platform after the finished print. During the prints on the M1 and M2 platforms, the print duration and resin loss due to adhesion to part and printer surfaces as well as residual resin were recorded. Table 7 summarizes these parameters.

The residual resin volume sticking to the part's unwashed surface was weighed out at 2.5 ml per part. Residual resin left in the printers after job finishing was measured at 62.4 ml for the M1 and 116.7 ml for the M2, resulting in 67.3 ml of excess resin for the M1 and 131.5 ml for the M2 printer. As build platform size doubles between M1 and M2, the excess resin amount (part surface and printer residuals) grows with nearly the same rate, namely with a factor of 1.95. Broken down to the printer's surface, this equals a resin loss of 0.60 ml/cm² for the M1 and 0.58 ml/cm² for the M2. This is used to estimate specific resin loss on the L1 platform at around 0.55 ml/cm².

The print duration of 5 h and 4 min on both M1 and M2 result in an effective print speed of 23.3 mm/h. This equals a build rate of 13.8 cm³/h (M1) and 41.3 cm³/h (M2). Based on the achieved print speed and larger platform size, the build rate of the L1 platform is estimated at 162.2 cm³/h.


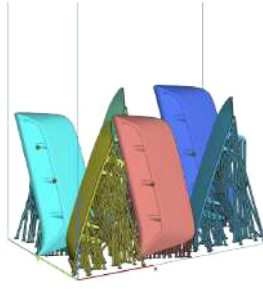
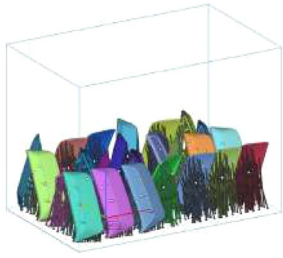
As predicted by the printer interface, the builds came out without noticeable errors or surface irregularities. Generated support could be easily separated from the part bodies. Upon successful completion of the build job, the parameters for this print setup were handed to the model parameter lists.

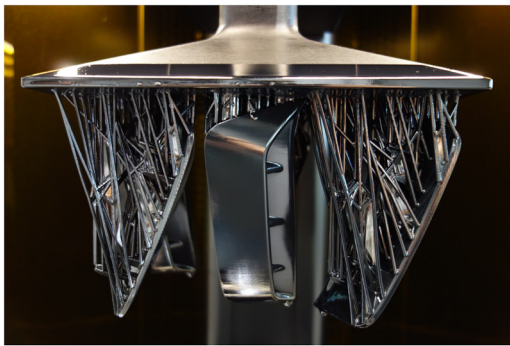
Table 5
Processing steps and necessary equipment for parts produced with EPX 82.

Step	Duration [min]	Equipment
Print	304	Printer
Washing	16	Washer & IPA bath
Support removal	2	–
Thermal curing	750	Oven

Table 6

Nesting results of the case study part on the Carbon M1, M2 and L1 printer platform.

Platform		M1	M2	L1
  				
Platform size (X,Y)	[mm]	141 × 79	190 × 118	400 × 250
Print height (Z)	[mm]	118	118	118
Parts per print	[pcs]	2	6	24
Total part volume	[cm ³]	43.21	129.63	518.57
Total support vol.	[cm ³]	26.46	79.38	317.52

**Fig. 8.** Case study parts after successfully finished printing experiment on the Carbon M2 platform.**Table 7**

Parameters recorded during the experimental prints and resulting estimations for the L1 platform.

		M1	M2	L1*
Adhesive loss per part	[ml]	2.5	2.5	2.5
Excess resin loss per print	[ml]	62.4	116.7	490.7
Specific resin loss	[ml/cm ²]	0.60	0.58	0.55
Print speed	[mm/h]	23.3	23.3	23.3
Build rate	[cm ³ /h]	13.8	41.3	162.2

Calculated prime cost per part

Upon execution of the cost model, the prime cost per part for a production environment surrounding the different printer platforms are calculated. Fig. 9 summarizes the results, listing the expected total production cost per part and their composition on the respective platform. Cost shares displayed on the inner ring are cumulative values attributed to the categories of material, labor, machine, overhead and expected yield cost. To get an impression about the dimensions of important cost contributing to each of these categories, the outer ring displays selected cost components calculated by the model. The detailed view provides support for

pre-selection of cost drivers for analysis in the subsequent sensitivity analysis. Components of yield and overhead costs are not displayed because these have been applied to the model as fixed rates which are not containing further information.

The prime cost per part show strong dependence on platform size, reaching from 48.51€ for the smallest M1 platform to 17.87€ on the L1 platform. However, the cost decrease is not proportional to platform size increase, as the L1 platform realizes a reduction of about 13.2% over the five-times smaller M2 platform while doubling the platform size between the M1 and M2 platforms reduces part cost by 57.6%. While the share of machine cost for the M1 and M2 is nearly equal between 42.6% and 40.7%, it rises to 52.8% with usage of the L1 platform. Especially for the large build platform, the printer contributes the major share of machine cost, which represents the highest cost component. Other researchers reported comparable findings regarding the high impact of machine cost on part cost in multiple AM processes [33,34,36]. These point towards a high relevance of the printing speed and machine investment, respectively, lease cost as a cost driver. Lindemann et al. [42] also reported on the effect of these parameters.

Material cost comprise the material consumed for the part body, supports and the excess resin which is washed off the parts or left in the printer after a completed build job. Because of the printing duration of over 5 h, excess resin cannot be reused. Its two-component formulation leads to an ongoing solidification process and degradation of printing properties, so excess material needs to be disposed. Across all platforms this effect causes the highest share in material cost ranging between 3.4% and 6.4% of part cost. As support material also needs to be disposed, these parameters also represent a high cost-driving and optimization potential. In general, the share of material cost increases with the build platform size from 7.0% to 16.2%.

Labor cost develop inversely proportional to platform size and part number per print, ranging from 30.2% to 11.5%. Using bigger platforms, cost for manual activities like cleaning and machine preparation are distributed over a higher number of parts per print, leading to a decrease of labor cost from 30.2% to 11.5% with increasing platform size. However, the amount of finishing cost increases from 1.9% to 5.0% because a growing number of parts needs individual support removal and handling. As all manual activities are assumed to be efficiently organized, the labor rate

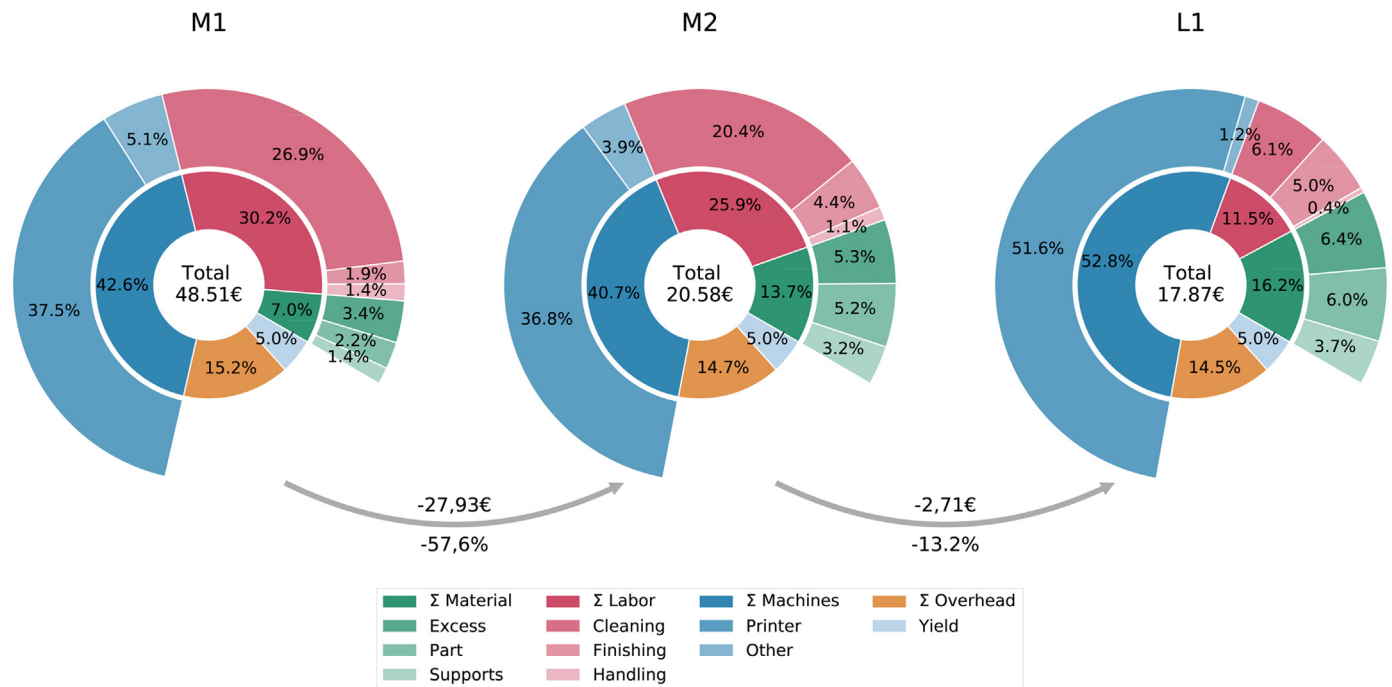


Fig. 9. Overview of the calculated prime cost per part and their components for the M1, M2 and L1 printer platform.

and underlying personnel cost are identified as a potential cost driver. Regarding the growing number of concepts for automation between printers as mentioned in “Introduction” section, the cost saving potential for automation of handling operations seems to be limited as these activities contribute to less than 1.4% of prime cost for all platform sizes. The following section presents the effects of a partially automated production environment on the prime cost per part.

Effects of platform handling automation

Recently proposed automation approaches use a robot arm or conveyor system to automatically load and unload finished prints from printers and post-processing equipment. As shown in Fig. 9 for a manual production approach, the cost for manual handling activities represent a minor cost component when it comes to total labor cost. The cost model is executed again, modeling automated handling and resin dispensing. Additional automation equipment is contributed for in the machine hour rate. Table 8 summarizes the effects of handling automation for the different platform sizes.

The results underline the limited effect of handling automation in production setting for this case study, realizing cost reductions between 0.5% and 1.2%. As the contribution of handling cost to the total labor cost per part decreases with increasing platform size, handling automation becomes less attractive for these machines. Regarding the subsequent sensitivity analysis, parameters for handling automation are not considered impactful cost drivers.

Cost driver evaluation

The following paragraphs evaluate the role and effect of selected cost drivers on the part prime cost for the presented case study using the sensitivity analysis method as introduced in “Sensitivity analysis” section. Based on the presented reasoning pattern, six parameters are identified for sensitivity analysis. Printer lease cost and print speed mainly determinate the printer machine cost. Changes in these parameters due to alteration of

Table 8

Change in cost per part through handling automation.

		M1	M2	L1
Machine cost	[€]	+0.25	+0.08	+0.02
	[%]	+1.2	+1.0	+0.2
Labor cost	[€]	−0.68	−0.23	−0.08
	[%]	−4.6	−4.2	−3.6
Overhead & yield cost	[€]	−0.11	−0.03	−0.01
	[%]	−1.1	−0.9	−0.4
Cost per part	[€]	−0.54	−0.18	−0.07
	[%]	−1.2	−1.0	−0.5

print speed or lease price negotiations are expected to have a high impact on part cost. The same logic applies to the general resin price and material waste during production, comprising support and excess resin. These factors are influenced through print optimization or varying material prices. As activities requiring labor are assumed to be efficiently organized, the underlying cost driving parameter is operator cost. These cost also vary depending on the location of production and therefore pose an influenceable cost driver. A first category summarizes the negotiable, resource-related cost drivers such as cost for printer lease, operator and resin cost. Cost drivers like print speed, the resin loss and support volume, which can be influenced by build optimization, are listed in a second category.

All parameters are varied within a range of $\pm 20\%$ around their original value for comparison of their effect on the part cost. Their behaviour is depicted in Fig. 10 with the first cost driver category listed in the upper graph row and the second category in the row below. For every cost driver and printer platform, the listed slope of the linear (regression) function indicates the responsiveness of the cost model to the input parameter variation. It can be interpreted as change in part cost per percent of change in the input parameters.

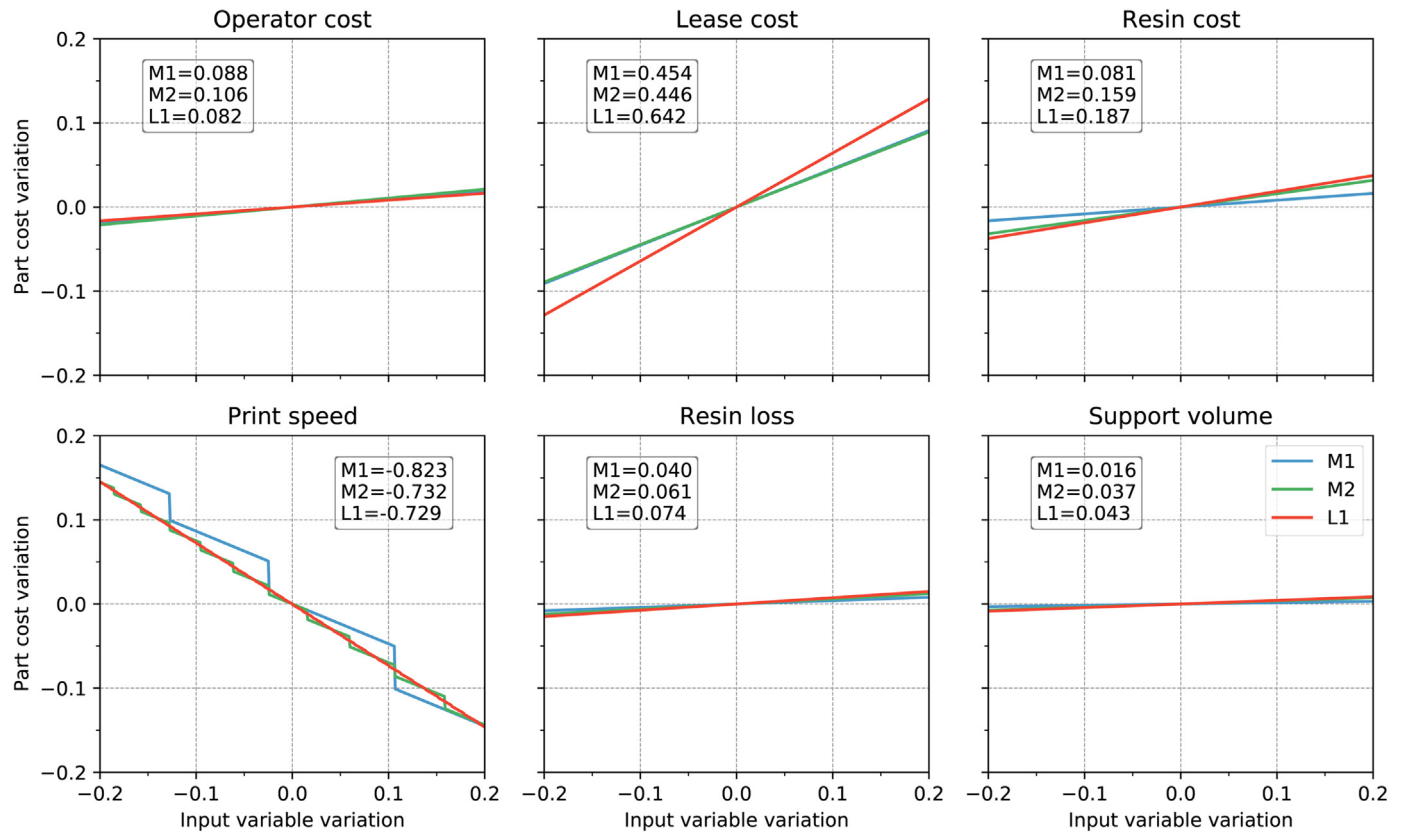


Fig. 10. Overview of the cost driver sensitivity for the selected parameters on M1, M2 and L1 printer platform.

For parameters associated with the first category, printer lease cost represent the most impactful cost driver. Ranging between a responsiveness of 0.454 for the small M1 platform to 0.642 for the L1 platform. Compared to operator cost and resin cost, here the spread between the different platforms is also the highest. While the responsiveness to changes in operator cost is very low for each platform, ranging from 0.082 (L1) to 0.106 (M2) with a small spread, a more clear dependence on resin cost is present. Here, increase in resin cost influences the large L1 platform the most, having a responsiveness of 0.187.

With regard to the second category of cost drivers, which are influenceable through technical adjustments and optimizations, changes in print speed by far have the highest effect on part cost. Furthermore, due to the modeled shift system and the use of a floor function inside calculations for the realized parts per day $N_{p,D}$ (see Table 11 in the Appendix), the behavior is non-linear. Taking into account the linear regression slope coefficients, the small M1 platform has the highest responsiveness (-0.823) to changes in print speed. With a mediocre spread, the L1 platform shows the lowest responsiveness with a value of -0.729 . For the other two cost drivers, resin loss and support volume, spread and responsiveness are very low. For resin loss, values between 0.040 (M1) and 0.074 (L1) are reported. Even lower values apply to support volume, ranging between a responsiveness of 0.016 (M1) and 0.043 (L1).

Expressed as changes in absolute part cost for a more practical perspective, Table 9 exemplarily summarizes the absolute variation results of the most impactful cost drivers 'Lease cost', 'Resin cost' and 'Print speed' for the different print platforms.

In general, these figures underline the potential impact of cost driver optimization, especially given the automotive background of the application example. Regardless of a make or buy approach, the

Table 9

Absolute change in part cost at variation boundaries ($\pm 20\%$).

	Variation	M1	M2	L1	Unit
Lease cost	$\pm 20\%$	± 4.41	± 1.84	± 2.29	[€]
Resin cost	$\pm 20\%$	± 0.79	± 0.65	± 0.67	[€]
Print speed	$+20\%$	-8.01	-2.98	-2.59	[€]
	-20%	$+7.03$	$+2.95$	$+2.61$	[€]

cost sensitivity for sourcing of automotive parts is very high and thus demands economic optimization. Also, careful weighing of chances and risks related to cost drivers is mandatory.

Discussion

Conclusions

The developed cost assessment framework and its application to the case study generated valuable insights into the cost structure of series production with DLP. It enables an assessment of cost structures for physically present printers and production systems as well as estimation for machines that might be subject to an investment or available at suppliers. Fundamental findings from the case study showed that increasing printer size positively influences prime cost per part. However, the relation is not proportional because of varying shares of machine cost. As already found in investigations of other AM processes, machine cost also contributes the highest share in part prime cost with DLP, ranging from about 37% to 52%. Consequently, cost drivers associated with machine cost like machine lease price or print speed bring the highest potential for further production cost reductions as detected in the sensitivity analysis.

With increasing platform size, the contribution of labor cost decreases, as time-intensive activities like machine cleaning between build jobs are distributed over a higher number of parts per print. However, the same applies to the cost of handling part platforms between prints and post processing. Thus, the effect of automation of handling activities on the part cost is very limited and decreases with increasing platform size. This applies to this case study, but could significantly change when another production model and shift-system is assumed. In contrast to handling, cost attributed to single part finishing activities become more relevant with a higher number of parts produced in a print. This underlines the need for new automation concepts for support removal and part finishing to lower prime cost in production.

The importance of material cost also grows with the platform size. Though bigger platforms operate more efficient concerning unused resin, high cost shares and thus also high potentials for cost optimization lie in the reduction of support structures and excess resin. In this case study, the degradation of two-component resins during longer print times leads to a high amount of unused resin which is not usable for a subsequent print and thus needs to be disposed. Here, development and application of single-component resins with comparable properties can improve the process cost and sustainability.

In general, bigger print platforms correlate with reductions in part cost in the analyzed case study. For all platform sizes the optimization of build-related cost drivers like print speed, material waste and support volume shows a high potential for further cost reductions. These parameters can often be influenced by the user depending on the build preparation and execution.

Limitations and future research

The proposed framework enables first estimations of part cost on different DLP platforms in a rapid manufacturing context. Though some build and model parameters were gathered through a sample print, other parameters are subject to the user's assumptions. It is questionable if the assumed parameters can realistically be achieved in the final production environment. However, for the targeted early product development phase, the approach offers a detailed breakdown of cost and influence of cost drivers, enabling first profound decision making regarding, e.g., utilized printer platforms and the operation concept or checking the plausibility of supplier quotes. Furthermore, its elements can be carried forward to a dynamic cost evaluation in a simulation environment, further enhancing cost estimations together with production times and necessary equipment.

The case study showed that the part cost difference between the two larger platforms is relatively low. Depending on the production volume, it might also be beneficial to produce on smaller machines, as they can face higher utilization in practice. Especially when larger machines are not fully utilized, the high investment, respectively, lease cost can lead to significant increases in part cost, underlining the need for an application-specific dynamic cost modeling approach.

While DLP already proves its capability to fulfill end-use parts' requirements and moves into series production like other AM technologies, there are still opportunities for further cost reductions in both, production resources and build optimization for DLP. For example, effects from alternative part positioning, supporting or redesign for additive manufacturing were not considered but are directly linked to the cost during production. Furthermore, improved support generation and minimization of waste not only contribute to better cost performance but also to a more sustainable manufacturing process with DLP. In this context, additional benefits of AM such as the possibility to produce locally in distributed manufacturing networks were not covered here but

need to be considered when AM is evaluated among other manufacturing options. Multiple effects down the supply chain should be taken into account to estimate the cost of AM and its sustainability in production in a more holistic way. Future research can address these topics and contribute to more cost transparency in this AM process family, ultimately advancing usage of AM in manufacturing through better cost prediction in the early product development stages.

Conflicts of interest

None declared.

Appendix A. Additional information for parameters and calculations

This appendix provides additional information about relevant parameters and calculations, which were applied during development of the cost model and its application to the presented case study.

A.1 Parameter notation and overview

Multiple parameters have been identified and acquired for the proposed cost model. For better understanding and transparency, these parameters are listed in Table 10 with their respective notation, grouped by their type.

Table 10
Summary of parameters for model input.

Parameter	Symbol	Unit
Printer platform x size	x	[mm]
Printer platform y size	y	[mm]
Geometric part volume	$V_{G,P}$	[cm ³]
Geometric support volume	$V_{G,S}$	[cm ³]
Part bounding box x size	$x_{B,P}$	[mm]
Part bounding box y size	$y_{B,P}$	[mm]
Part bounding box z size	$z_{B,P}$	[mm]
Printer room footprint	$A_{F,P}$	[m ²]
Washer room footprint	$A_{F,W}$	[m ²]
Oven room footprint	$A_{F,O}$	[m ²]
Printer power rating	$P_{E,P}$	[kW]
Washer power rating	$P_{E,W}$	[kW]
Robot power rating	$P_{E,R}$	[kW]
Oven power rating	$P_{E,O}$	[kW]
Number of parts per build	$N_{P,B}$	–
Number of shifts per day	n_S	–
Number of operational days per year	n_O	–
Lease for printer and platforms	$C_{DL,P}$	[k€/a]
Lease for part washer	$C_{DL,W}$	[k€/a]
Invest cost for robot and periphery	$C_{I,R}$	[k€/a]
Invest cost for curing oven	$C_{I,O}$	[k€/a]
Resin cost	C_{Mat}	[€/L]
Operator cost	C_L	[€/h]
Printing time	t_P	[h]
Washing time	t_W	[min]
Resin dispensing	t_D	[min]
Platform handling	t_H	[min]
Platform cleaning	t_C	[min]
Part de-supporting	t_{DS}	[min]
Thermal curing	t_{TC}	[h]
Shift clean-up time	t_{SC}	[h]
Time per shift	t_S	[h]
Depreciation time	t_{Dep}	[a]
Specific resin loss	k_L	[ml/cm ²]
Printer utilization		–

Table 10 (Continued)

Parameter	Symbol	Unit
Washer utilization	$k_{U,P}$	–
Robot utilization	$k_{U,W}$	–
Oven utilization	$k_{U,O}$	–
Maintenance factor	k_M	–
S&A on material	$k_{SA,M}$	–
S&A on production	$k_{SA,P}$	–
Overhead on material	$k_{O,M}$	–
Overhead on production	$k_{O,P}$	–
Yield	k_Y	–
Power rate	k_E	[€/kWh]
Room rate	k_R	[€/m ² a]
Conversion rate \$/€	k_C	–

Table 11

Summary of calculated parameters and cost estimating relationships.

Parameter	Equation	Unit
Part volume per build	$V_B = N_{P,B} \cdot V_{G,P}$	[cm ³]
Support volume per build	$V_S = N_{P,B} \cdot V_{G,S}$	[cm ³]
Excess volume per build	$V_E = k_L \cdot x \cdot y$	[cm ³]
Print speed	$v_P = \frac{z_{B,P}}{t_P}$	[cm/h]
Average build rate	$b_P = \frac{V_B + V_S}{t_P}$	[cm ³ /h]
Material cost per part	$C_{Mat} = \frac{(V_B + V_S + V_E) \cdot C_{Mat}}{N_{P,B}}$	[€]
Labor cost per part	$C_L = \left(\frac{t_D + t_H + t_C}{N_{P,B}} + t_{DS} + \frac{t_{SC}}{N_{P,S}} \right) \cdot C_L$	[€]
Machine hour	$C_{Mac,i} = C_{E,i} + \frac{C_{R,i} + C_{DL,i}}{t_{A,i} \cdot k_{U,i}}$	[€/h]
Equipment energy cost	$C_{E,i} = P_{E,i} \cdot k_E$	[€/h]
Equipment room cost	$C_{R,i} = A_{F,i} \cdot k_R$	[€/a]
Daily availability	$t_{A,D,i} = n_S \cdot (t_S - t_{SC})$	[h]
Yearly availability	$t_{A,i} = n_O \cdot t_{A,D,i}$	[h/a]
Printer machine cost	$C_{Mac,P} = \frac{C_{Mac,P} \cdot t_P}{N_{P,B}}$	[€]
Washer machine cost	$C_{Mac,W} = \frac{C_{Mac,W} \cdot t_W}{N_{P,B}}$	[€]
Robot machine cost	$C_{Mac,R} = \frac{C_{Mac,R} \cdot t_H}{N_{P,B}}$	[€]
Oven machine cost	$C_{Mac,O} = \frac{C_{Mac,O} \cdot t_{TC}}{N_{P,D}}$	[€]
Robot depreciation cost	$C_{DL,R} = \frac{C_{DL,R} \cdot k_M}{t_{Dep}}$	[€/a]
Oven depreciation cost	$C_{DL,O} = \frac{C_{DL,O} \cdot k_M}{t_{Dep}}$	[€/a]
Production cost	$C_P = C_{Mac,P} + C_{Mac,W} + C_{Mac,R} + C_{Mac,O}$	[€]
Parts per day	$N_{P,D} = \left[\frac{t_{A,D,P}}{t_P + t_H} \cdot k_{U,P} \cdot N_{P,B} \right]$	–
Parts per shift	$N_{P,S} = \frac{N_{P,D}}{n_S}$	–
Total part cost before yield	$C_{Part,BY} = (C_P + C_L) \cdot (1 + k_{SA,P} + k_{O,P}) + C_{Mat} \cdot (1 + k_{SA,M} + k_{O,M})$	[€]
Total part cost after yield	$C_{Part,AY} = \frac{C_{Part,BY}}{k_Y}$	[€]

A.2 Relationships for parameter calculation and cost-estimation

The cost model introduced in “Cost model” section contains a number of cost estimating relationships and side calculations, which are necessary to conduct the sensitivity analysis and achieve the presented results. Table 11 provides an overview over all equations for the resulting cost-estimating relationships, which were applied in the model in addition to the relationships mentioned in the introduction of the cost model.

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