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Self-learning calculation for selective laser melting

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Abstract

Selective laser melting (SLM) is increasingly used in the industrial production of metallic parts. This creates the need for an efficient and accurate quotation costing. The manufacturing costs of a part mainly result from the machine running time for coating and exposure. At the time of the offer calculation the final orientation of the part in the build chamber and the composition of the build job are typically not known. Addressing this need, this paper presents and evaluates different statistical based methods for an automated and self-learning calculation for SLM given a part's CAD data.

Keywords: Calculation ; Quotation costing ; Self-learning ; Selective laser melting (SLM) ; Additive manufacturing (AM).

1. Introduction

Additive manufacturing (AM) is increasingly used in the industrial part production. Especially Selective Laser Melting (SLM) established for the powder-based generation of metallic components. AM builds up parts layer by layer based on given 3D geometry data [5,7]. Beside of AM, digitization and networking are current trends in manufacturing engineering. In recent times, the first 3D printing service providers offer the option to place orders online [23]. Cloud-based platforms, which enable automated order acceptance and processing, are in the focus of current research [17,18]. An essential part of a cloud-based manufacturing platform is an effective and efficient quotation costing [17]. This paper presents an automated, self-learning calculation for SLM, which is implemented within a web-based platform. The customer can upload the geometry data of a part via an online form (see Fig. 1). Subsequently, the geometry is checked and an offer is calculated.

The paper is structured as follows: Section 2 presents basics of the SLM process. Section 3 gives an overview of the related work. Section 4 introduces the developed calculation method and the underlying cost model. Section 5 evaluates the method, especially regarding its accuracy. Section 6 gives a conclusion and outlook.

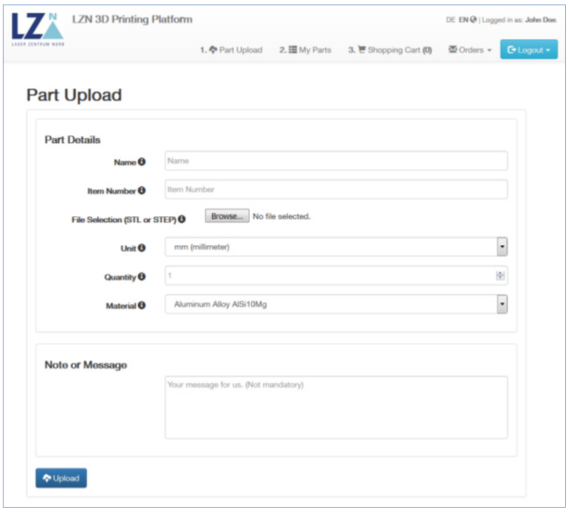

Fig. 1. Part upload via the implemented web platform.

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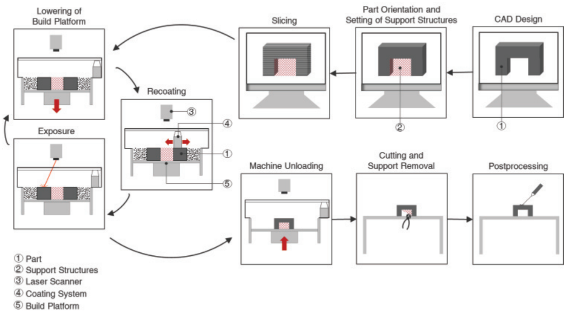

Fig. 2. Basic principle of additive manufacturing using SLM (based on [13]).

2. Selective Laser Melting

SLM is an AM powder bed based, micro welding process [5,7]. Fig. 2 shows the basic principle of the SLM process. The starting point is the CAD data of a part. For the data preparation it is converted into an STL file. The STL format (Standard Triangulation Language) has established as de facto industry standard in AM [2,10]. The STL format describes an object by its triangulated surface geometry. In the data preparation phase the build job is composed. This also includes the setting of a part's orientation in the build chamber and the construction of support structures, which fix the part to the build platform. Within SLM multiple different parts can be built simultaneously in one build job. The stacking of parts above each over, as done for Selective Laser Sintering (SLS), is not used in practice, because of the required support structures. The slicing generates the layered data with the exposure vectors for the generation process.

The SLM process itself has three main steps: the lowering of the build platform, the recoating with a new powder layer, and the exposure via a laser scanner system. For the cost calculation the lowering of the build platform and the recoating are considered as one step. Finally, the machine is unloaded. Parts are separated from the build platform and supports are removed. This is followed by a post processing, which may include a final machining of functional surfaces.

Beside of the build job with a part's generation, the complete process chain also includes preliminary and post processing steps [14]. Fig. 3 gives an overview of the full production costs based on the main process steps. The full production costs are divided into material and manufacturing costs. The manufacturing costs are again divided into special direct manufacturing costs, direct manufacturing costs and indirect manufacturing costs. This paper focuses on a cost calculation of the generation process or build process (including coating and exposure).

3. Related Work

This section provides an overview of the relevant, existing cost models, which serve as basis for the development of an automated and self-learning quotation costing for SLM in this paper.

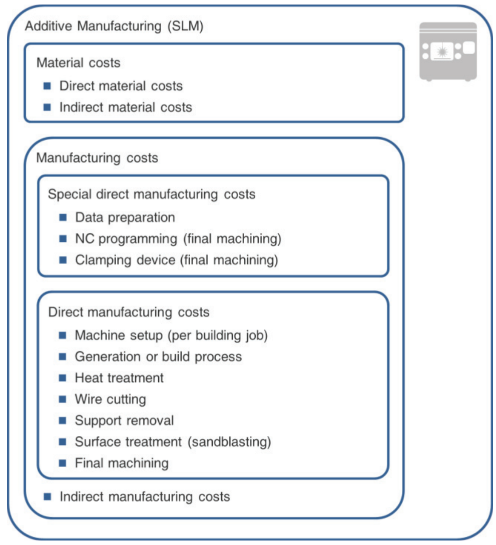

Fig. 3. Structure of full production costs for SLM [19].

Alexander et al. developed a cost model with the aim of finding a part's cost minimal orientation [1]. The model assumes the production of one single part and is evaluated for Stereolithography (SLA) and Fused Deposition Modeling (FDM).

Huang et al. present the concept of a web-based service system for rapid prototyping [9]. The system includes a calculation module for SLA. Basis of the cost model is a slicing of a part's STL data. The orientation of the part is given by the user.

Luo et al. also describe a web-based E-commerce system [12]. Their cost model is not based on a slicing of the data, but on an analytical calculation including the number of required layers and the material volume to be built. The part orientation is given by user input.

Lan et al. present two cost models for a web-based calculation system for SLA [11]. The first model is a rough calculation using a part's weight as single input parameter. The second model considers the process times for coating and exposure, but needs the part orientation as input value.

While the cost models, presented so far, mostly focus on rapid prototyping, Hopkinson and Dickens analyze rapid manufacturing use cases [8]. The authors exemplary compare the costs for injection molding, SLA, FDM, and SLS for a mass production with only equal parts in a build job.

Ruffo and Hague present three cost models with the aim of calculating the costs for a single part in simultaneous production with SLS [21]. The first model presents a splitting of the costs based on the part's volume. The second model is based on a single production of the part. The third model assumes a mass production of parts with the same geometry.

Grund developed an analytical cost model for SLM for the simultaneous production of multiple different parts in one build job [6]. The process time for one single part is determined by the time for exposure and the time for coating. The coating time is split over the parts in one build job via the build height of the parts, the exposure time via the volume of the parts. The usage of the cost model requires detailed knowledge about the composition of the calculated build job.

Schmidt also presents an analytical cost model for SLM with coating and exposure [22], but assumes the simultaneous production of equal parts. The model is extended by a cost calculation for preliminary and post processing steps, which is based on known handling and process times.

Munguía et al. propose a method for the estimation of the build time for SLS by using artificial neural networks (ANNs) [15]. Input parameters for the ANN are a part's build height, volume, and volume of the bounding box.

Di Angelo and Di Stefano also use ANNs for build time estimation [3]. The method should also be applicable for different AM technologies, such as SLS and SLM. For the ANN numerous input parameters are necessary, e.g. build direction of the part and information about support structures.

Rickenbacher et al. present a statistical approach for the estimation of the build time for a complete build job with simultaneous production of multiple different parts [16]. The model is based on a linear regression analysis. The regression coefficients are estimated from past build jobs. In order to get the costs for one single part, the calculated build costs are split up according to volume and build height of the parts.

In summary, numerous, different cost models for AM processes were developed in the past. However, for an automated calculation within a web-based platform solution, the existing approaches cannot be used or are only partially suitable. The two main reasons are that existing models either require knowledge about the production process (e.g. composition of build job, build height of a component), which is not available at the time of the online calculation, or are too imprecise, since the costs are only calculated for the complete build job (and not for the contained components) or for individual production (one component per build job). This creates the need of research for a cost model, which allows an automated, web-based application.

4. Calculation for Selective Laser Melting

The objective of this paper is the development of a cost model for the SLM build process, which can be used within a web-based platform for an automated quotation costing. Fig. 4 shows the changeover from a manual quotation process to an automated, web-based method.

Based on the web-based quotation the customer decides whether to order the part. The part is only going into production, when the customer has placed an order via the web platform. In the work and data preparation phase the build job is composed by an engineer or technician (Section 2). Thus, at the time of the quotation costing the final orientation of the part in the build chamber and the composition of the build job are not known. This lack of information about the later manufacturing process at the time of the quotation costing is the main challenge for the development of an automated preliminary calculation.

Input for the calculation is a part's STL file, which is given by the user or customer via a web upload. In order to execute the algorithms on CAD data (e.g. STEP), the input data of a part is converted into STL previously. The given geometry is automatically analyzed to determine a part's key characteristics: volume, surface, and dimensions.

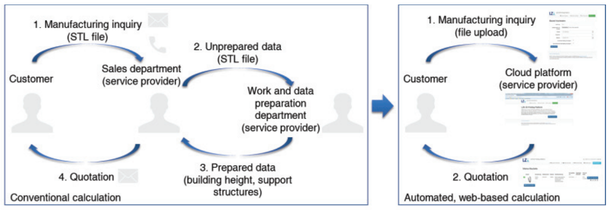

Fig. 4. Changeover from a manual quotation process to an automated, web-based method [17].

4.1. Calculation Method and Cost Model

The method uses analytical and statistical based functions to determine the build costs for one part with SLM. The build costs for one part consist of the build time for the part multiplied with the hourly costs of a SLM machine:

$$C_{Part} = t_{Part} \cdot C_{mh} \quad (1)$$

where C_{Part} are the build costs for one part, t_{Part} the build time for the part, and C_{mh} the hourly costs of a SLM machine.

The build time for the part is composed of the build times for coating and exposure:

$$t_{Part} = t_{Exp} + t_{Coat} \quad (2)$$

where t_{Part} is the build time for the part, t_{Exp} the time for exposure, and t_{Coat} the time for coating. An analysis of 25 past build jobs shows that the coating time can take up to 60% of the total build time. In average the coating time has a share of 36% on the total build time.

The time for exposure for one part calculates as follows:

$$t_{Exp} = \frac{(V_{Part} + V_{Sup})}{v_{Melt}} \quad (3)$$

$$V_{Sup} = V_{Part} \cdot a_{Sup} \quad (4)$$

where t_{Exp} is the time for exposure, v_{Melt} the exposure rate or melting rate, V_{Part} the volume of the part, and V_{Sup} the volume of required support structures (estimated using an statistical average factor a_{Sup}).

For the calculation of the coating time the average capacity utilization of a build job is used. It is defined as follows:

$$u_{BJ} = \frac{V_{Used,Per}}{V_{BJ,Per}} = \frac{\sum_{i=1}^{n} V_{Used,i}}{\sum_{i=1}^{n} (h_{Max,i} \cdot l_{BC} \cdot w_{BC})} \quad (5)$$

where u_{BJ} is the average capacity utilization of a build job, $V_{Used,Per}$ the sum of used volume (volume occupied by parts and support structures) in past build jobs within a period of time, $V_{BJ,Per}$ the sum of the possible build volume of the past build jobs within the period of time, i the i-th of the past build jobs, n the number of past build jobs, $V_{Used,i}$ the used volume in the i-th build job, l_{BC} the length of the build chamber, w_{BC} the width of the build chamber, and $h_{Max,i}$ the maximum height of the i-th build job.

After defining the average capacity utilization, it is possible to calculate the time for coating for a single part:

$$t_{Coat} = \frac{h_{Gen,Part}}{h_{Recoat}} \cdot t_{Recoat} \cdot \frac{(V_{Part} + V_{Sup})}{u_{BJ} \cdot h_{Gen,Part} \cdot l_{BC} \cdot w_{BC}} = \frac{t_{Recoat} \cdot (V_{Part} + V_{Sup})}{h_{Recoat} \cdot u_{BJ} \cdot l_{BC} \cdot w_{BC}} \quad (6)$$

where t_{Coat} is the time for coating, t_{Recoat} the time for one layer recoating, h_{Recoat} the layer height or thickness of one recoating, u_{BJ} the average capacity utilization of a build job, l_{BC} the length of the build chamber, w_{BC} the width of the build chamber, V_{Part} the volume of the part, V_{Sup} the volume of support structures, and $h_{Gen,Part}$ the build height of a part after orientation in the build chamber (can be crossed out and is not necessary for the calculation). Knowledge about a part's build direction is not mandatory for performing the calculation.

For 25 build jobs (mixed different parts), which were analyzed within this paper, an overall capacity utilization of 3.6% could be measured. A further analysis of the build jobs reveals that the build height distribution varies widely. Fig. 5 shows the distribution of the build height. Often a few large parts are in the same build job with many small parts. It can be concluded that the capacity utilization highly depends on the build height. The dependence of the capacity utilization on the build height is shown in Fig. 6. This varying utilization should also be considered in the cost calculation. Therefore, two variants for a more accurate cost calculation are developed. Section 4.2 presents a method, which allows a prediction of the expected capacity utilization for a given part. Section 4.3 presents a model for the prediction of a components build height, which can be used for the cost calculation afterwards.

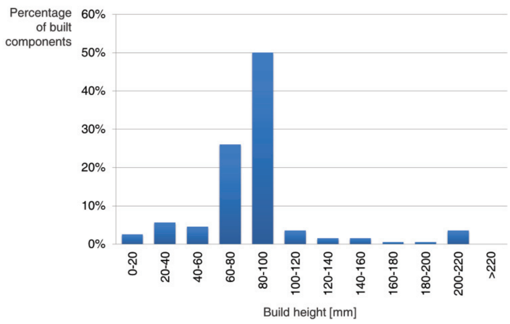

Fig. 5. Build height of components in 25 past build jobs.

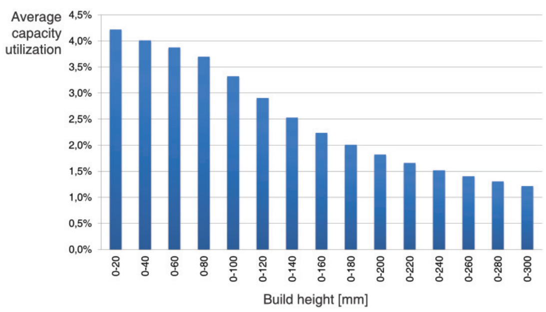

Fig. 6. Capacity utilization depending on the build height in past build jobs.

4.2. Prediction of Capacity Utilization

The following section describes a model for the direct prediction of the expected (height-dependent) capacity utilization for a given part. The prediction model is statistical based and uses a linear regression. In order to assign the independent variables unambiguously, the dimensions of the given component are sorted by length. During the development the regression coefficients, which are not significant (p-value greater than 0.05), are gradually excluded. Analyzed capacity utilizations of past build jobs form the database for the training of the linear regression. This leads to the following prediction model for the capacity utilization:

$$u_{BJ} = \alpha_0 + \alpha_1 \cdot dim_{Part_1} \quad (7)$$

where u_{BJ} is the predicted capacity utilization when building the given part, dim_{Part1} the longest edge of the part's dimensions, α_0 the regression constant, and α_1 the regression coefficient. The capacity utilization may not fall below the utilization for single production of the component.

The predicted capacity utilization u_{BJ} can be used in Formula 6 to calculate the expected coating time for the given part. This method should be more precise than using an overall average factor (as the stated 3.6%), which does not consider the probable build orientation of a part.

4.3. Prediction of Part Build Height

While the previous prediction model (Section 4.2) does not include an explicit estimation of a part's build height, the following model predicts the expected build height of a part. Based on a linear regression the probable build height can be estimated by following statistical model:

$$h_{Gen,Part} = \beta_1 \cdot dim_{Part_1} + \beta_2 \cdot dim_{Part_2} \quad (8)$$

where $h_{Gen,Part}$ is the predicted build height of a part (after orientation in the build chamber), dim_{Part1} the longest edge of the given part's dimensions, dim_{Part2} the second longest edge of the given part's dimensions, and β_1, β_2 the regression coefficients.

The estimated build height for a part $h_{Gen,Part}$ serves as input for the histogram, which describes the relationship between utilization and build height (shown in Fig. 6). The capacity utilization can be determined from the stated histogram and be used in Formula 6.

4.4. Self-learning Calculation

The presented prediction models (Section 4.2 for the capacity utilization and Section 4.3 for the build height) are statistical based on past build jobs. Both models can be used in a self-learning system, which teaches and optimizes itself by incremental learning. Fig. 7 shows the concept of a self-learning calculation in AM. New build jobs, which have gone into production, can directly be used for a training of the regression models. By this means, the database for the training of the prediction models grows with every new build job, which has gone into production. The system optimizes itself incrementally over the time, since it can learn from more situations. More precise prices can be calculated.

5. Evaluation

In the following the three presented variants of the cost model are evaluated and compared regarding their accuracy. First, the experimental setup of the evaluation is described.

5.1. Experimental Setup

The evaluation focuses on the accuracy (or effectiveness) of the presented cost models. Therefore, the calculated results of the developed costing algorithms are compared to a post calculation, which is based on real process times of production jobs. For the evaluation 25 past build jobs were divided into two parts: 15 build jobs are for the training of the method and 10 for the evaluation. Out of the 10 evaluation build jobs 20 different parts are used for the comparison of the accuracy. For the post calculation the exact, real build heights of the parts as well as exposure and coating times of the 10 build jobs are used and downscaled to the individual parts. For the distribution of the coating time an even volume distribution over the layers is assumed.

For the comparison of the variants two accuracy measures are used: the mean absolute percentage error (MAPE) and the mean squared error (MSE). The MAPE is the average of the absolute percentage deviations between the performed calculation of the developed costing method (preliminary calculation) and the post calculation. The MSE is the average of the squares of the deviations between the preliminary calculation and the post calculation. By squaring, outliers have greater impact on the measurement result.

5.2. Overall Capacity Utilization

The usage of an overall capacity utilization factor (same average capacity utilization for every part regardless of a part's dimensions) shows a MAPE of 9.22% on the build time. The MSE is 0.67h^2 (hours to square). In previous publications a MAPE of 8.2% is stated for the usage of an overall capacity utilization factor [17,19]. The reason for the slight difference to the presented result of 9.22% is the usage of another, partially extended data set in the present evaluation. Fig. 8 shows the results with a comparison to the post calculation for the 20 tested components.

5.3. Prediction of Capacity Utilization

The usage of the statistical model for the prediction of the capacity utilization (depending on a part's dimensions) for the cost calculation (Section 4.2) shows a MAPE of 8.78% and MSE of 0.31 h^2 on the build time. Fig. 9 shows the test results.

5.4. Prediction of Part Build Height

The model for the estimation of a part's build height with subsequent assignment of the capacity utilization by a histogram of past build jobs (Section 4.3) shows a MAPE of 8.99% and MSE of 0.21 h^2 on the build time. Fig. 10 shows the results for the 20 evaluated parts.

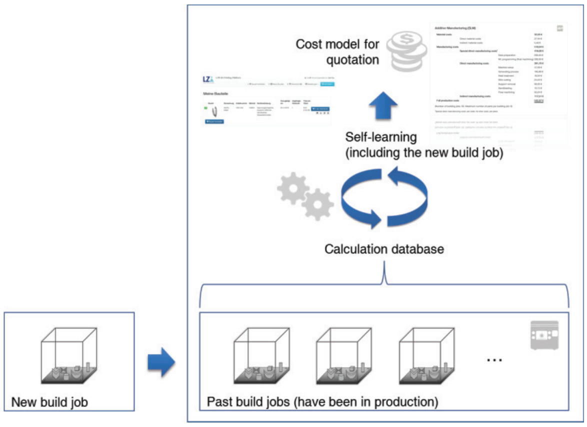

Fig. 7. Concept of a self-learning calculation for additive manufacturing.

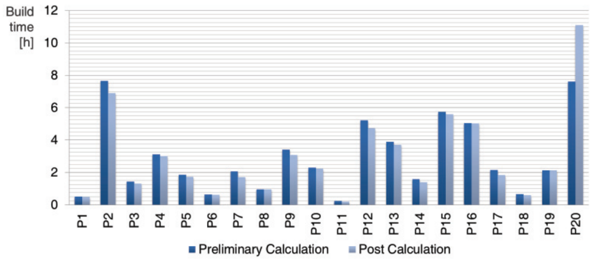

Fig. 8. Comparison of preliminary and post calculation using an overall capacity utilization factor (1. variant).

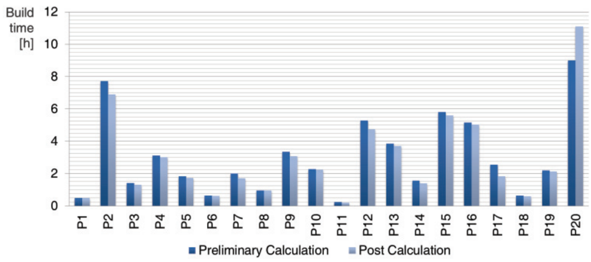

Fig. 9. Comparison of preliminary and post calculation using the direct prediction model for the capacity utilization (2. variant).

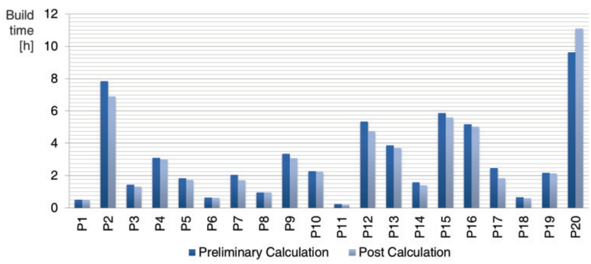

Fig. 10. Comparison of preliminary and post calculation using the prediction of a part's build height (3. variant).

5.5. Summary

The direct prediction of the capacity utilization (Section 5.3) shows the best evaluation results for a cost calculation regarding the absolute percentage error with a MAPE of 8.78%. It should be used for an automated quotation costing. The model, which includes the prediction of a part's build height, (Section 5.4) has a slightly worse MAPE, but a better MSE, which is an indicator that it has less outliers. For the prediction of the build height it is unlikely that alternative approaches, such as ANNs or decision trees, achieve better results than the presented linear regression, since also for these approaches a histogram is still needed, which brings a certain inaccuracy into the computation.

6. Conclusion and Outlook

This paper presents a calculation method and cost model, which enables an automated calculation and quotation costing for SLM. The method is implemented as part of a web-based platform. It allows a quotation directly after the user has uploaded a part's geometry or CAD data. The costing is based on an analytical and statistical model, which allows the implementation of a self-learning calculation system. It can learn from past build jobs and on this way improve the accuracy of the calculation. The evaluation compares three variants of the cost model. It could be shown that the direct prediction of the capacity utilization shows the most accurate calculation results.

AM allows a high degree of design freedom compared to conventional manufacturing technologies. This makes it possible to manufacture complex, optimized, lightweight structures [4]. Therefore, important topics for future research are the automated determination of a component's lightweight potential (through structural optimization) and the integration of design potentials in the cost calculation [20].

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