CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2021

2nd Conference on Production Systems and Logistics

# Sensitivity Analysis of a Simulation Model for the Determination of the Utilization of a Production Environment with the LPBF-Process

Aziz Ghannouchi[1], Tobias Stittgen[1], Johannes Henrich Schleifenbaum[1]
[1]RWTH Aachen University Digital Additive Production DAP, Germany

**Abstract**

Additive Manufacturing is on the brink of industrialization. In addition to the technical aspect, the aspect of production planning and optimization is continuously gaining importance with the technology being introduced into production environments. In order to allow a production logistics positioning for a production environment equipped with Laser Powder Bed Fusion machines, a simulation model has been developed at the RWTH Aachen University Chair for Digital Additive Production DAP. By means of this simulation model, production logistics key performance indicators (KPIs) such as the utilization are calculated as a function of nine parameters describing the production environment. To demonstrate the validity of the simulation model and allow a better understanding of its behaviour, the influence of each input on the utilization is investigated. In this study, a Global Sensitivity Analysis (GSA) based on the Monte Carlo method is performed to quantify the importance of the parameters. For this purpose, a Variance Based Sensitivity Analysis (VBSA) is conducted, followed by a Regional Sensitivity Analysis (RSA), and a GSA based on the PAWN method, allowing to perform all three settings of GSA, namely Factor Prioritization, Factor Fixing, and Factor Mapping. Finally, the knowledge brought by the sensitivity analysis allows for a user-friendly simplification of the production environment model, thus permitting a prioritized increase of the utilization.

**Keywords**

Monte Carlo Method; Latin Hypercube Sampling; Variance Based Sensitivity Analysis; Regional Sensitivity Analysis; PAWN; Additive Manufacturing; Laser Powder Bed Fusion; Production Logistics; LPBF

## 1. Introduction

Additive Manufacturing (AM) is on the brink of industrialization [1–3]. In particular, Laser Powder Bed Fusion (LPBF) is becoming more significant to manufacture individualized and complex parts [4]. As the demand in AM parts is growing, especially in the aviation, automotive and medical fields [5–8], AM service providing companies have to act efficiently from the operational point of view to be economically profitable. While from a technical aspect, LPBF is becoming mature and reliable, other aspects such as production planning are lagging behind. This is presented in the works of Stittgen, where the manufacturers using this technology are shown to only reach a limited utilization [1,9].

The overall objective of this study is therefore to generate insights regarding the production planning and data preparation for the LPBF process chain, data preparation being the process of assigning parts to so-called buildjobs. By using a Monte Carlo based Global Sensitivity Analysis (GSA), the importance of the factors describing the configuration of an LPBF production environment is examined, ultimately allowing to provide guidelines for industrial end users on how to increase the utilization of their capital intensive equipment.

## 2. Scope of the Study

First, the Dilemma of Operations Planning in the field of production logistics is described. Then, the simulation model of LPBF production environments developed at the RWTH Aachen Chair for Digital Additive Production (DAP) is presented. Finally, Sensitivity Analysis is introduced, along with the settings aimed for in this study and the methods used.

### 2.1 Dilemma of Operations Planning in Production Logistics

As almost every technical advantage in the field of manufacturing is exposed to continuous change, in order to be competitive on the market, manufacturing companies need to not only constantly improve their products and production processes, but also optimize aspects of production logistics. This means manufacturers must strive to pursue greater delivery capabilities and reliability with the lowest logistics and production costs possible [10]. Consequently, these companies must strive to minimize their throughput time, minimize their lateness, maximize the utilization of their machines and operators, and reduce their Work in Process (WIP). These four variables are defined by Nyhuis and Wiendahl in order to systematically describe and model the fundamental interrelations between production logistics Key Performance Indicators (KPIs) as shown in Table 1 [10].

Table 1: Definitions of the Production Logistics Key Performance Indicators

| KPI | Definition |
|---|---|
| Lateness | The difference between the targeted processing end time and the actual processing end time |
| Throughput Time | The amount of time required for a production order from the completion of the previous order until the end of the considered process |
| Utilization | The ratio of the mean output to the possible maximum output |
| Work in Process | Cumulated work content (WC) of the orders queued for processing and those being processed |

Nevertheless, when trying to maximize the utilization and minimize the three KPIs lateness, throughput time and WIP, the manufacturers encounter the so-called dilemma of operations planning [11]. This means that certain production logistics objectives, quantified by the KPIs, are in conflict [10]. Therefore, companies need to set goals on which production logistics KPIs need to be prioritized, and how to improve these prioritized indicators.

In this study, the focus is set on the utilization of the machines, as the equipment of an LPBF production environment is capital intensive and the KPI is therefore a priority from an internal point of view for the company.

### 2.2 Simulation Model of LPBF Production Environments

In addition to the technical challenges such as the development of stable process parameters, material considerations, or design guidelines for Additive Manufacturing, manufacturers using LPBF currently face operational challenges regarding the following aspects amongst others:

- Lot sizing: this aspect is fundamentally different from conventional processes, as LPBF allows to manufacture several different parts at the same time in one job.

- Machine and operator availability: as the operators are only required to mount and unmount the jobs. Their presence is not necessary while the jobs are running.
- The distribution of the work content as it does not follow a normal distribution and differs from conventional processes.

Compared to conventional manufacturing processes, LPBF production environments are characterized by a high level of automation, the non-necessity of tools, an unmanned production, and the possibility to manufacture parts of different geometries at the same time [12]. Furthermore, the work content distributions of LPBF jobs are longer than those of conventional processes such as CNC-milling [13]. Therefore, operations planning needs to be conducted specifically for this technology.

In this context, a simulation model following the described specifics has been developed at DAP. By means of this tool, an LPBF production environment is simulated, allowing to calculate the utilization of the machines while considering the inputs described below (a detailed description of the model can be found in [13]):

- $N_M$: the number of available machines in the production environment
- $T_M$: the necessary amount of time to mount the LPBF machines, measured in hours
- $T_U$: the necessary amount of time to unmount the LPBF machines, measured in hours
- $O_1$: the number of operators present in the first shift
- $O_2$: the number of operators present in the second shift
- $O_3$: the number of operators present in the third shift
- $a_{WC}$: Shape parameter of the distribution of the work content
- $b_{WC}$: Scale parameter of the distribution of the work content
- RR: Release rate, the rate of orders that are released for production, measured by production orders per day

Following the works of Stittgen, the work content of the production jobs is described following a Gamma-distribution, as opposed to the logistics operating curves models [9,13]. This distribution is chosen according to the field data gathered at industrial LPBF end users and is considered in the simulation model.

## 2.3 Sensitivity Analysis

As the production environment is defined in the DAP simulation model by using nine parameters, sensitivity analysis is a powerful tool to investigate the influence of the single factors on the KPI, allowing to identify the most influential ones, as well as the negligible ones. Sensitivity Analysis is defined by Saltelli as being the study of how the variation in the output of a model is attributed to variations of its inputs. The influence of the single input parameters on the outputs is therefore investigated [15,14]. In the context of this study, sensitivity analysis is used to investigate the influence of the parameters describing the configuration of a production environment on the utilization of the machines. In the following, the possible settings of sensitivity analysis are introduced, followed by the three methods used in this study.

### 2.3.1 Settings of Sensitivity Analysis

The goals pursued in the framework of a Sensitivity Analysis are called settings. The three following settings are distinguished:

**Factor Prioritization** allows to rank the parameters according to their influence on the variability of the output.

**Factor Fixing** allows to identify the parameters whose influence on the output is negligible.

**Factor Mapping** allows to determine the region of so-called behavioral inputs, which are inputs that lead to a chosen region of interest in the output. This region of interest is defined by a threshold.

### 2.3.2 Methods Used for this Study

In their work, Pianosi et al. list several GSA methods [16]. For this study, the following three methods are chosen, as they allow to to fulfill all three settings of Sensitivity Analysis. Furthermore, as they rely on three different mathematical principles, a cross-validation is performed to validate the results obtained.

**Variance Based Sensitivity Analysis (VBSA)** relies on the contribution of each parameter on the variance of the output. While the main effects measure the direct contribution of a parameter on the output, the total effects measure the impact of the studied parameter in interaction with all other factors. Therefore, main effects are suitable for the setting of Factor Prioritization, while total effects are used for the setting of Factor Fixing [15].

**Regional Sensitivity Analysis (RSA)** is aimed at identifying a region in the input space that leads to a chosen output region of interest. A threshold is chosen for the output to define the region of interest. The input sets are then split into behavioral and non-behavioral inputs according to the output they lead to, thus fulfilling the setting of Factor Mapping. Furthermore, the empirical cumulated density functions (CDFs) of the behavioral and non-behavioral inputs are defined and visualized. The maximum vertical difference between the two curves obtained for each parameter is calculated by using the Kolmogorov-Smirnov statistic, and represents a sensitivity index used for Factor Prioritization [17].

**PAWN** is a density-based method as it considers the cumulated density function of the output. The unconditional CDF and conditional CDFs of the output are defined, the conditional CDFs being the ones where individual factors are constrained within a chosen interval. The divergence between the CDFs is then calculated and represents the PAWN sensitivity indices, which fulfill the settings of Factor Prioritization and Factor Fixing [18,19].

### 2.3.3 Point Generation

The GSA methods described in the previous section rely on the repeated run of the simulation model on a large number of points. These points are generated with the aid of the Monte Carlo Method or a Quasi Monte Carlo Method [20,15]. In the works of Kucherenko et al., the Latin Hypercube Sampling (LHS) method is proven to be effective and leading to fast convergence [21].

## 3. Workflow of the Study

In this section, the steps of the conduction of the study are presented. First, the ranges and distributions of the input parameters are defined. Second, the input samples are generated. Then, the simulation model is run on the generated inputs. Afterwards, Global Sensitivity Analysis is performed by using the three methods introduced in the previous section. The results for all three settings are presented. In a further step, another GSA is performed on the behavioral inputs identified by means of Factor Mapping. Finally, relying on the generated data, further interpretation is presented regarding the planning of LPBF production environments.

### 3.1 Definition of Ranges and Distributions for the Input Parameters

The ranges and distributions of the parameters are defined as represented in Table 2. They are chosen such that feasible LPBF production scenarios are covered. The input parameters are assumed to be independent.

Due to the discrete nature of time steps used in the simulation model, the values of the mount and unmount time ($T_M$ and $T_U$) are discrete.

Table 2: Ranges and Distributions of the Input Parameters of the GSA

| Parameter | Distribution | Range | Unit |
|---|---|---|---|
| $N_M$ | Uniform, discrete | [1 ... 10] | [-] |
| $T_M$ | Uniform, discrete | [1 ... 4] | [h] |
| $T_U$ | Uniform, discrete | [1 ... 4] | [h] |
| $O_1$ | Uniform, discrete | [0 ... 5] | [-] |
| $O_2$ | Uniform, discrete | [0 ... 5] | [-] |
| $O_3$ | Uniform, discrete | [0 ... 5] | [-] |
| $a_{WC}$ | See Equation 1 | [1 ... 144] | [-] |
| $b_{WC}$ | See Equation 2 | [0.1 ... 25] | [-] |
| RR | Uniform | [0.1 ... 12] | Orders/Day |

For the distribution parameters of the work content, the values follow customized distributions as shown in Equation 1 for $a_{WC}$ (the shape parameter) and Equation 2 for $b_{WC}$ (the scale parameter). The ranges are defined in the works of Stittgen [13]. The distributions represent realistic scenarios of LPBF buildjobs, as a uniform distribution leads to a large number of points with an unrealistically high mean work content.

$$x \in [1\ ;\ 144]\ ,\ PDF_{a_{WC}}(x) = \min\left(25, \frac{120h}{x}\right) \quad (1)$$

$$x \in [0.1\ ;\ 25]\ ,\ PDF_{b_{WC}}(x) = \min\left(144, \frac{120h}{x}\right) \quad (2)$$

### 3.2 Generation of the Inputs and Simulation Run

The input samples are generated using the Latin Hypercube Sampling method, each input representing a distinct production scenario [21]. N = 6,000 inputs are generated, covering the entirety of LPBF production scenarios. The investigated simulation model is then run on each of the generated inputs, allowing to calculate their respective utilizations. Because the model is complex and the conduction of the GSA requires a large number of model runs, the high performance cluster of RWTH Aachen University is used.

### 3.3 Global Sensitivity Analysis

In this section, the results of the Global Sensitivity Analysis are presented. In Figure 1, the sensitivity indices of each parameter obtained with all three methods are represented. All results are verified by means of a convergence analysis along with a robustness analysis [22].

#### 3.3.1 Factor Prioritization

As described in Section 2.4, the setting of Factor Prioritization is fulfilled through all three methods: the parameters with the highest impact on the utilization of the machines are be deduced from the main effects of VBSA, as well as from the sensitivity indices delivered by RSA and PAWN. As shown in Figure 1 (a, c and d), the parameters with the highest sensitivity indices are the distribution parameters of the WC. As a result, they are the parameters with the highest impact on the utilization. The number of machines $N_M$ as well as the production order release rate RR are the parameters with the subsequent sensitivity indices and are therefore likewise subsequent regarding the impact on the KPI.

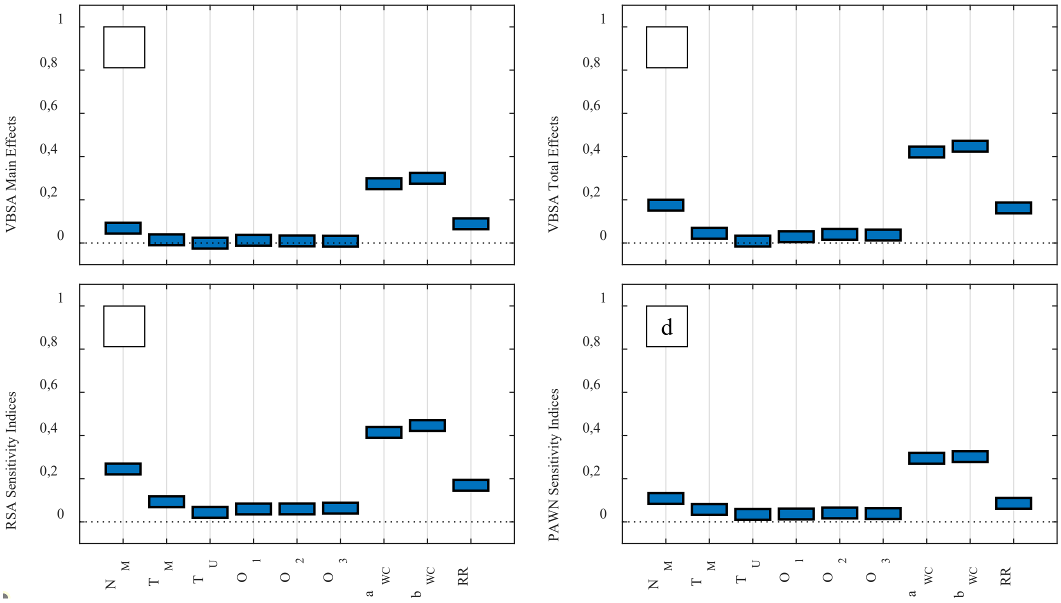


Figure 1: Sensitivity Indices of VBSA, RSA and PAWN for the Complete Design Space

### 3.3.2 Factor Fixing

As described in Section 2.4, the setting of Factor Fixing is fulfilled through the total effects of the VBSA as well as through the PAWN sensitivity indices. A threshold of 5% is chosen to identify a parameter as non-influential, meaning that a parameter with a sensitivity index below 5% is considered as non-influential on the utilization and can therefore be fixed to any value in order to simplify the model [22]. As shown in Figure 1 (b and d), the parameters $T_M$, $T_U$, $O_1$, $O_2$, and $O_3$ have a sensitivity index below the chosen threshold. Consequently, they have a negligible effect on the utilization of the machines of the production environment. The results of this setting are validated by using the method of Andres [23].

### 3.3.3 Factor Mapping

The setting of Factor Mapping is performed by means of the Regional Sensitivity Analysis (RSA). First, the output region of interest is defined by a threshold of 60%, this value being a benchmark observed with industrial end users and therefore represents a lower bound for the utilization that is to be aimed for by a company. This means inputs leading to a utilization greater than 60% are considered behavioral, while inputs leading to a utilization below this threshold are considered non-behavioral. The results of the setting of factor mapping are represented in Figure 2. The whole considered ranges of each parameter allow to reach the output region of interest. Therefore, for each value of each parameter, there are combinations of the other parameters that allow to reach a utilization of more than 60%. In addition, as the behavioral inputs are a set of points leading to a high utilization, a set of possible configurations for the LPBF production environment is obtained.

## 3.4 Sensitivity Analysis on the Behavioral Inputs

In the previous section, Global Sensitivity Analysis is performed on the whole design space of the inputs. In particular, by means of the Regional Sensitivity Analysis, a set of behavioral inputs leading to a utilization greater than 60% is identified. In this section, as suggested in the works of Noacco et al., in order to gain more insights on the behavior of the simulation model, a further GSA is performed after removing the poorly performing inputs [24]. Therefore a GSA is performed on those behavioral inputs. The aim is to investigate the importance of each of the parameters within the points that lead to a utilization greater than 60%.

As VBSA requires a tailored sampling, this method is not used for this investigation. Instead, the two methods used are Regional Sensitivity Analysis (RSA) and PAWN. As a further maximization of the utilization is aimed at, for the case of the RSA, a new threshold for the utilization is set to 90%. The results obtained by using these two methods are represented in Figure 3.

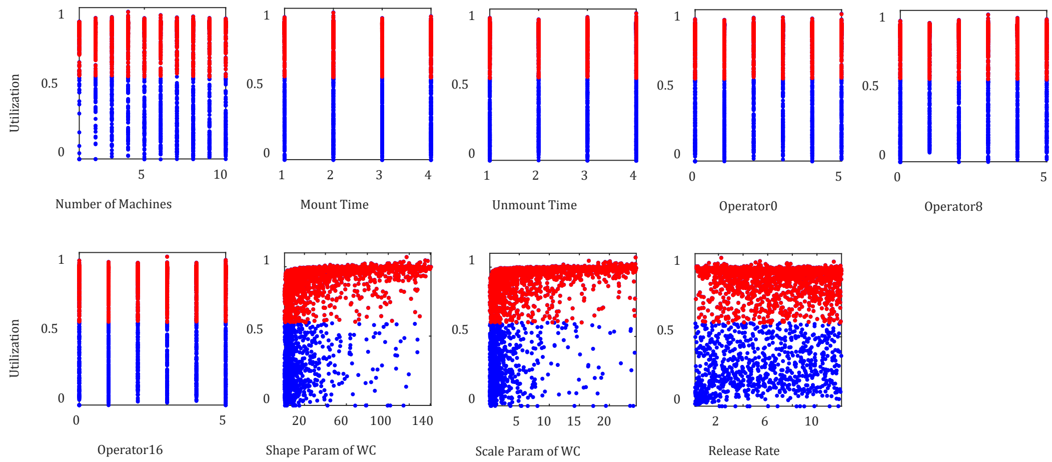


Figure 2: Scatterplots of the utilization as a function of all parameters

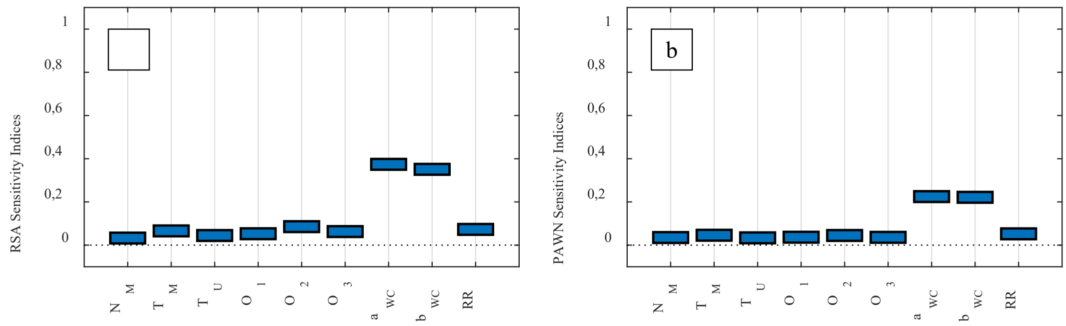


Figure 3: Sensitivity Indices of RSA and PAWN in the Set of Behavioral Inputs

As shown in Figure 3, and similarly to the analysis of the complete design space (Section 3.3), the parameters $a_{WC}$ and $b_{WC}$ have the highest sensitivity indices and are therefore the most influential parameters on the utilization of the production environment. As for the parameters $T_M$, $T_U$, $O_1$, $O_2$, and $O_3$, they have a low influence. Nevertheless, as opposed to the analysis in the complete design space, the parameters $N_M$ as well as RR have a low impact within the set of behavioral inputs, as their sensitivity indices are below 5%. This means that once a utilization of more than 60% is reached, the number of machines in the production environment as well as the number of orders that are released per day have a lower impact on the utilization, meaning that a further maximization of the utilization is achieved only by considering the work content.

## 3.5 Further Interpretation of the Results

In this section, using the generated points and their corresponding outputs, further insights are presented regarding the planning of an LPBF production environment.

### 3.5.1 Impact of the Fluctuation of the Work Content on the Utilization

In this section, the impact of the fluctuation of the WC on the utilization is investigated. First, the variation coefficient of the WC is calculated for all inputs, as it is a standardized measure of dispersion. The points are then divided into equally spaced intervals according to the calculated value. Subsequently, for each interval, the mean utilization is calculated and represented as a function of the variation coefficient of the WC as shown in Figure 4. As presented in the figure, the mean utilization is beyond 90% for a variation coefficient lower than 0.1. The KPI decreases with an increasing variation coefficient until a convergence value close to 30% is reached. As a conclusion, for an LPBF production environment, in order to reach a high utilization, manufacturers need to aim for a low WC variation coefficient, meaning build jobs with a low fluctuation of the work content. The results are therefore compatible with the fourth law of production logistics introduced by Nyhuis and Wiendahl, stating that “the variance and the means of the work content determine the logistic potential of the shop” [10].

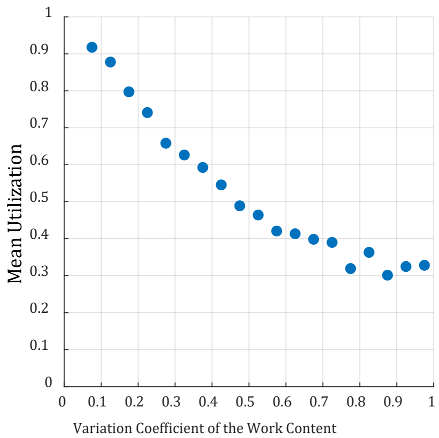


Figure 4: Mean Utilization as a Function of the Variation Coefficient of the WC

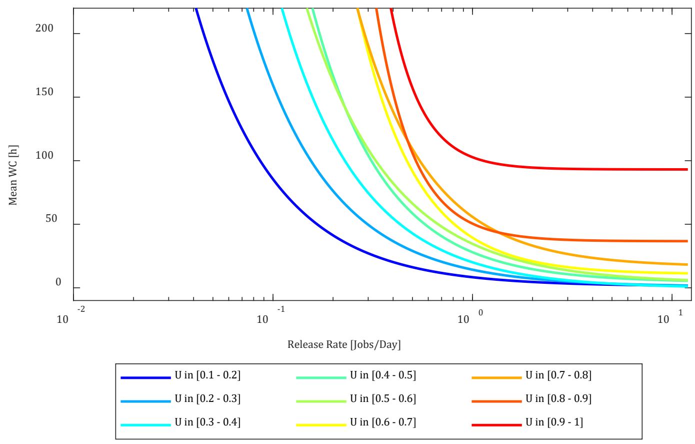


Figure 5: Mean Reachable Utilization as a Function of the Mean WC and the Production Order Release Rate

### 3.5.2 Guidelines for Data Preparation

A possible application of the results lies in the area of data preparation, a process step inherently connected to LPBF manufacturing and corresponding to the operations of lot sizing and nesting. As the number of operators as well as the mount and unmount time have a low impact on the utilization, a relationship is deduced between the mean work content, the production order release rate, the number of machines, and the utilization. First, the points are split according to the number of machines. Then, they are divided into ten equally spaced intervals according to their utilization (U), as shown in Figure 5 for the case of three machines. For each interval, the mean WC is plotted against the release rate. The proposed chart is therefore a tool used as a guideline for data preparation. For example, in the case of a targeted utilization of 80-90%, if a mean WC of 50 hours is sought after by the manufacturer, one production order has to be released per day. The knowledge of the target WC and the corresponding release rate allow a directed data preparation, so as to release jobs with the targeted length and frequency.

## 4. Conclusion and Outlook

In this study, a Global Sensitivity Analysis is conducted on a simulation model of an LPBF production environment. Performing the GSA leads to a better understanding of the behavior of the simulation model and of the impact of the single parameters of the utilization. The results obtained through the GSA allow to conclude the following regarding the utilization of an LPBF production environment:

- The most influential parameters are the distribution parameters of the work content, followed by the number of machines and the production order release rate.
- For the considered range of each input, there are combinations of the other parameters that allow to obtain a utilization of 60% or more.
- Beyond a utilization of 60%, while the distribution parameters of the work content are the most influential factors, the number of machines as well as the production order release rate have a low

impact on the utilization, meaning that they play a minor role to further maximize the production logistics KPI.

- A higher utilization of the machines can be reached with a low fluctuation of the work content.

In future works, further key performance indicators such as the throughput time need to be considered, since the utilization of the equipment is the only investigated KPI in this study. Furthermore, in the investigated model, the jobs are released according to the First In First Out (FIFO) principle. Therefore, in future works, an extension is to be developed in order to take other nesting and scheduling possibilities into consideration. Finally, further investigation is necessary to link the configuration of the production environments to factors such as lot sizing strategies, and the features of the parts to be manufactured within a given timeframe.

**Acknowledgements**

This work was carried out within the framework of the IDAM project (13N15084) funded by the German Federal Ministry for Education and Research (BMBF). Simulations were performed with computing resources granted by RWTH Aachen University under project rwth0638. The Global Sensitivity Analysis was performed by using the SAFE Toolbox, developed at the University of Bristol [24,25].

**References**

[1] Ciampi, E., Touloumian, A., 2018. Additive Manufacturing: Shaping up for Industrialization: Three catalysts are pushing 3D printing in a scaling-up phase. Oliver Wyman.

[2] Langefeld, B., Moehrle, M., Balzer, C., Schildbach, P., 2018. Advancements in metal 3D printing: Beyond powder bed - Additive Manufacturing on the brink of industrialization. Roland Berger.

[3] Proff, H., Staffen, A., 2019. Challenges of Additive Manufacturing: Why companies don't use Additive Manufacturing in serial production.

[4] Gebhardt, A., Hötter, J.-S., 2016. Additive manufacturing: 3D printing for prototyping and manufacturing. Hanser Publishers; Hanser Publications, Munich, Cincinnati.

[5] Javaid, M., Haleem, A., 2019. Current status and applications of additive manufacturing in dentistry: A literature-based review. Journal of oral biology and craniofacial research 9 (3), 179–185.

[6] Javaid, M., Haleem, A., 2018. Additive manufacturing applications in medical cases: A literature based review. Alexandria Journal of Medicine 54 (4), 411–422.

[7] Leal, R., Barreiros, F.M., Alves, L., Romeiro, F., Vasco, J.C., Santos, M., Marto, C., 2017. Additive manufacturing tooling for the automotive industry. Int J Adv Manuf Technol 92 (5-8), 1671–1676.

[8] Najmon, J.C., Raeisi, S., Tovar, A., 2019. Review of additive manufacturing technologies and applications in the aerospace industry. Additive Manufacturing for the Aerospace Industry.

[9] Stittgen, T., Schleifenbaum, J.H., 2019. Towards Operating Curves of Additive Manufacturing Equipment: Production Logistics and its Contribution to Increased Productivity and Reduced Throughput Time. 53rd CIRP Conference on Manufacturing Systems.

[10] Nyhuis, P., Wiendahl, H.-P., 2009. Fundamentals of Production Logistics. Springer Berlin Heidelberg, Berlin, Heidelberg.

[11] Gutenberg, E., 1951. Grundlagen der Betriebswirtschaftslehre: Erster Band: Die Produktion. Springer.

[12] Gibson, I., Rosen, D.W., Stucker, B., 2010. Additive Manufacturing Technologies. Springer US, Boston, MA.

[13] Stittgen, T., Schleifenbaum, J.H., 2021. Simulation of utilization for LPBF manufacturing systems. Prod. Eng. Res. Devel. 15 (1), 45–56.

[14] Saltelli, A., 2007. Sensitivity analysis in practice: A guide to assessing scientific models, Reprinted. ed. Wiley, Hoboken, NJ.

[15] Saltelli, A., 2008. Global sensitivity analysis. The Primer. John Wiley, Chichester England, Hoboken NJ.

[16] Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., Wagener, T., 2016. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling & Software 79, 214–232.

[17] Spear, R.C. and Hornberger, G.M., 1980. Eutrophication in Peel Inlet - II Identification of Critical Uncertainties via Generalized Sensitivity Analysis.

[18] Pianosi, F., Wagener, T., 2015. A simple and efficient method for global sensitivity analysis based on cumulative distribution functions. Environmental Modelling & Software 67, 1–11.

[19] Pianosi, F., Wagener, T., 2018. Distribution-based sensitivity analysis from a generic input-output sample. Environmental Modelling & Software 108, 197–207.

[20] Lemieux, C., 2009. Monte Carlo and Quasi-Monte Carlo Sampling. Springer New York, New York, NY.

[21] Kucherenko, S., Albrecht, D., Saltelli, A., 2015. Exploring multi-dimensional spaces: A comparison of latin hypercube and quasi Monte Carlo Sampling Techniques.

[22] Sarrazin, F., Pianosi, F., Wagener, T., 2016. Global Sensitivity Analysis of environmental models: Convergence and validation. Environmental Modelling & Software 79, 135–152.

[23] Andres, T.H., 1997. Sampling methods and sensitivity analysis for large parameter sets. Journal of Statistical Computation and Simulation 57 (1-4), 77–110.

[24] Noacco, V., Sarrazin, F., Wagener, T., Pianosi, F., 2019. Matlab/R workflows to assess critical choices in Global Sensitivity Analysis using the SAFE toolbox. Earth-Science Reviews 194, 1–18.

[25] Pianosi, F., Sarrazin, F., Wagener, T., 2015. A Matlab toolbox for Global Sensitivity Analysis. Environmental Modelling & Software 70, 80–85.

## Biography

**Aziz Ghannouchi** is a mechanical engineering post-graduate student at RWTH Aachen University. Since 2019, he has been a student assistant at the Digital Production group of the RWTH Chair of Digital Additive Production DAP.

**Tobias Stittgen** studied Industrial Engineering with a focus on production technology at RWTH Aachen University. After graduating, he was the responsible sales engineer for European automotive OEMs and suppliers at Laserline GmbH. Having returned to Aachen in 2017, he is now leading the Digital Production group at the RWTH Aachen University Chair Digital Additive Production DAP and at the same time responsible for sales and technology at the Aachen Center for Additive Manufacturing ACAM.