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APPLICATION OF EXPERIMENTAL DESIGN-BASED PREDICTIVE MODELS AND OPTIMIZATION IN ADDITIVE MANUFACTURING – A REVIEW

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Experiments play a crucial role in additive manufacturing to help researchers develop new materials with enhanced properties or in several types of process optimization tasks. Design of Experiments (DoE) is a valuable tool that is efficient, statistically rigorous and offers a systematic approach to experimentation. In this article, several types of DoE methods such as one-factor-at-a-time (OFAT), full and fractional factorial designs, Taguchi, response surface methodology (RSM) and descriptive screening designs (DSD) are briefly described in addition to some single- and multi-objective optimization methods. The optimization methods apply utility theory (UT), Taguchi and desirability optimization as well as some non-conventional, artificial intelligence-based multi-objective optimization methods illustrated by examples from the field of additive manufacturing. In the second part, the potential factors and response variables are reviewed during the investigation of the seven main categories of additive manufacturing, namely binder jetting (BJT), directed energy deposition (DED), material extrusion (MEX), material jetting (MJT), powder bed fusion (PBF), sheet lamination (SHL) and vat photopolymerization (VPP).

Keywords: Response Surface Method, experimental design, additive manufacturing technologies, optimization method, DoE, Taguchi method, Definitive Screening Design

1. Introduction

In manufacturing technology, several methods are applied to prepare prototypes, whether for low-volume or mass production. One of the leading modern technologies for machining parts and products is additive manufacturing (AM) whereby objects are built layer by layer, while in conventional manufacturing (CM), the process typically involves subtractive methods where a material is removed from a bulk structure.

There are some advantages of AM as opposed to CM such as design flexibility, complex geometries, the generation of less waste during the manufacturing process and its environmentally-friendly nature. On the other hand, CM is more cost-effective regarding mass production. The production speed is significantly faster, a wider range of materials are used, often a better surface finish is achieved and tighter tolerances. By combining AM and CM processes, industrial manufacturing processes are optimized.

According to a standard [1], AM is defined as a process that builds parts by joining materials layer by layer using 3D model data. The standard defined seven process categories for AM are as follows: binder jetting (BJT), directed energy deposition (DED), material extrusion (MEX), material jetting (MJT), powder bed fusion (PBF), sheet lamination (SHL) and vat photopolymerization (VPP).

The qualification of technological processes and components is crucial when describing the behaviour of examined procedures. The performed experiments and their subsequent evaluation play crucial roles in scientific methods, research and decision-making in the manufacturing industry. Several types of design of experiments (DoE) exist, starting from the simplest one-factor-at-a-time (OFAT) method up to the I-optimized response surface methods (RSM). The evaluation of the measured data could be followed by visual interpretation, statistical tests, regression and optimization.

In this article, the experimental design methods as well as their evaluation and optimization are reviewed before being explained within the field of AM processes (Chapter 2). The purpose of this work is to clarify the steps of evaluation of different procedures as well as explain the differences between the used DoE methods and optimization approximations. Choosing appropriate input or control parameters and response variable(s) for the investigation of a certain quality is particularly difficult when experimenting. In Chapter 3, the possible factors concerning the seven different AM processes are

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Table 1: Abbreviations

AM	Additive Manufacturing	CM	Conventional Manufacturing
BJT	Binder Jetting	DED	Directed Energy Deposition
MEX	Material Extrusion	MJT	Material Jetting
PBF	Power Bed Fusion	SHL	Sheet Lamination
VPP	Vat Photopolymerization	DoE	Design of Experiments
OFAT	One-Factor-At-a-Time	RSM	Response Surface Method
DSD	Definite Screening Design	CCD	Central Composite Design
GA	Genetic Algorithm	GRA	Grey Relational Analysis
S/N	Signal-to-Noise	DOM	Desirability Optimization Method
PSO	Particle Swarm Optimisation	UT	Utility Theory
num.	numerical optimization	GWO	Grey Wolf Algorithm

collected separately and the frequently used response variables illustrated by examples from recent AM research. The abbreviations used in this article are presented in *Table 1*.

2. Experiments, modelling and optimization

Investigations in the field of AM consist of several important parts such as experimentation, designing an appropriate part and mathematical evaluation of the data. The purpose of AM research could be to improve the quality of a process by carrying out experimental work. Numerous parameters can affect the quality of an AM process. By applying a DoE approach, the expense and duration of experimental work could be decreased significantly. Initially, the main goal of parameter screening, that is, describing the process mathematically, optimizing factors or process robustness, must be defined [2].

The flowchart whereby the AM process is examined is shown in *Figure 1*. The Design of Experiments - Experimentation - Evaluation of Data - Optimization (DoE-Exp-Eval-Opt) process can reveal the main elements of the work and provide an opportunity to clarify the main purpose of the investigations or research. The first main step of the research is to design the experimental work. It can be stated that "all experiments are designed experiments, it is just that some are poorly designed, and some are well-designed" [2],[3]. To investigate the behaviour of a certain process, the effects of the so-called input parameters as well as the controllable and uncontrollable factors influencing the output of the process must be examined. It is important to define all the response variables and factors as well as their levels carefully before performing experiments. The different experimental designs are described in Chapter 2.1.

The second main step when examining AM is experimentation itself. The selection and creation of the design [4]-[6] is followed by the AM of the specimen. Response parameters should be measured properly. The quality and validity of the data play important roles during AM. Some examples from the metrology of AM parts are presented [7]-[11].

The next step is the evaluation of data (*Figure 1*). Data visualization helps scientists understand and interpret information more effectively [12],[13]. Statistical analysis of the data allows the effects of the factors on the experimental results to be investigated and characterized. Methods are available from the simplest two-sample hypothesis tests up to the more advanced and complex hypothesis tests. In Chapter 2.2, some frequently used tests to evaluate statistical data are shown. If the AM process must be described by mathematical methods, linear or nonlinear regression analysis might be most suitable.

Optimization is the last optional step of the DoE-Exp-Eval-Opt process when examining AM. Several methods are found in the literature for single or multi-response optimization of manufacturing processes, a few of which are detailed in Chapter 2.3. Within the following subchapters, the citations from a particular DoE method concern the practice of AM. The DoE methods according to AM technologies are presented in Chapter 3.

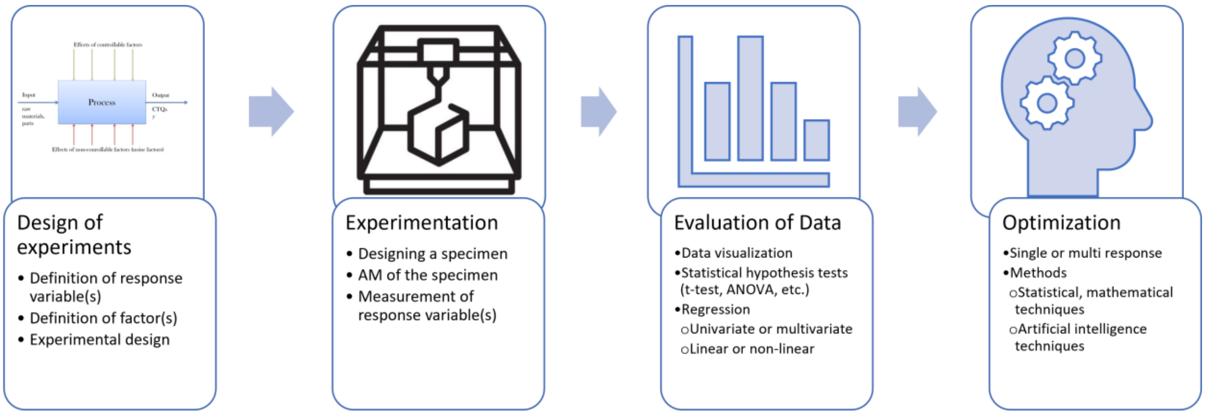

Figure 1: Main steps during AM examinations - the DoE-Exp-Eval-Opt process

2.1. Experimental designs

In this chapter, the most commonly used methods for the experimental design of AM technologies are described. Researchers often use this selection of methods to tailor their experimental settings, even if further mathematical equations and the optimization of a process are unnecessary. Five main categories of the DoE are briefly defined. The mathematical modelling of these designs is found in Chapter 2.2.

One-factor-at-a-time (OFAT)

One experimental strategy that is extensively applied is the OFAT approach [2]. The OFAT method consists of selecting a starting point, or baseline set of levels, for each factor before successively varying each factor over a particular range while keeping the other factors constant at their baseline levels [14],[15]. Once all the tests have been performed, a series of graphs are usually constructed showing how the response variable is affected by varying each factor separately while all the other factors are kept constant. The purpose of this approach is to investigate the impact of individual factors on a process without having to consider potential interactions between factors.

The OFAT method is suggested to be used during pre-experiments. Pre-experiments can play an important role in making sure that the experimental design is correct and effective before carrying out the actual research or experiment. These can help reduce the risk of errors and increase the success of the research project or experiment. Since the main experiment usually involves several control parameters for examinations, the correct experimental strategy is to conduct a factorial experiment.

Factorial design

During factorial designs, several factors are varied simultaneously instead of one at a time, that is, 3 control parameters, namely 3 layer thicknesses, 2 drying times and 4 baseline temperatures. If all possible combinations are examined, then the factorial design consists of 3 x 2 x 4 = 24 experimental runs. This type of factorial design is referred to as the full factorial design [16]-[20] whereby all combinations of each factor at all levels are tested, thereby including the examination of all possible interactions as well as main effects and higher-order interactions. If all the factors have 2 levels, the usual notation for the n-factor full factorial design is 2^n, which is equal to the number of experimental runs. If each factor has 3 levels, then 3^n experimental runs are performed. By increasing the number of levels of the control parameters, the number of experimental runs required will rise exponentially.

One type of factorial design which allows researchers to study the main effects and some desired interaction effects over a minimum number of trials or experimental runs is called a fractional factorial design. In the case of fractional factorial designs, which are orthogonal arrays where the settings for the independent variables are orthogonal to one another so it is possible to estimate them independently, a fraction (e.g. 1/2, 1/4, 1/8) of the experimental runs can be conducted. Two-level fractional factorial designs are expressed using the notation $2^{(k-p)}$ where k denotes the number of variables (factors) investigated and p describes the size of the fraction of the full factorial search space used [2].

The main purpose of fractional factorial designs is to decide which control parameters or factors have the most influence on the response variable(s) when a relatively small number of experiments are conducted. Therefore, experimental screening designs are used when the number of factors is larger than 6 [21]-[23]. A sequential experimentation strategy could be applied when fractional factorial designs are used correctly [2,14,24]. Screening designs consist of several types such as Plackett-Burman [25],[26] and Latin square designs [27] or Taguchi methods.

Taguchi methods

Taguchi has developed experimental designs using orthogonal arrays (OA) [28] where the factors can have 2, 3, 4 or more levels and the main effects can be evaluated. This form of experimental designs is common and popular among researchers who suppose that the effect of parameters on the response variable is approximately linear. One main advantage of Taguchi methods is that several levels, that is, more than 2, of a certain parameter can be investigated, moreover, a smaller number of experiments have to be performed compared to in full factorial experiments (*Table 2*). A huge number of Taguchi OAs are found in the field of AM from various areas [29]-[35].

Table 2: Comparison of the number of experiments conducted in full factorial designs and Taguchi methods

Number of Factors	Levels of Factors	Taguchi OA	No. of exp. Taguchi	No. of exp. Full factorial
3	2	L4 (2^3)	4	8
7	2	L8 (2^7)	8	128
4	3	L9 (3^4)	9	81
11	2	L12 (2^{11})	11	2048
1;7	2;3	L18 ($2^1 \cdot 3^7$)	18	4374

Response surface methodology (RSM)

RSM is a collection of mathematical and statistical techniques to model and analyse problems in which a response of interest is influenced by several variables and the objective is to optimize this response. The response surface is usually represented by graphs on a surface or contour plot. RSM consists of two different types, namely Central Composite Designs (CCD) and Box-Behnken Designs (BBD). As an example, three factorial experimental designs along with their factor levels are presented in *Table 3*. RSM CCDs involve a combination of factorial designs and axial points. The number of

Table 3: The factor levels in coded form of a CCD, face-centred CCD and Box-Behnken design for three factors

RSM CCD				RSM FC CCD				RSM BBD		
PtType	A	B	C	PtType	A	B	C	A	B	C
cube	-1	-1	-1	cube	-1	-1	-1	-1	-1	0
cube	1	-1	-1	cube	1	-1	-1	1	-1	0
cube	-1	1	-1	cube	-1	1	-1	-1	1	0
cube	1	1	-1	cube	1	1	-1	1	1	0
cube	-1	-1	1	cube	-1	-1	1	-1	0	-1
cube	1	-1	1	cube	1	-1	1	1	0	-1
cube	-1	1	1	cube	-1	1	1	-1	0	1
cube	1	1	1	cube	1	1	1	1	0	1
axial	-1.681792831	0	0	axial	-1	0	0	0	-1	-1
axial	1.681792831	0	0	axial	1	0	0	0	1	-1
axial	0	-1.681792831	0	axial	0	-1	0	0	-1	1
axial	0	1.681792831	0	axial	0	1	0	0	1	1
axial	0	0	-1.681792831	axial	0	0	-1	0	0	0
axial	0	0	1.681792831	axial	0	0	1	0	0	0
center	0	0	0	center	0	0	0	0	0	0
center	0	0	0	center	0	0	0			
center	0	0	0	center	0	0	0			

levels for each factor can vary depending on the specific experimental design. CCDs are flexible and enable the number of levels and the ranges for each factor to be chosen based on specific requirements and knowledge of the process under investigation. Levels should be chosen carefully to accurately model and optimize the response variable according to the available data points. CCD is an extension of the factorial design, and includes both factorial points and axial points. The axial points are placed at a distance α from the centre. A special type of CCD is face-centred central composite design (FC CCD), which is particularly useful when the centre point, that is, the point at the centre of the design space, is either unnecessary or infeasible for experimentation. In the case of FC CCD $\alpha = 1$, only 3 levels are found for each factor compared to 5 in CCD [36].

RSM BBD is an independent quadratic design since an embedded factorial or fractional factorial design is not included. Three levels of each factor are found, while the design consists of a combination of low, high and centre levels for each factor [2]. BBDs typically require fewer experiments compared to CCDs, making the former more efficient when the budget or resources are limited. CCD is often considered more efficient in terms of modelling complex response surfaces when the purpose of the experiments is to develop a regression model for the data (see the examples in *Tables 4–7* presented later in this article).

Despite the importance of CCDs and BBDs, researchers sometimes cannot afford the required number of experimental runs. Therefore, optimal designs have been developed that follow the so-called alphabetic optimality criteria [36], some of which focus on accurately estimating model parameters while others on predicting the design region well. One type of optimal design known as I-optimal design is found from the field of additive manufacturing [37],[38], which seeks to optimise prediction variance.

Definitive screening designs (DSD)

Response surface methods can describe the relationship between the factors and the response variable if more than two levels for each factor must be chosen. When 2-3 factors are considered, approximately 20 experimental runs are conducted. In the case of 6 factors, a full RSM CCD consists of 90 experimental runs, while when 10 factors are examined, a RSM BBD contains 170 runs. In order to reduce the number of experimental runs but continue to benefit from the advantages of RSM, a new three-level screening design known as definitive screening design (DSD) was developed whereby the number of experimental runs is one more than twice the number of factors [39]. In the case of 6 factors, the number of experimental runs is 13, while when 10 factors are selected, 21 runs are performed, which is far less than in RSM designs. RSM and DSD for 8 factors and one response variable for MEX-printed PLA parts were compared [38]. DSD was found to be more economical than RSM due to the reduced number of experimental runs. 17 experimental runs were planned based on a DSD compared to 55 on a RSM design. Several DSD experimental designs are found in the literature [40]-[43].

2.2. Data evaluation

After conducting the designed experiments, data must be statistically evaluated. Firstly, the results must be visualized by groups in graphs such as individual value, box and violin plots or histograms. Visualizing data in groups or categories is a common approach to gain insights into how data is distributed as well as identify patterns and differences between these groups. The graphs produced enable accurate hypotheses to be suggested during the following statistical tests.

During the statistical tests following a DoE, the following null hypothesis is frequently used, that is, there is no significant difference between the means of the groups compared. If two groups exist, then the two-sample t-test is the most appropriate method. If more than two groups are found for one factor and more than two factors are involved, then the common test is analysis of variance (ANOVA), which helps determine whether the variation between the means of groups is statistically significant or can be attributed to random sampling variation.

If the DoE consists of more factors and the types of variables are different from numerical ones, e.g. they are categorical variables, the general linear model (GLM) is a more general framework that can handle various types of dependent variables by taking into account a broader range of data types and statistical models in addition to the comparison of means [2].

Regression

Previously mentioned tests of significance comparing means could be sufficient for researchers. Sometimes the purpose of research is not only to define the significance of a certain factor or parameter but to describe the process mathematically and accurately by regression equations. Although several types of regression equations or models exist, in this paper, statistical regression approximations are addressed [2].

The simplest regression model which can be fitted to three-factor experimental designs is a multiple linear regression model with only main effects:

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \varepsilon \qquad (1)$$

where y denotes the response variable, β_i represents the regression coefficients, x_i are the values of th i^{th} variable and ε stands for the random error term. While statistically evaluating the screening of two-level designs and Taguchi methods, this type of equation with only main effects could be developed [32],[44]. The minimum number of experimental runs is the number of factors plus one.

If the DoE contains more experimental runs than the minimum number required, the interaction between the factors can be estimated. In the case of a full factorial 2^3 DoE, the following multiple linear regression can be estimated:

$$\begin{aligned} y &= \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 \\ &+ \beta_{12} \cdot x_1 \cdot x_2 + \beta_{13} \cdot x_1 \cdot x_3 + \beta_{23} \cdot x_2 \cdot x_3 \\ &+ \beta_{123} \cdot x_1 \cdot x_2 \cdot x_3 + \varepsilon \end{aligned} \qquad (2)$$

where 8 β_i should be estimated so a minimum of 8 experimental runs must be conducted. Within this form of multiple linear regression, there are 3 main effects (***x_1, x_2, x_3***), 3 interactions between two factors (***$x_1 \cdot x_2$, $x_2 \cdot x_3$, $x_1 \cdot x_3$***) and 1 interaction between three factors. (***$x_1 \cdot x_2 \cdot x_3$***). This type of regression was applied in a wire-based electron beam additive manufacturing process [45].

If the DoE contains a factor with more than two levels, then quadratic effects of that factor could be estimated besides the main effects and interactions. The following equation is an example of a factorial design consisting of at least 3 levels and at least 10 experimental runs:

$$\begin{aligned} y &= \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \\ &\beta_{12} \cdot x_1 \cdot x_2 + \beta_{13} \cdot x_1 \cdot x_3 + \beta_{23} \cdot x_2 \cdot x_3 + \\ &\beta_{11} \cdot {x_1}^2 + \beta_{22} \cdot {x_2}^2 + \beta_{33} \cdot {x_3}^2 + \varepsilon \end{aligned} \qquad (3)$$

This latest type of regression models has been addressed in the literature [46],[47].

These are the most common types of statistical regression model used when studying AM technologies. Besides these models, some are emerging in artificial neural network (ANN) models to determine the relationship between the input and output parameters of AM processes. Research articles have been published where the modelling capability of RSM and ANN methods is compared or combined to describe AM processes [29,48,49].

2.3. Optimization

The regression model parameters can be estimated and equations visualized graphically as a response surface. Having determined the equation, the minimum, maximum or target value of a certain response variable can be calculated as an optimization goal. This type of optimization is referred to as numerical and denoted in *Tables 4–7*.

Based on the purpose of the research, typically two or more response variables are investigated in a designed experiment. Two types of optimizations related to the handling of response variables are found, namely single-objective and multi-objective optimizations. If the single-objective optimization is chosen, the calculation is easier, while the multi-objective optimization can use even neural network for problem-solving.

The use of utility theory (UT) simplifies multi-objective optimization into single-objective optimization. In this theory, a utility, that is, a value of individual response factors (*y_1, y_2, ..., y_n*), is calculated and finally a combined value calculated by using the relations. If X_i measures the effectiveness of an attribute (characteristic) i and n attributes evaluate the outcome space, the overall utility function is a linear sum of individual utilities which can be adjusted by providing a weight, transforming the overall utility function into:

$$U(X_1, X_2, \dots, X_n) = \sum_{i=1}^{n} W_i U_i(X_i) \qquad (4)$$

where $U_i(X_i)$ denotes the utility of the i^{th} attribute, W_i stands for the weight assigned to the attribute i and the sum of the weights for all attributes is equal to 1 [50]. If the composite measure is maximized, the evaluation of utility will automatically be optimized. UT assumes that the response variables are independent which might not be the case in practice. UT was used to analyse the response parameters of surface roughness, dimensional accuracy and flatness together by Maurya et al. [32].

The Taguchi method for optimization

Single-objective optimization could be performed by the Taguchi signal-to-noise (*S/N*) method, which is a robust design and optimization whereby the larger the *S/N* ratio calculated, the better the certain level of a factor. Based on the objective function, several types of optimization problem can arise: (i) smaller-the-better [51], (ii) larger-the-better [31],[52] and (iii) nominal-the-best [28,53,54].

Multi-objective optimization with Taguchi orthogonal arrays could be conducted by grey relational analysis (GRA), which is based on the grey system theory to convert multi-response problems into single-response ones [55]. First, GRA normalises experimental data between 0 and 1 before a grey relational coefficient is calculated that determines the ratio between the desired (ideal) values and the actual (experimental) response data. A grey relational grade is then calculated as a weighted sum that considers the grey relational coefficient corresponding to each process response and their corresponding weights [56]. In the literature, the compressive strength, measured porosity and dimensional accuracy of fabricated porous scaffolds were optimized simultaneously with this method [57].

Desirability Optimization Method (DOM)

One of the first approaches to multi-response optimisation based on a desirability function was proposed using process targets and response deviations to represent a single-objective function [58]. The desirability function is used to determine the desirability of the process parameters set compared to all potential solutions and with respect to the required nominal response values. Individual desirability (d_i) evaluates how the process parameters settings optimize the i^{th} single response, while composite desirability (D) evaluates how the settings optimize a set of responses overall. The individual desirability functions for each response variable should be defined. The desirability function has a lower and an upper limit, goal (maximize, minimize or target) and importance [59]. Composite desirability is defined as the weighted geometric mean of the individual desirabilities for the responses:

$$D = \sqrt[n]{d_1 \cdot d_2 \cdot \ldots \cdot d_n} \tag{5}$$

Desirability has a range of 0 to 1 whereby 1 represents the ideal case and 0 indicates that at least 1 response falls outside the acceptable limits.

Non-conventional, artificial intelligence (AI)-based multi-objective optimization methods

Metaheuristic search techniques belong to artificial intelligence and have drawn significant attention over the last two decades for solving multi-response optimisation problems. In the case of 10 different AI optimizations (namely Genetic Algorithm Optimization, Simulated Annealing Algorithm Optimization, Particle Swarm Optimization, Grey-Wolf Optimization Algorithm, Moth Flame Optimization Algorithm, Whale Optimization Algorithm, Jaya Optimization Algorithm, Sunflower Optimization Algorithm, Lichtenberg Optimization Algorithm and Forensic-Based Investigation Optimization Algorithm) for the MEX manufacturing process, response variables [60] have been utilized to predict the optimal settings of experiments. Genetic algorithm optimization (GA) - a stochastic search technique inspired by the principles of natural evolution - has been proven as a potent multi-directional heuristic search method for optimising highly nonlinear, non-convex and complex functions since it is less likely to get trapped at a local optimum than traditional gradient-based search methods. The individuals in a population are then evaluated based on their fitness value whereby the individuals with the highest fitness values are taken as bases ('parents') for the next generation. The procedure is iterative, that is, continues till the termination criterion is reached. Some examples of GA-based multi-response optimization are found in the literature [18,29,31,61,62].

Another evolutionary metaheuristic technique is Particle Swarm Optimization (PSO) inspired by the social behaviour of flocks of birds and schools of fish. Similarly to GA, PSO is also a population-based heuristic computational method whereby the population of the potential solutions is referred to as a swarm and each individual solution within the swarm is called a particle. The algorithm is initialised with a population of random solutions (a flock of birds where a bird is called a particle) and searches for the optimum by updating generations. Unlike GA, PSO has no evolution operators such as crossover and mutation. Two research articles presented one example each of this type of optimization [63],[64].

A new metaheuristic algorithm, namely Grey Wolf Optimization, inspired by the social hierarchy and hunting behaviour of grey wolves (Canis lupus) was developed [65]. This modern population-based algorithm was used to optimize the process whereby the functional relationship between five important FDM process parameters concerning polyethylene terephthalate glycol (PETG) was studied regarding their effect on the flexural strength of this material [66]. The maximum flexural strength obtained by the algorithm was approximately 14% higher than the best result obtained by the series of experiments.

3. Modelling in different types of additive manufacturing

3.1. Binder Jetting (BJT)

Binder Jetting (BJT) is an AM process in which a liquid bonding agent is selectively deposited to join powder materials together [1]. BJT can work with various types of materials, including metals, ceramics, polymers and composites. Metal powders such as stainless steel, aluminium and titanium are used in aerospace, automotive and medical device manufacturing as well as in ceramic powders in dental implants and electronics, sand powders in moulds in addition to polymer powders to create prototypes. The binding agent is used to selectively bond and solidify the powdered material in specific areas layer by layer to create a three-dimensional object. The binding agent chosen depends on the material being printed and the desired properties of the final object.

Several parameters or factors influence the quality of the BJT process (*Appendix - Figure 2*). In the case of DoE, the main goal is to study the effects of the various parameters on the response variable and quality characteristic of a certain manufacturing process. Since most of the factor levels are controllable, they are potential factors for DoE investigations. The input and/or controllable parameters in the case of BJT can be divided into five main categories, namely Material, Manufacturing process, Temperature, Time and Equipment. Two types of material, that is, powders and fluids, as well as their characteristics are important in BJT. The temperature and the different time conditions can affect the output of the process. The parameters set for the equipment such as the build, number of layers, binder drop and roller properties play a crucial role in the manufactured specimen. The parameters set in the manufacturing process, that is, feed-to-powder ratio, layer thickness and binder saturation, also affect the AM process.

One critical quality characteristic when examining the binder jetting AM process other than compressive strength and porosity is transverse rupture strength (TRS) that measures the maximum stress a material can withstand just before it breaks when subjected to a bending load [57],[67]. Since the dimensional accuracy can also influence the quality of the BJT process, the shrinkage percentage ((actual dimension of a sample — designed dimension of a sample)/(designed dimension of a sample) x 100 %) can be determined [51]. Besides the dimensional accuracy, the surface roughness of the produced specimen can be a response variable [29].

In the case of the BJT process, 3-5 factors are varied by DoE methods and mainly the linear effects of the parameters investigated (*Table 4*). The main purpose of the studies is to describe the process mathematically and optimize the BJT process for the selected response variable(s).

3.2. Directed Energy Deposition (DED)

Table 4: DoE in the fields of BJT and DED (abbreviations are based on [1])

Ref.	AM method	Input	Output	DoE type	Optimization
[29]	BJT-SSt/M/ ASTMF75	5	4	Taguchi L27	multiobjective, GA
[57]	BJT-SSt/C/Paris	5	3	Taguchi L27	multiobjective, GRA
[51]	BJT-SSt/M/316L	3	1	Taguchi L9	single-objective, S/N
[46]	BJT-SSt/Ag,PET	3	2	RSM BBD	multiobjective, DOM
[67]	BJT-SSt/SS316L	4	1	Taguchi L27	single-objective, S/N
[61]	DED-Arc/M/CS	3	2	RSM CCD	multiobjective, GA
[68]	DED-Arc/M/BainiteS	5	4	RSM BBD	multiobjective, DOM
[59]	DED-LB/M/Inconel718	3	5	RSM CCD	multiobjective, DOM
[69]	DED-LB/M/CRS	5	6	RSM CCD	-
[30]	DED-Arc/M/IN718,SS316L	5	3	Taguchi L27	-
[30]	DED-Arc/M/Ti6Al4V	5	3	Taguchi L27	-
[45]	DED-EB/M/Ti6Al4V	3	2	Taguchi L27	single-objective, S/N
[52]	DED-EB/M/Ti6Al4V	3	1	Taguchi L9	single-objective, S/N
[70]	DED-Arc/M/TZM	3	4	RSM CCD	multiobjective, DOM
[71]	DED-Arc/M/5A06	3	2	RSM CCD	single-objective, num.
[72]	DED-Arc/M/Hastelloy X	4	5	Taguchi L16	-
[53]	DED-Arc/M/Plasmadur51122	9	4	Taguchi L18	single-objective, S/N

Directed energy deposition (DED) is an additive manufacturing process in which the focused thermal energy is used to fuse materials by melting them as they are being deposited [1]. The energy source in DED can be a high-powered laser, electron beam or plasma arc. DED is used mainly in the aerospace, automotive, rapid tooling and biomedical industries to produce functional metal parts, add material to existing parts and for repairs [73]. The material selected depends on the specific application. Titanium, aluminium and nickel alloys are used in the aerospace industry, while titanium and cobalt-chromium ones are applied in medical equipment [74].

The typical workflow of the metal additive manufacturing process is design, conversion, file transfer, configuration, print, removal, machining (optional), heat treatment (optional), inspection (optional) and handover (optional) [75]. The quality of the DED additive manufactured specimen depends on several factors such as the material, feeding, equipment and energy source (*Appendix - Figure 3*). Two types of materials have to be chosen, one for the wire/powder and another for the substrate. While the feeding parameters in addition to the feed rates of the carrier gas and wire/powder can be set, the geometric position, angle and direction are other optional factors when investigating a DED process. Regarding the equipment itself, temperature settings and manufacturing strategies as well as the energy source could also affect the quality of the part produced.

The response variables of DoE during the investigation of DED processes are usually related to the geometry and characteristics of the bead deposited. The geometries of these beads are width, height, angles and dilution [30,61,69], however, the hardness [59], roughness [72], porosity [53] or coefficient of friction [45] could be measured as outputs. According to *Table 4*, mainly 3-5 factors are chosen to describe the DED process, but a screening design, that is, Taguchi L18, varies 9 factors simultaneously.

3.3. Material Extrusion (MEX)

Material extrusion is an AM process in which material is selectively dispensed through a nozzle or orifice [1]. A wide variety of materials can be extruded using MEX: thermoplastics such as acrylonitrile styrene acrylate (ASA), acrylonitrile butadiene styrene (ABS), polycarbonate, polyetherimide, polylactic acid (PLA), high impact polystyrene (HIPS), thermoplastic polyurethane (TPU) and aliphatic polyamides (PA, nylon) as well as high-performance plastics such as polyether ether ketone (PEEK) and polyetherimide (PEI) [76]. MEX additive manufacturing technologies have gained widespread popularity and applications due to their simplicity, reliability and affordability.

The possible factors for DoE during MEX experimentation can be divided into four categories, namely Temperature, Equipment, Material and the Manufacturing process (*Appendix - Figure 4*). The temperature conditions - e.g. that of the build platform, nozzle as well as the printing and cooling conditions - play a significant role as far as the quality of a MEX-produced specimen is concerned. Regarding the equipment, the fan speed and diameter of the nozzle are optional factors, moreover, the characteristics of the material can affect the output parameters. The manufacturing process consists of such parameters as the infill and its properties, flow rate, support, wall and layer thickness as well as build orientation.

The quality of the MEX process could be described by dimensional parameters and mechanical properties. The dimensional accuracy of the produced specimen is characterized by its length, width, thickness or dimensional error [60,77-81]. The surface quality of the part is measured by its surface roughness [38],[82] as well as by geometrical dimensioning and tolerancing (GD&T) parameters [83]. Its mechanical properties such as strength refer to the capacity of a material to cope with external loads and stresses. During MEX processes, the following mechanical properties can be used as response variables of DoE: flexural strength [31,62,66,84], tensile strength [85],[86] and the Young's modulus [77],[87]. The energy factor and consumption as response variables in a MEX experimental design were optimized by Barbose et al. [88].

DoE methods are widely used for the description and optimization of the MEX additive manufacturing process. Applications of all types of DoE methods from the simplest to more advanced designs are found in the literature (*Table 5*). More screening designs such as Taguchi L27 for linear effects and definitive screening design for quadratic effects are available.

Table 5: DoE in the field of MEX (abbreviations are based on [1])

Ref.	AM method	I.	O.	DoE type	Optimization
[66]	MEX-TRB/P/PET-G	5	1	RSM FC CCD	single-objective, GWO
[89]	MEX-TRB/P/PLA	4	2	RSM FC CCD	single-objective, num.
[64]	MEX-TRB/P/PLA	4	1	RSM CCD	multiobjective, PSO
[31]	MEX-TRB/P/ABS	4	1	Taguchi L18	single-objective, S/N, GA
[78]	MEX-TRB/P/TPU	3	2	RSM CCD	multiobjective, DOM
[85]	MEX-TRB/P/PLA,PHA	3	2	RSM BBD	multiobjective, DOM
[84]	MEX-TRB/P/PEEK	3	5	RSM BBD	single-objective, num.
[77]	MEX-TRB/P/PLA	4	8	Taguchi L9	single-objective, S/N
[88]	MEX-TRB/P/PLA	4	1	RSM FC CCD	single-objective, num.
[79]	MEX-TRB/P/TPU	3	3	Taguchi L9	single-objective, S/N
[80]	MEX-TRB/P/PLA	3	7	Taguchi L9	multiobjective, DOM
[62]	MEX-TRB/P/ABS	3	1	RSM CCD	single-objective, GA
[90]	MEX-TRB/P/ABS	4	2	Taguchi L16	single-objective, S/N
[54]	MEX-TRB/P/ABS	4	2	Taguchi L9	single-objective, S/N
[81]	MEX-TRB/P/PLA	3	3	Full factorial 2^3	multiobjective, GRA
[81]	MEX-TRB/P/ABS	3	3	Full factorial 2^3	multiobjective, GRA
[83]	MEX-TRB/P/ABS	13	10	Taguchi L27	single-objective, S/N
[38]	MEX-TRB/P/PLA	8	1	I-optimal	single-objective, DOM
[38]	MEX-TRB/P/PLA	8	1	DSD	single-objective, DOM
[37]	MEX-TRB/P/ABS	6	1	I-optimal	single-objective, DOM
[60]	MEX-TRB/P/ABS	5	6	Taguchi L27	multiobjective, GA, PSO, etc.
[86]	MEX-TRB/P/PLA	3	2	RSM CCD	multiobjective, DOM
[82]	MEX-TRB/P/ABS	3	2	Taguchi L8	Single-objective, S/N
[40]	MEX-TRB/P/PLA	8	4	DSD	multiobjective, DOM
[41]	MEX-TRB/P/PLA	6	6	DSD	-

3.4. Material Jetting (MJT)

Material jetting (MJT) is an AM process in which droplets of feedstock material are selectively deposited [1]. It is possible to apply thin layer thicknesses that enable high-quality parts to be printed as well as diminish staircase effects and thin walls [91]. MJT can be applied in rapid prototyping, the aerospace industry, dental and orthodontic applications, jewellery, architecture and construction. The materials used in MJT are usually thermoset photopolymers.

The possible input or controllable parameters during the experimentation of MJT manufacturing processes are shown in *Appendix - Figure 5*. The quality of the process can be affected by 4 categories, namely Material, Temperature, Equipment and Manufacturing process. Like the MEX technology, the temperature of parts of the equipment, that is, the nozzle, platform and printer, can cause deviations in the response variables of MJT. The chemical and mechanical characteristics of the material are important factors as far as the parameters of the equipment, i.e. build position, orientation and layer thickness, are concerned. Four factors influence manufacturing processes, namely the curing process, drop properties, inkjet printhead parameters and type of support.

The dimensional accuracy, surface roughness and mechanical properties of MJT-printed parts are crucial to obtain correct and reliable results after measurements are taken and ensure they function properly following final assembly. The length, width and height of the specimen [17,18,92]; the roundness and cylindricity [20]; as well as the surface roughness were analysed as response variables [16,32,93]. Mechanical properties such as tensile strength were examined [14],[94] and the colour of the MJT-produced part can be output parameters referring to its quality [95]. DoE methods are used to characterize the MJT process and each type of experimental design can be found in the literature as presented in *Table 6*.

Table 6: DoE in the fields of MJT PBF (abbreviations are based on [1])

Ref.	AM method	I.	O.	DoE type	Optimization
[20]	MJT-UV/P/MED610	2	2	Full factorial 2^2	-
[16]	MJT-UV/P/FullCure70	3	1	Full factorial $2 \cdot 3 \cdot 19$	-
[17]	MJT-UV/P/RGD835	3	3	Full factorial 2^3	-
[94]	MJT-UV/P/Verowhite	3	2	Full factorial 2^3	-
[14]	MJT-UV/P/RGD835	7	3	Fractional factorial 2^{7-3}	-
[92]	MJT-UV/P/720RGD	3	2	Taguchi L4	multiobjective, GRA
[32]	MJT-UV/P/RGD840	3	6	Taguchi L8	multiobjective, UT
[18]	MJT-UV/P/Vero	4	3	Full factorial 2^4	multiobjective, GA
[95]	MJT-UV/P/RGD8**	3	1	RSM CCD	single-objective, DOM
[43]	MJT-UV/DM/FLX9895	7	1	DSD	-
[48]	PBF-IrL/P/UHMWPE	6	1	RSM BBD	single-objective, num.
[96]	PBF-LB/M/Ti6Al4V	4	3	RSM CCD	-
[97]	PBF-LB/M/NiTi	3	3	RSM CCD	-
[98]	PBF-LB/M/AlSi10Mg	4	1	RSM CCD	single-objective, DOM
[99]	PBF-LB/M/Ti6Al4V	2	2	RSM	-
[100]	PBF-LB/M/ODSN	3	3	Taguchi L25	single-objective, S/N
[100]	PBF-LB/M/ODSN	3	3	RSM BBD	single-objective, S/N
[49]	PBF-LB/M/AlSi10Mg	4	1	RSM CCD	-
[101]	PBF-LB/M/AlTiCrFeCoNi	2	1	Full factorial 2^2	-
[102]	PBF-LB/M/316LSS	4	12	Taguchi L64	single-objective, S/N
[103]	PBF-LB/M/Inconel625	4	2	Taguchi L9	multiobjective, GRA
[33]	PBF-Arc/M/IN718	4	2	Taguchi L16	multiobjective, GRA
[42]	PBF-LB/M/CoCrW	5	1	DSD	-

3.5. Powder Bed Fusion (PBF)

Powder bed fusion (PBF) is an AM process in which thermal energy selectively fuses regions of a powder bed [1]. As one of the most applied processes, PBF is increasingly being used to manufacture products in, for example, the aerospace, medical, automotive, tooling and consumer goods industries. One of the significant advantages of PBF is its ability to produce highly customized and personalized products, supporting a wide range of materials including metals, polymers and ceramics.

The input and controllable parameters of the PBF additive manufacturing process can be divided into four categories, namely Equipment, Material, Energy Source and Manufacturing process (*Appendix - Figure 6*). Within the Equipment category, the layer thickness, working distance and gas flow can affect the output of the PBF process. The material composition and characteristics of the powder such as its distribution, particle shape and density are other examinable factors. Different energy sources and their settings affect the quality. The most investigated parameters by DoE are hatch space, temperature and scanning within the Manufacturing process category.

The response variables for characterizing the PBF process could be dimensional such as the length, width and depth of the melt pool [96] as well as the surface roughness [99],[103] and dilution rate [33]. The porosity of the manufactured specimen [44,49,98] is particularly critical as it can significantly affect the mechanical properties of components, cause structural failures as well as decrease their strength and Young's modulus. Some researchers have measured the mechanical properties of the specimen [48],[100] and hardness of the produced part [101].

Details about the DoE and optimization in the case of PBF processes are contained in *Table 6*. Typically 3-5 input parameters are varied during the experimental designs and every type of DoE can be an example of this technology.

3.6. Sheet Lamination (SHL)

Sheet lamination (SHL) is an AM process in which sheets of material are bonded together to form a part [1]. The raw materials (worksheets) are cut by lasers or cutters depending on their geometry before the lamination process. The sheets are stacked layer by layer and bonded by diffusion instead of melting. Laminated object manufacturing (LOM) and ultrasonic additive manufacturing (UAM) are the main techniques in this process. The processing speed is relatively high with low operating costs and easy material handling. Various materials such as polymers, ceramics, paper and metals can be used in this SHL process, the main advantages of which are its ability to be integrated into a hybrid manufacturing system by working with ceramic and composite fibre materials without the need for support structures. The main limitation of this process is the limited availability of materials and the removal of excess materials after lamination.

The possible factors of DoE are presented in *Appendix - Figure 7* in the case of the SHL process that can be divided into three categories, that is, Equipment, Material and Manufacturing process, based on a literature review. The temperature, force and pressure can be varied to investigate the performance of the SHL process. The material characteristics such as thermal properties, flexibility, strength or type can affect the quality of the process. Moreover, the speed, sheet thickness and type of heat source or binding method are possible factors when examining quality in the case of the SHL additive manufacturing process.

The response variables of the SHL process can be measured from bending and tensile tests [34,47,104] or linear weld density [105]. Some applications of sheet lamination in the field of DoE can be seen in *Table 7*.

3.7. Vat Photopolymerization (VPP)

Vat photopolymerization (VPP) is an AM process in which a liquid photopolymer in a vat is selectively cured by light-activated polymerization [1]. VPP is widely utilized in the fields of engineering, manufacturing, dentistry, healthcare, education, entertainment, jewellery and audiology. Dental applications of VPP are emerging, e.g. the mechanical properties of 3D-printed resin-based dental parts like their biocompatibility, accuracy as well as antimicrobial and surface properties [109].

The possible factors of experiments concerning the VPP process are detailed in *Appendix - Figure 8*. The quality performance of the VPP process can be influenced by the parts of the equipment such as the tank, light source or platform. The chemical, mechanical and physical characteristics of the resin can affect the VPP process. The environmental conditions such as temperature and humidity as well as the design of the specimen are possible factors worth investigating within this field. The manufacturing process parameters such as print speed, post-processing and duration can be varied.

Response variables of the VPP process include tensile strength, hardness and energy consumption [19],[106] as well as printing time [107]. Among the dimensional parameters of the specimen, its length, width, GD&T parameters, shrinkage and surface roughness can be investigated [35],[108]. During VPP, mainly Taguchi and RSM methods with multi-objective optimization are addressed in the literature (*Table 7*).

Table 7: DoE in the fields of SHL and VPP (abbreviations are based on [1])

Ref.	AM method	I.	O.	DoE type	Optimization
[104]	SHL-AJ/LPH042	7	1	Taguchi L8	-
[104]	SHL-AJ/LPH080	7	1	Taguchi L8	-
[34]	SHL-UC/CS4130	4	2	Taguchi L16	-
[105]	SHL-UC/Al3003	4	1	Taguchi L16	-
[47]	SHL-AJ/ABS	4	2	RSM	multiobjective, DOM
[19]	VPP-UVL/P	3	6	Full factorial 2^3	multiobjective, num.
[106]	VPP-UVL/P/ANYCUBIC	2	2	RSD CCD	-
[63]	VPP-UVL/P	5	2	Taguchi L27	multiobjective, PSO
[35]	VPP-UVL/P/	3	2	Taguchi L9	multiobjective, DOM
[107]	VPP-UVM/P	3	2	RSM CCD	multiobjective, DOM
[108]	VPP-UVL/P	5	20	Taguchi L27	-

4. Discussion

This review describing the critical-to-quality characteristics of a certain additive manufacturing process contains several important steps and decisions. It is important to precisely declare the purpose of carrying out research before designing experiments. Although several types of DoE are available in the mathematical literature, in the field of AM, Taguchi and RSM methods are the most common. Nowadays, definitive screening designs are emerging. Augmenting a DSD will greatly assist practitioners to avoid the problems of underfitting and overfitting [110].

The RSM approach is based on a philosophy of sequential experimentation, whereby the objective is to approximate the response with a low-order polynomial in a relatively small region of interest that contains the optimum solution. Some computer experimenters advocate a somewhat different philosophy by seeking to create a model that approximates the true response surface over a much wider range of design variables, sometimes extending over the entire region of operability [36]. Even though only a few applications of sequential experimentation have been studied in the literature, it may still be useful in the future.

The role of the DoE-Exp-Eval-Opt process (*Figure 1*) is not only important in research into AM processes but perhaps during mass-production AM processes to decrease costs and increase the quality of a certain type of additive manufactured part.

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5. Appendix: Ishikawa diagrams

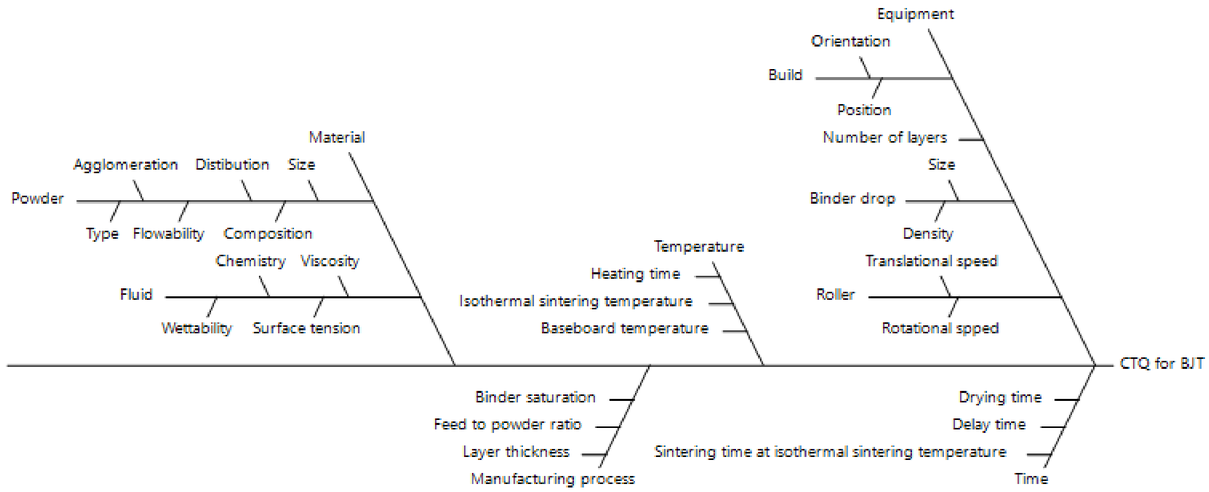

Figure 2: Possible factors for the critical-to-quality (CTQ) characteristics of BJT additive manufacturing

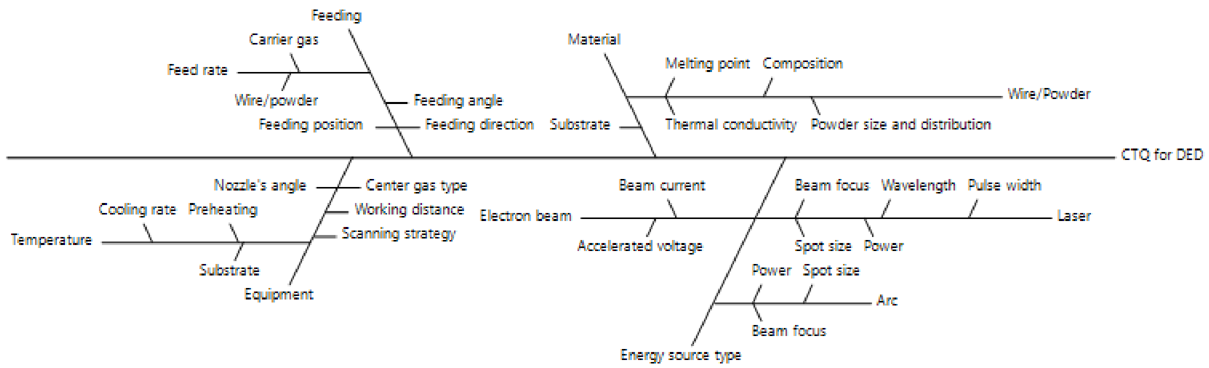

Figure 3: Possible factors for the critical-to-quality (CTQ) characteristics of DED additive manufacturing

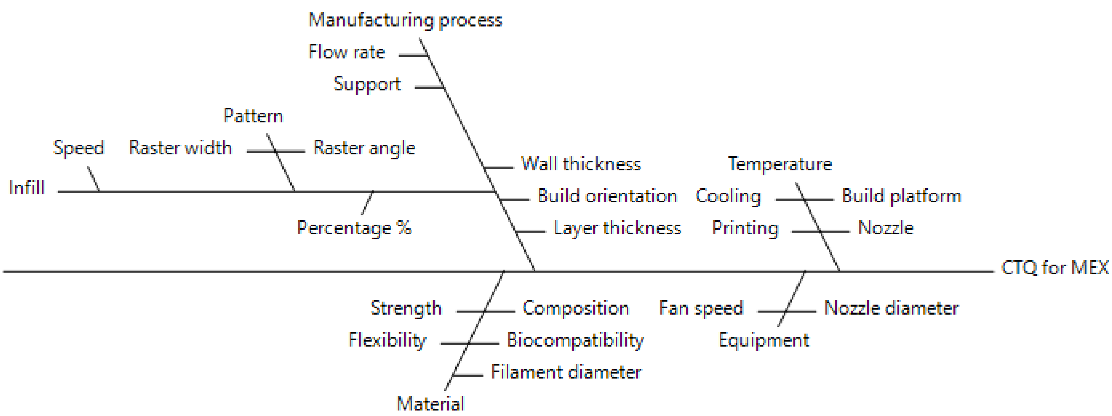

Figure 4: Possible factors for the critical-to-quality (CTQ) characteristics of MEX additive manufacturing

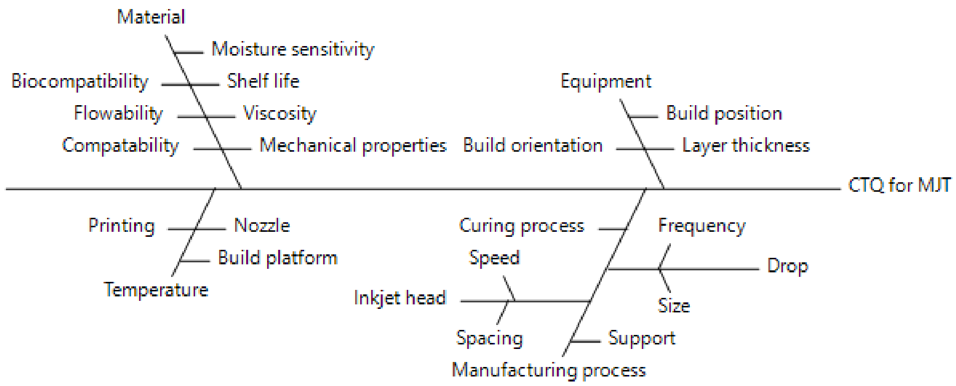

Figure 5: Possible factors for the critical-to-quality (CTQ) characteristics of MJT additive manufacturing

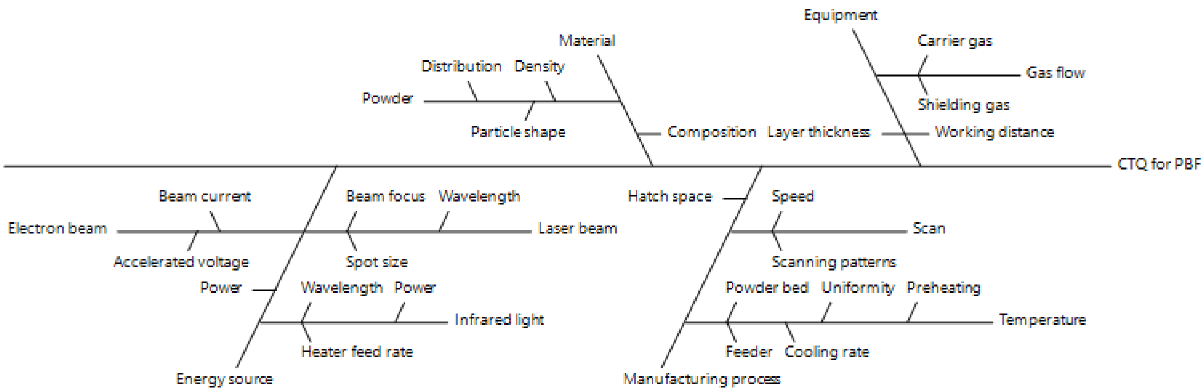

Figure 6: Possible factors for the critical-to-quality (CTQ) characteristics of PBF additive manufacturing

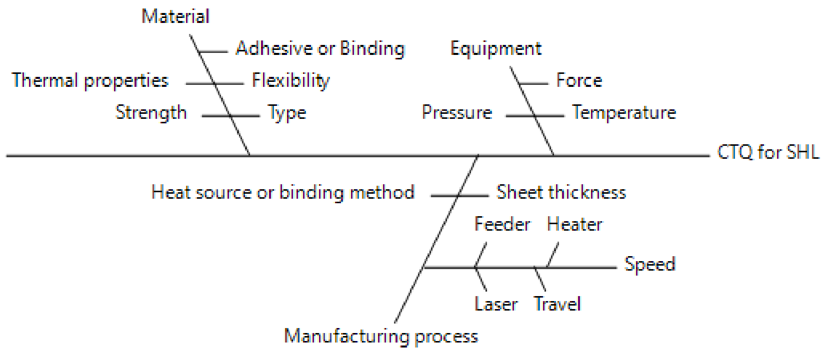

Figure 7: Possible factors for the critical-to-quality (CTQ) characteristics of SHL additive manufacturing

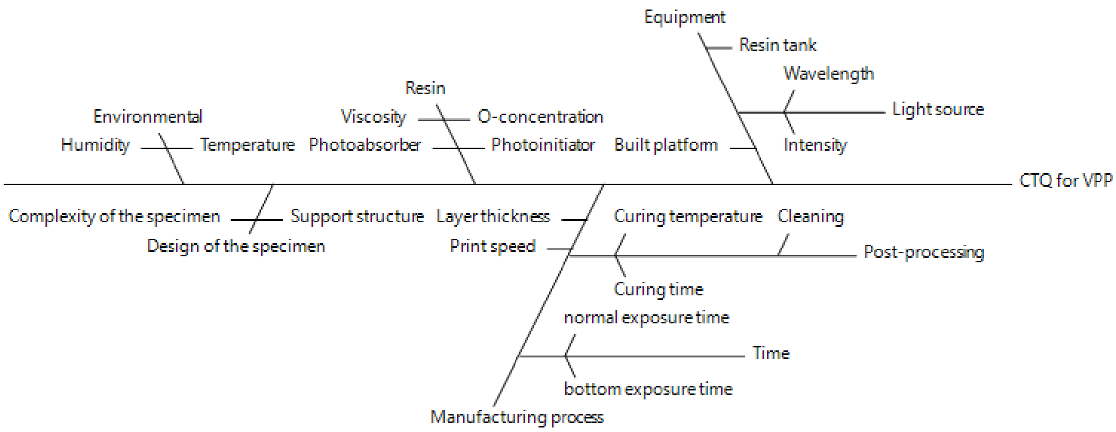

Figure 8: Possible factors for the critical-to-quality (CTQ) characteristics of VPP additive manufacturing