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FULL RESEARCH ARTICLE

Process parameter determination for small recycling plants for the production of filament for FFF printing using the Taguchi method

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Abstract
With the increasing use of the filament fabrication process, the in-house production of filament and the recycling of PLA waste is becoming more and more important. Small desktop filament extruders with associated peripherals enable small businesses and private users to carry out these recycling processes. Determing the right process parameters is of crucial importance here. These are usually only issued by the polymer manufacturer and the machine manufacturer. However, the development of own process parameters is important for new polymer compounds, as well as polymers with unknown manufacturers, as is typical in recycling. The common Taguchi method, which is used for process optimisation within the FFF process, was also used in this article to produce improved parameter sets for the production of filament using a single screw extruder (3devo Precision) with four heating zones. In this experimental field, the Taguchi method did not prove promising. Due to the small dimensions and compact design of such desktop filament extrusion machines, it was found that the setting parameters cannot be considered independently. The main parameters influencing the process were identified as the extruder screw speed, the cooling capacity and the temperature of the heating coil at the hopper. Nevertheless, parameter sets for PLA pellets and recycled PLA could be developed which have a better performance in terms of homogeneity of the diameter over time compared to the previously available parameter sets.

Keywords 3D-printing · Taguchi · Small filament production · Recycling thermoplastics

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Abbrevations

DOE	Design of experiment
FDM	Fused deposition modeling
FFF	Fused filament fabrication
OA	Orthogonal array
PLA	Polylactic acid
SNR	Signal-Noise-Ratio

1 Introduction

The amount of plastic and plastic waste produced has increased dramatically worldwide since its invention in the early twentieth century [1]. In 2019, 368 million tons of plastic were produced worldwide [2]. Despite the large production volumes, recycling of plastics is still limited. In Germany, 60% of our waste is currently thermally recycled, i.e. incinerated. Only 17% of plastic waste is recycled, of which only a small proportion has the quality of new plastic [3].

An increase in recycling rates is possible by changing the main plastic: poly lactic acid (PLA) can be recycled in several ways. On the one hand, PLA is compostable. However, since this does not produce new plastic, basically only the waste with the greatest ecological impact is destroyed. On the other hand, PLA is also chemically and mechanically recyclable, resulting in significantly less impact on the environment [4]. Mechanical recycling leads to only about 10% of the impact on climate, humans, and fossil resources (compared to composting). From one kilogram of PLA, 0.96 kg of recycled PLA can theoretically be obtained mechanically. This clearly shows that using PLA as our main plastic can have a positive impact [5]. While chemical recycling of post-consumer PLA usually requires industrial laboratory conditions, as shown by Majgaokar et al. [6], mechanical recycling has become possible both industrially and privately. In commercial operations, the cleaned material is mechanically reduced in size, melted and extruded or injected through a matrix. The process parameters are optimized for this purpose which always results in the comparable component and material qualities [7]. PLA is suited for recycling. However, due to the poorer thermal and mechanical properties, it is mainly used in applications with lower requirements. An overview of the degradation of the mechanical properties is given by Zenkiewicz et al. [8] and Sikroska et al. [9]. Possibilities such as thermal annealing, chemical modification, chain externs and blending to reverse this trend and optimise the recycled PLA were conducted by Badia and Ribes-Greus [10]. The purity of the recyclate is of immense importance in the production process. Gere and Czingany [11] and Buasri et al. [12] show that co-polymers of PLA and PET with usable mechanical properties are possible. Nevertheless, it is also evident in this case that this can only have a positive effect in a certain quantity ratio.

In the private sector, applications are mainly found for additive manufacturing. PLA is the most widely used filament raw material for fused deposition modeling (FDM). Plastic waste (e.g. support material, old products) can also be shredded, melted and processed into new filament. Desktop machines available for this purpose, deliver inconsistent material qualities due to unclean input products and inappropriate process parameters which strongly influence the printing and properties of the additively manufactured part [13]. The process parameters itself were mostly determined by trial and error only. However, due to its wide applicability, usability by almost every household and the possibility to understand the recycling process, desktop manufacturing offers many potentials in the recycling sector.

Desktop manufacturing means the use of a miniaturised production system. The machines have a size that allows them to be operated on or under a normal desk [14]. This is possible because of the development and further affordability of smaller machines (e.g. 3D printers, laser cutters) and the trend follows the development of the personal computer in the 1980s, and many industry representatives predict a similar impact from desktop manufacturing [15]. Desktop machines can be found, for example, in decentralized, open production sites such as OpenLabs (like FabLabs, but publicly accessible and open-source hardware machines are used) [16]. The machines can basically be operated by all interested parties after prior instruction which offers the possibility of learning, innovating and producing, especially in recycling [17]. In addition, since the machines (e.g. 3D printers, filament recyclers) are open-source hardware, they may also be replicated and reproduced, which offers enormous scaling potential [18].

The production of filament on an industrial scale is done on large extrusion lines. Through the miniaturisation of these, for example shown in the patent [19], filament can now also be produced in prototype construction, on a laboratory scale as well as in the private sector. In the production of filament, not only pure polymer is used. Also the recycling of polymers is increasingly taken into account, as shown by Cafiero et al. [20] for polymers from electronic waste, Tao et al. [21] for waste office paper PLA composite or Pringle et al. [22] for the recycling of wood into filament. The process parameters for pure polymers are provided by the manufacturer as material cards. Parameter sets for other polymer blends or polymers for which the manufacturer's data cannot be accessed, e.g. due to recycling, must be determined by experiment.

However, the process parameters are mostly determined through trial and error based on the manufacturer values leading to disadvantages in the quality of the material and the printed component.

One way to improve process parameters is the Taguchi method. The method, developed by Dr. Genichi Taguchi in Japan, focuses on the improvement the quality of products or processes. The objective is to reduce the deviations of a process from the nominal value, even if it is within the tolerances, since even these deviations no longer produce an ideal product [23]. This approach is very applicable to the recycling and subsequent use of filament in additive manufacturing since target deviations in both the recycling and printing processes result in a defective part and quality losses [24].

The challenges in determining process parameters in research or small-scale industrial 3D printing systems already arise with the materials or semi-finished products used, especially if they are composed of recyclates. Typical material quality variations due to raw material origin, mixing ratios, degree of contamination, process variations during semi-finished product production and transport and storage conditions have a significant influence on the 3D printing process. This has a direct influence on the determination of the process parameters and their variances.

In addition, 3D printing systems for research and small-scale industrial use are generally not sophisticated and are usually not based on comprehensively validated technologies of devices. Both facts often lead to higher variability of equipment and process parameters for research and development purposes, technologically immature machine elements and uncertainties in process control. That poses additional challenges in parameter definition for a safe manufacturing process due to the multi-criteria character and unpredictable variations.

The design of experiments (DOE) method is used to determine the process parameters as target-oriented and efficiently as possible against the background of high variance and complexity. The DOE is an efficient and statistical method to determine the relevant influencing factors for a process or also for a product from numerous of parameters. Thanks to an experimental design, these factors are varied largely independently of each other to derive their effects on the target variables and thus a cause-effect model. During the evaluation, it is assessed whether all the intended targets can be achieved or whether, for example, certain targets are contradictory. The goal-oriented visual processing of the data serves as a basis for further decisions.

2 Methodology

As any process of material conversion, the overall process of recycling thermoplastic material into filaments which are suitable for fused filament fabrication (FFF) 3D printing, is subdivided into multiple steps. The recycling process is summarized in the flow chart shown in Fig. 1.

First, the specific material which is supposed to be recycled has to be sorted from the total of collected waste material. Ideally, this step is considered in advance, rendering the step of waste sorting obsolete. In our case, this was achieved by collecting in polymer-specific containers. In a second step, the waste material is prepared for recycling by improving its manageability for the following process steps. Therefore, it is crushed to smaller bits if the initial waste objects exceed a certain size. This step is necessary because desktop shredders are often severely limited in the size of shredded material due to the size of the opening. Since homogeneity of the flakes is crucial for consecutive steps of the recycling process, the flakes are shredded repeatedly until a homogeneous consistency is achieved. If necessary, this step can be completed by cleaning the crushed or shredded material from, i.e. food residue by rinsing it with water.

Once the flakes are homogenized in size, they are dried after cleaning and mixed. This is the third step of the process. Besides removing any moisture that might interfere with the melting process in later steps, this also allows homogenizing batches from separate shredding runs. This also supports a more uniform result in the subsequent step of melting and extruding.

In this step, a thermoplastic extrusion machine is used as shown in Fig. 2. The device is capable of extruding filaments of aked or granulated thermoplastic material which can later be used in 3D printing applications. It consists of a hopper or another form of material supply system by which the shredded thermoplastic flakes are fed into the machine. From there the flakes are transferred into a heated barrel (usually having multiple heat zones with independent temperature settings) which contains a screw that conveys the material into the heated zones of the barrel. When the heated

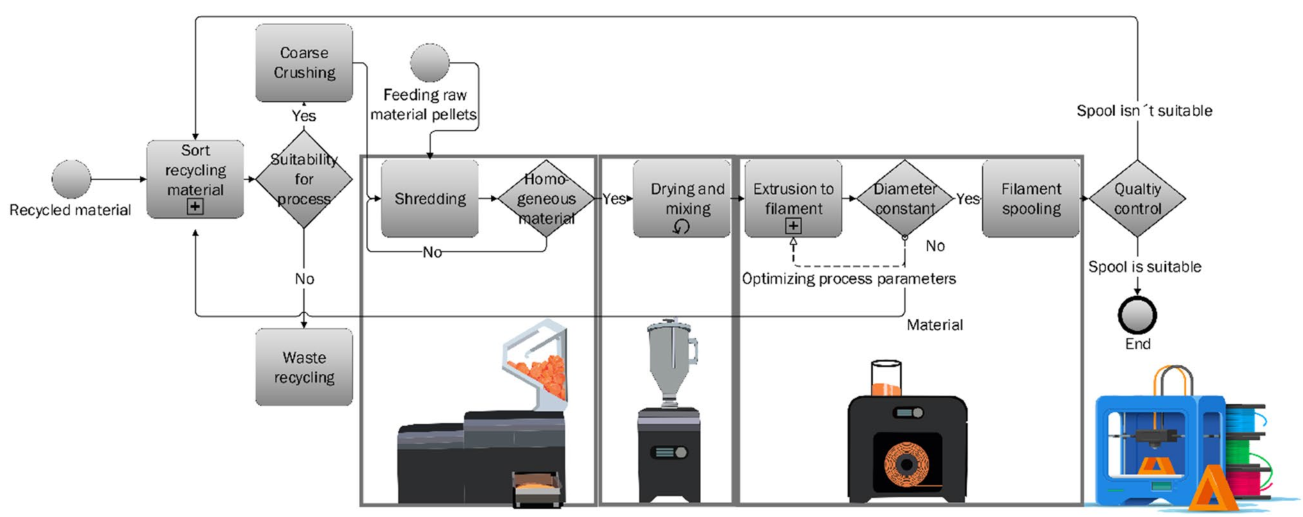


Fig. 1 Recycling process step chain. Representation of the necessary process steps with the associated equipment from raw material to usable filament

Fig. 2 Desktop Recycling setup "SHR3D IT" shredder, "AIRID" polymer dryer and "PRECISION" extruder. Desktop recycling plant with shredder, dryer and extrusion line for the production of filament from various polymers in small-scale industry and research

zones are reached, the material begins to melt and becomes moldable. Due to the geometry of the screw, the material is compacted as it is conveyed to the nozzle. In addition, during this process of plastification, the material is not only compacted but also homogenized and separated from air that might be trapped within in the plastified material. When being conveyed towards the extrusion nozzle, the material is exposed to a steadily rising level of pressure. This pressure, which reaches its maximum right before the extrusion nozzle, finally drives the molten thermoplastic material through the nozzle. Depending on the configuration of the extrusion machine, the diameter of the resulting filament is either defined by the diameter of the nozzle itself or by a subsequent closed loop system of a pulling mechanism and a filament thickness sensor. A cooling apparatus for faster filament solidification completes the assembly [19]. After solidification, the extruded filament is wound onto a suitable spool, which can be used as the raw material for FFF 3D printing.

As the sheer amount of parameters as well as the interdependencies with each other form a highly complex system which has a direct impact on the final product determining and optimizing the material specific parameter set is one of the most important aspects of the entire recycling process. As every thermoplastic material requires its own specific set of process parameters, the development and improvement of suitable parameters is essential for creating filaments which apply to the tight tolerances required by 3D printing applications (especially regarding diameter and material properties).

As the aforementioned tolerances of the filament are crucial to a good quality 3D print, the recycling process concludes in the fifth and last step of quality control. The scope of the conducted quality control can vary with regard to the different requirements that might occur from different applications of the extruded filament. Due to the nature of FFF printing, the most crucial requirement is consistency as well as dimensional accuracy of the filament. These properties can usually be checked by manual measurements or, if the extrusion machine logs the raw data of its thickness sensor, by interpreting these data. The raw data variables recorded by the "Precision" extruder are listed in Table 1. Once the filament passes quality control, it is ready to use for 3D printing. Filament that failed quality control can be shredded and processed again with improved parameters.

The intent is to concentrate on the vital fewer parameters rather than the trivial many within the confines of the engineering and cost constraints. An orthogonal array (OA) represents a matrix in which each row represents the levels or states of the selected factors and each column represents a specific factor whose influence on the response variable is of interest. OA have the property that every factor setting occurs the same number of times for every test setting of all other factors. This allows us to make a balanced comparison among factor levels under a variety of conditions. Using an OA minimises the number of runs while retaining the pairwise balancing properties.

To design a robust process, it is necessary to identify all input variables and disturbance variables and to determine their mutual interactions on the required output signal or result. Used process parameters and sensor data which were used in this research are shown in Fig. 3. The input variables must be varied in fixed values in such a way that the optimum value is determined for each variable. However, a variation of all variables and stages is not always reasonable and can lead to considerable costs and effort in case of numerous variables and stages. To keep the effort and costs low, the Taguchi method can be used. For a static system, the method applies the source values or signals from the process to the deviations or noise that occur [25].

Table 1 Logged variables by the extruder

Variable code	Unit	Name	Meaning
Time	s	Time	Time since log started
SetT1	°C	Set temperature Heater1	Set temperature of H1 chosen by user
Temp1	°C	Measured temp Heater1	Actual temperature of H1
dc1	%	Duty cycle Heater1	Supplied power percentage to H1
Err1	–	Error thermocouple1	Amount of measurement faults th1
SetT2	°C	Set temperature Heater2	Set temperature of H1 chosen by user
Temp2	°C	Measured temp Heater2	Actual temperature of H2
dc2	%	Duty cycle Heater2	Supplied power percentage to H2
Err2	–	Error thermocouple2	Amount of measurement faults th2
SetT3	°C	Set temperature Heater3	Set temperature of H1 chosen by user
Temp3	°C	Measured temp Heater3	Actual temperature of H3
dc3	%	Duty cycle Heater3	Supplied power percentage to H3
Err3	–	error thermocouple3	amount of measurement faults th3
SetT4	°C	Set temperature Heater4	Set temperature of H1 chosen by user
Temp4	°C	Measured temp Heater4	Actual temperature of H4
dc4	%	Duty cycle Heater4	Supplied power percentage to H4
Err4	–	Error thermocouple4	Amount of measurement faults th4
intT4	°C	Internal temperature	Temperature under the hood
ExtCur	mA	Extruder current	Electrical current for extruder rotation
ExtPWM	0–255	Cooling fan PulseWidthModulation	Supplied power frequency to cooling fan (Converted to %motor in excel template)
ExtTmp	°C	Extruder temperature	Temperature of the extruder motor
Overht	0/1	If machine overheats	
FAULT	0/1	If motor driver is defective	
SetRPM	100*nb/min	Set screw speed	Screw speed chosen by user
RPM	100*nb/min	Measured screw speed	Actual screw speed
FT	µm	Filament thickness	Measured thickness of filament
FTAVG	µm	Average filament thickness	Average thickness of measured filament
Puller	Ticks	Puller ticks	Rotational speed of stepper motors of puller wheels
MemFree	Memory		
Status	–	Status of the machine	Status: idle/homing/heating/running
WndrSpd	Ticks	Winder speed	Rotational speed of winder mechanism
PosSpd	Ticks	Positioner speed	Movement speed of positioner mechanism
Length	mm	Length of spooled filament	Length of spooled filament
Volume	mm^3	Volume of spooled filament	Volume of spooled filament
SpDia	mm	Diameter of current spooling	Diameter of current spooling
SpFill	%	Percentage (/full spool)	Percentage (/full spool)

$$\frac{S}{N} = \frac{\bar{y}^2}{\sigma^2} = \max. \tag{1}$$

The goal is to maximize the *S*/*N* ratio, this results from the fact that the noise is the denominator, and it is important to minimise it to obtain a robust process. This is to ensure that the resulting values are uniform in both the positive and negative direction. The so-called signal-to-noise ratio (SNR) is formed from the *S*/*N* value for the evaluation. The ratio is logarithmic, which has the consequence that a comparison is easily possible even with a larger spectrum of values [25].

$$\mathrm{SNR} = 10 \log\left(\frac{S}{N}\right). \tag{2}$$

For the evaluation with the Taguchi method the arithmetic mean and the scatter square are determined and set into a certain relation. This depends on whether the target value should be as large as possible (larger-the-better LTB), as small as possible (smaller-the-better STB) or nominal (nominal-the-best NTB) [25].

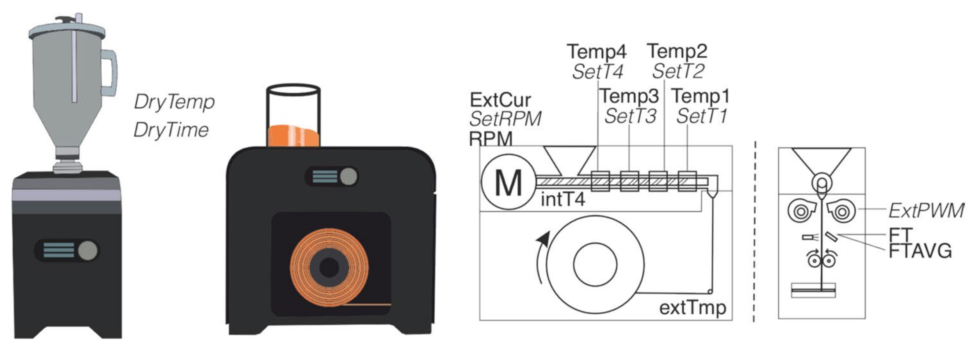


Fig. 3 Process parameters and sensor data. Illustration of the measurable sensor data and *adjustable process parameter*

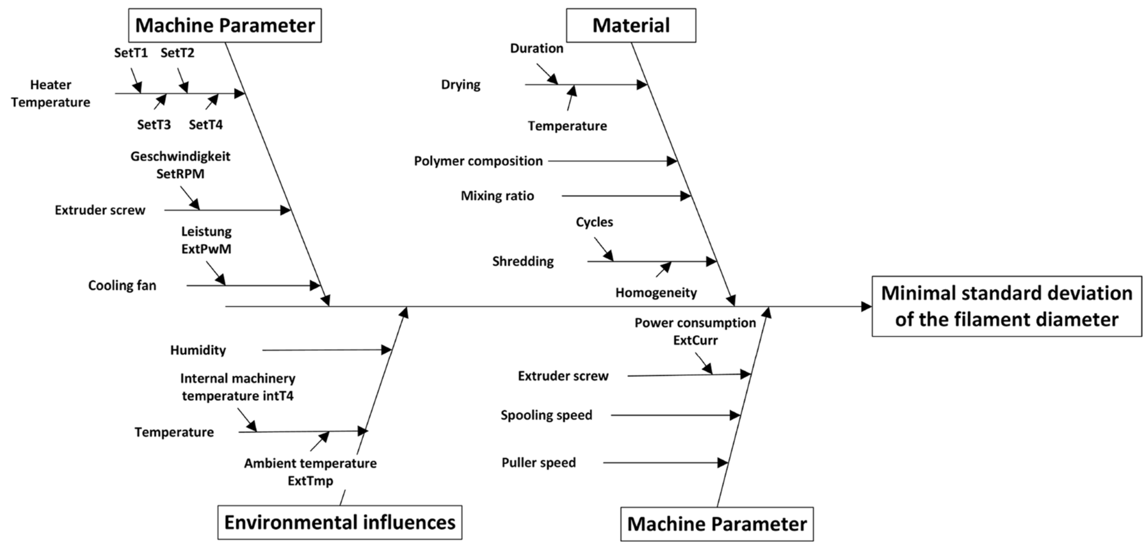


Fig. 4 Ishigawa Influences on filament production process. The upper half shows the variables that can be influenced. In the lower area all which cannot be influenced by the user

$$\mathrm{STB} = \mathrm{SNR} = 10 \log \left(\frac{1}{\bar{y}^2 + \sigma^2} y_0^2 \right). \quad (3)$$

The variation of the different combinations and settings is achieved by building an orthogonal array that determines the number of experiments and the variation of the variables. The size of the array depends on the number of variables and levels. It is also important that the combination of variables and levels in the array is randomized to minimise the risk of a systematic error. Thus, it is possible to keep the effort and the costs low because fewer experiments are necessary. After the metrics are available by means of the experiments, it is useful to perform an analysis of variance (ANOVA) or multiple regression analysis to analyze the results in terms of the statement ability [25].

Finally, the experiment is to be validated with the ideal values determined in such a way. If the results are insufficient, it is possible that not all interactions among the variables have been considered. The disadvantage of the Taguchi method is that DOEs not determine the reason for the interactions, it only combines the variables systematically. However, the method has proven itself many times in many applications and scenarios. This is also the case in the work of Gomez-Gras et al. [26] and Camposeco-Negrete [23], where the aim is to optimize the additive manufacturing process FDM regarding certain parameters such as layer thickness, fill density, fill structure, etc. Other works worth mentioning in this context are those of Durão et al. [27] and Zandi et al. [28] who followed a similar approach using the Taguchi method to optimize the FDM additive manufacturing process.

Using the Taguchi method mentioned before, a parameter determination can be carried out with moderate effort. In technical processes, there are often a large number of influenceable and non-influenceable parameters.

These parameters are shown in Fig. 4 for the filament fabrication process. In the upper area are the parameters that can be influenced by the operator, in the lower area are the environmental influences or variables controlled by the machine which cannot be directly influenced by the user.

The target value is the minimum standard deviation of the filament diameter. For this purpose, an L18 OA is created. With such a design, it is possible to use seven parameters in three stages as well as one parameter in two stages. Figure 2 shows the configuration of the test setup. The equipment is also shown in Fig. 3 where essential ***sensor data*** as well as all *freely adjustable parameters* are shown. Important parameters are the drying temperature *DryTemp* and drying time *DryTime* for the dryer. The most important parameters of the extruder are the extruder screw speed *SetRPM*, the four temperatures of the heating elements *SetT1-T4* and the cooling fan power *ExtPWM*. These parameters were integrated into OAs as three stage parameters. Most of these parameters are monitored by sensors shown in Fig. 3 in bold. The filament thickness sensor is used to control the tension mechanism and thus regulate the filament diameter ***FT/FTAVG***. Table 1 contains a list of all logged variables. The recommended manufacturer data for pure PLA is used as starting point for the parameters. Based on these, the values were varied. A list of the parameters used is shown in Table 2. The individual trials are conducted in randomised order.

With the created experimental plan, the trials were carried out with pure PLA pellets and recycled PLA flakes. Subsequently, the logged data were analysed using the statistics software such as *STATISTICA* by *TIBCO*. Within this experiment and the subsequent evaluation, *TIBCO STATISTICA version 13* was used. For this purpose, the data was eliminated of outliers and then statistically analysed. The standard deviation is defined as the target value. A minimisation leads to a more constant process over time and in the finished spool to a high quality thanks to a low diameter deviation. The individual standard deviation results are then inserted into the orthogonal array. A Taguchi analysis is then performed with the minimum value set as the desired value. The analysis shows the influence of the parameters on the target value as well as the best parameter stages for the most influential parameters for the optimal setting of the process.

3 Results

For the production of filament from PLA pellets, a better set of parameters than the basic parameters specified by the manufacturer could be worked out by means of the analysis carried out. These are listed in Table 3. Here it can be seen that the process temperatures of PLA pellets and recycled PLA differ. PLA pellets require a lower process temperature due to their homogeneous initial size. Recycled PLA requires a higher temperature so that a homogeneous melt is

Table 2 Experimental design for pure PLA pellets one factor with two stages and seven factors with three stages

Run	Empty	SetT1	SetT2	SetT3	SetT4	ExtPwm	DryTime	SetRpm
6	1	180	190	190	170	30	2	50
9	1	190	190	170	190	50	1	50
12	2	170	190	180	180	30	1	70
5	1	180	180	180	190	100	1	35
15	2	180	190	170	180	100	2	35
17	2	190	180	170	190	30	2	70
13	2	180	170	180	190	30	3	50
14	2	180	180	190	170	50	1	70
10	2	170	170	190	190	50	2	35
7	1	190	170	180	170	100	2	70
4	1	180	170	170	180	50	3	70
8	1	190	180	190	180	30	3	35
3	1	170	190	190	190	100	3	70
1	1	170	170	170	170	30	1	35
18	2	190	190	180	170	50	3	35
11	2	170	180	170	170	100	3	50
16	2	190	170	190	180	100	1	50
2	1	170	180	180	180	50	2	50

Table 3 Optimised parameters for PLA pellets and recycled PLA

	ExtPwm	SetRPM	DryTime [h]	*SetT*1 [°C]	*SetT*2 [°C]	*SetT*3 [°C]	*SetT*4 [°C]
PLA pellets	100	50		170	180	170	170
Recycled PLA	060	50	3	170	200	200	185

formed. Flakes that are not completely melted lead to diameter inconsistencies.

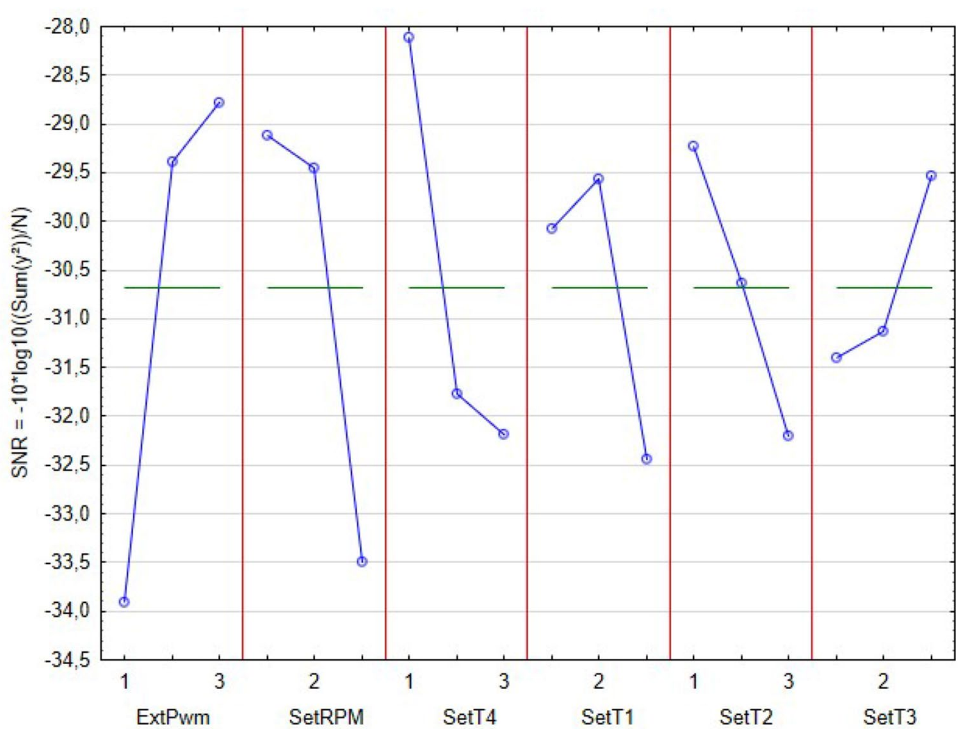
However, a parameter set that was randomly selected by the DOE is even better than the optimum calculated by the Taguchi analysis and is listed as the PLA pellets optimal parameter. On average, the results for recycled PLA were not suitable in terms of quality for further use. However, the analysis and evaluation show optimised values that are suitable for use. Furthermore, it shows that a screening process should be introduced after shredding. Homogeneity is an important influencing factor that needs to be investigated in subsequent studies.

Figures 5 and 6 show the calculated SNR values for the most influential parameters. It is obvious that the highest level for the external fans leads to a better result. This is also in line with practical experience. The faster the filament can be cooled, the more consistent the results. Both diagrams also show that the extruder speed has a negative influence on the signal-to-noise ratio as the speed increases. This result can also be quickly validated as the main factor in practice. The increased flow rate leads to the filament not being able to cool down within the short cooling path. As a result, the filament is deformed by the tension rollers and becomes oval in the process. The priorities differ in the two plots, so in the study of recycled PLA parameters such as drying time are higher in priority. Temperature 1 is therefore not listed among the most important parameters in Fig. 6.

4 Discussion

There are differences in the results of the SNR values between the two quite similar experiments. This can be attributed to the fact that the Taguchi method is not directly suitable for inferring interactions between the parameters, but should only be used for main effects. In particular, the temperatures influence each other, as the heating elements are close to each other in terms of construction space and the polymer acts as a heat accumulator. This leads to temperature deviations from the set values. Nevertheless, an optimised parameter set could be calculated utilizing the analysis carried out, which has a lower standard deviation of 28.77 µm in the validation experiment in contrast to the average standard deviation of 42.77 µm for all experiments. However, it also shows that better parameters can be found by chance in the DOE, as shown by test run 11, which with a standard deviation of 14.57 µm offers the best value for constant production for pure PLA pellets. This correlation can also be seen in Fig. 7, where the deviation of the graphs of optimised PLA and run 11 is significantly closer to the target value 1750 µm and also shows less deviation compared to run 13, which is in the middle of the standard deviation. Moreover, the tolerance limits are not violated during production with the parameters from Run 11. Filament with a larger filament diameter, even in certain spots, is not suitable for later use in the FFF process, as it leads to difficulties in transporting the filament to the nozzle. Undersized

Fig. 5 Average Eta by factor levels PLA pellets. The parameters ExtPwm, SetRPM and SetT4 are the primary parameters which have direct process optimisation possibilities. All parameters are below the mean square error and thus have a weak significance



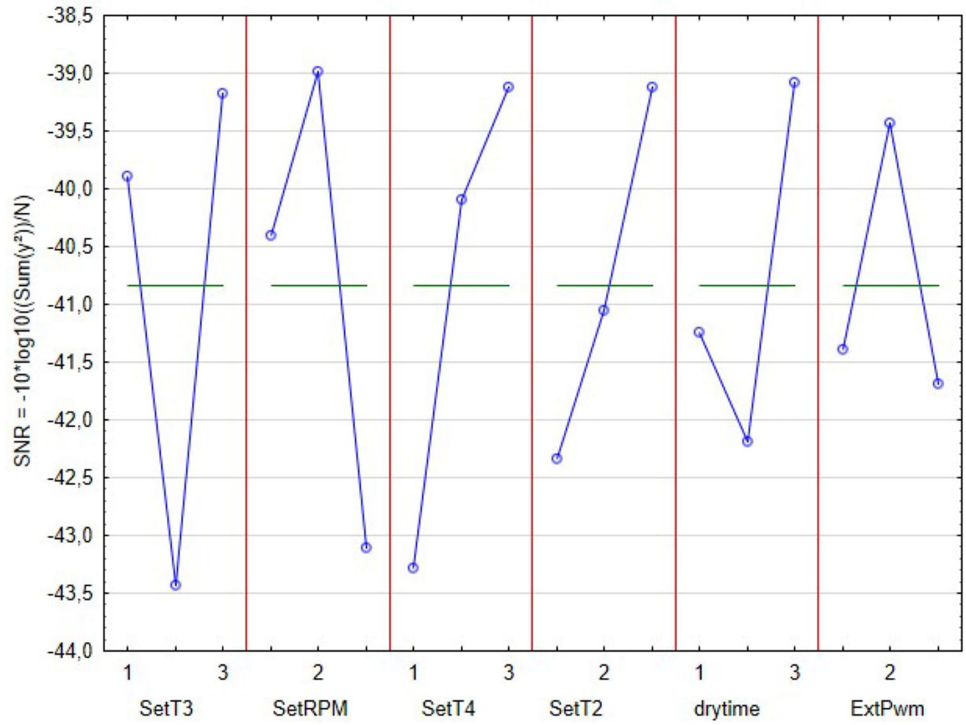


Fig. 6 Average Eta by factor levels recycled PLA. The parameters SetT2, ExtPwm, SetT4 and SetRPM are the primary parameters which have direct process optimisation possibilities, whereby only SetT2 and SetRPM have a positive influence. The remaining parameter influences are below the mean square error

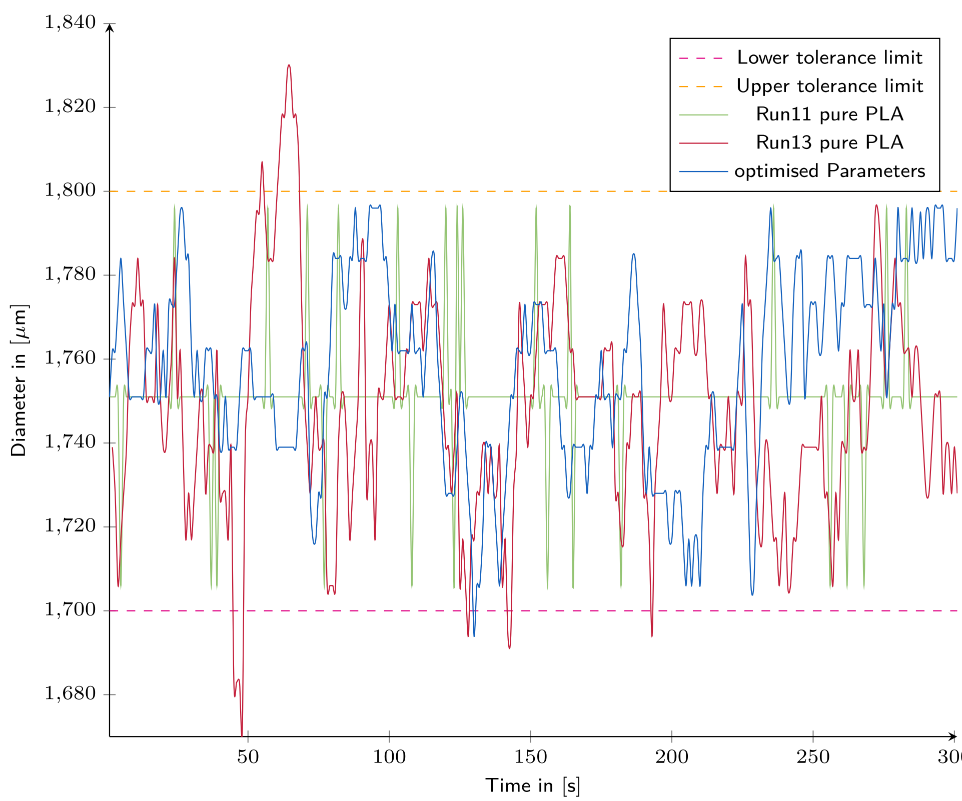


Fig. 7 Curve of the measured diameters of experiment for the first 300 s number 13 pure PLA (red) and the run with optimised parameters after the Taguchi analysis (blue). Run 11 (green) shows the parameter set found by chance

filament leads to the so-called underextrusion phenomenon and weakens the component structure. Therefore, it is necessary that the investigated parameter sets do not touch or exceed the tolerance limits. Especially for industrial application quality gates have to be established!

Variations in material and semi-finished products as well as the adverse technological maturity of research and small-scale industrial facilities for 3D printing lead to multi-criteria and complex challenges in determining safe process parameters. For efficient and systematic parameter determination, the DOE method was therefore used as a first step. After deriving an experimental design, the factors were varied largely independently of each other to derive their effects on the target value and thus a cause–effect model. In the further course, the complex interdependencies between the parameters must be investigated. For this purpose, methods of experimental validation shall be used within the framework of setting up and applying a so-called test pyramid. The test pyramid provides results at different levels of parameter determination up to a safe overall process control and to verify the corresponding requirements. Through the subdivision into different test levels, multi-criteria parameter studies can be carried out with high efficiency in addition to a systematic approach. The reduction of test costs and times due to the increasing concentration or continuation of functioning approaches with simultaneously increasing test scopes per level shall be emphasized. This means that sample size, test complexity, production lead time of the specimen and test cost increase from the bottom to the top. This also ensures that the required test results are available quantitatively as well as qualitatively during the respective research or development phase. Starting with test coupons, more complex elements and finally holistic systems are subsequently tested. Moreover, the extensive validation series by using the test pyramid approach can be accounted as a basis for multi-criteria simulation methods. This method offers the possibility to considerably simplify and reduce the effort required for future process parameter studies.

5 Conclusions

The experimental analysis carried out in this paper has shown that parameter analysis using DOE approaches, such as Taguchi in this case, can find optimised parameters. Nevertheless, optimised parameter sets could be determined by conducting analyses which improved the quality of the produced filament. Thus, the application can be classified as not optimal but successful. The recycled filament can therefore be reused. The advantages of an L18 array will continue to be used in the future for an initial assessment of the process. The extruder screw speed, the cooling and the heating element temperature T4 at the material feed were identified as the main influencing parameters. These should be optimised as a matter of priority in further trials. Subsequently, a test pyramid could be used consistently to better define interdependencies with simple coupon tests in the beginning. However, it is important to note that with numerous parameters and few experiment runs, only the main influences can be recorded and no interdependencies. Furthermore, it is shown that the interactions between the temperatures lead to problems in the unambiguous evaluation of the signal-to-noise ratio. A DOE with more experiments, such as 2^k factorial designs or full factorial designs, offers a better possibility to determine interactions between the parameters.

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