Improvement of tensile strength of fused deposition modelling (FDM) part using artificial neural network and genetic algorithm techniques

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Abstract

Purpose – This paper presents an experimental investigation in establishing the relationship between FDM process parameters and tensile strength of polycarbonate (PC) samples using the I-Optimal design.

Design/methodology/approach – I-optimal design methodology is used to plan the experiments by means of Minitab-17.1 software. Samples are manufactured using Stratsys FDM 400mc and tested as per ISO standards. Additionally, an artificial neural network model was developed and compared to the regression model in order to select an appropriate model for optimisation. Finally, the genetic algorithm (GA) solver is executed for improvement of tensile strength of FDM built PC components.

Findings – This study demonstrates that the selected process parameters (raster angle, raster to raster air gap, build orientation about Y axis and the number of contours) had significant effect on tensile strength with raster angle being the most influential factor. Increasing the build orientation about Y axis produced specimens with compact structures that resulted in improved fracture resistance.

Research limitations/implications – The fitted regression model has a *p*-value less than 0.05 which suggests that the model terms significantly represent the tensile strength of PC samples. Further, from the normal probability plot it was found that the residuals follow a straight line, thus the developed model provides adequate predictions. Furthermore, from the validation runs, a close agreement between the predicted and actual values was seen along the reference line which further supports satisfactory model predictions.

Practical implications – This study successfully investigated the effects of the selected process parameters - raster angle, raster to raster air gap, build orientation about Y axis and the number of contours - on tensile strength of PC samples utilising the I-optimal design and ANOVA. In addition, for prediction of the part strength, regression and ANN models were developed. The selected ANN model was optimised using the GA-solver for determination of optimal parameter settings.

Originality/value – The proposed ANN-GA approach is more appropriate to establish the non-linear relationship between the selected process parameters and tensile strength. Further, the proposed ANN-GA methodology can assist in manufacture of various industrial products with Nylon, polyethylene terephthalate glycol (PETG) and PET as new 3DP materials.

Keywords Tensile strength, Polycarbonate, FDM, I-optimal design, ANOVA, ANN, GA

Paper type Research paper

1. Introduction

Fused deposition modeling (FDM) is an additive manufacturing (AM) technique that involves the layering of deposited molten plastic to create three dimensional (3D) objects from a

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computer-aided design (CAD) model. This technique has gained traction over the past two and half decades as a disruptive manufacturing technology that fulfils industry needs in the areas of aerospace, automobile, medical, electronics and telecommunication. But the quality of FDM parts has been limited due to poor mechanical properties (Rajpurohit and Harshit, 2019) and improper selection of process parameters (Murugan *et al.*, 2018; Sukindar *et al.*, 2017).

To address the above issues, several studies have been conducted on characterisation of thermoplastics where engineered plastics can replace their metal counter parts. However, for improvement of the FDM part quality, optimisation of the process variables has been focused by previous researches in terms of various mechanical properties such as tensile, compressive, impact and flexural strength (Dev and Srivasatava, 2022; Bardiya*et al.*, 2021; Chen *et al.*, 2020; Porter *et al.*, 2019). Apparently it was observed that tensile strength is the most commonly measured and desired property for 3D printed samples (Abdullah *et al.*, 2018; Chen *et al.*, 2020). But without proper selection of predictive models, the FDM process optimisation for achieving the desired mechanical property can be a tedious and costly exercise (Murugan *et al.*, 2022).

Further, the past literature indicates that the infill design parameters that include layer thickness, deposition speed, density, pattern and width had a significant effect on the strength of 3D printed components (Harpool *et al.*, 2021; Bardiya *et al.*, 2021; Mohammed and Chowdary, 2020; Aloyaydi *et al.*, 2019; Rajpurohit and Dave, 2018; Abdullah *et al.*, 2018; Luzanin *et al.*, 2017; Fernandez-Vicente *et al.*, 2015). Furthermore, in the rotating equipment, the direction of applied forces has a great influence on part functionality that generally dictated by positional parameters of the 3D printing process. In this regard, Balderrama-Armendariz *et al.* (2018) stated that build orientation and raster angle are the important positional parameters that need technician involvement for adjustment in the AM process. In addition, the study concluded that the raster angle contributes significantly for improvement of the part mechanical strength. Afrose *et al.* (2016) proved that the 3D print samples built with 0° raster angle exhibited the highest tensile strength compared to those of 45 and 90°. Gonabadi *et al.* (2020), examined the impact of build orientation and infill density on the mechanical properties of PLA samples. In conclusion, the study stated that the tensile strength and Young's modulus will be increased with increase in infill density.

Moreover, air gap was shown direct influence on the mechanical properties of FDM parts (Balderrama-Armendariz *et al.*, 2018). Rayegani and Onwubolu (2014) conducted an optimisation study and shown that the 3D printed part tensile strength was at its highest value with negative air gap. Gonabadi *et al.* (2020) examined the impact of various 3D printing parameters such as build orientation and infill density on the mechanical properties of PLA samples.

Further, practitioners are looking for efficient and effective tools and techniques to standardise the FDM selection process when a disruptive technology such as AM deployed in the traditional production shop floors (Gibson *et al.*, 2014). Predictive models which are statistically derived may solve these problems by allowing for better process selection as well as increasing commercial viability of FDM components by reducing costs without compromising the part quality.

Artificial neural network (ANN) is the most widely used technique in the AM field, owing to its ability to handle large datasets and superior computational capability (Mahmood *et al.*, 2021). Literature also witnessed development of predictive models by ANN approach for accurate estimation of part toughness, part thickness and production cost (Moradi *et al.*, 2020; Mohamad *et al.*, 2017). Further, Giri *et al.* (2021) performed optimisation of FDM process parameters for a dual extruder 3D printer by means of ANN modelling and proved that the task of training the large datasets and optimising them can be effectively accomplished by using the function approximation of ANN. The study proved that the ANN has capability to carry out intricate pattern identification and develop a functional relationship as well as reducing the need to solve physical models.

On the other hand, literature evidenced the full factorial experimental approach which has been used in the majority of studies (Arivazhagan and Masood, 2012; Rayegani and Onwubolu, 2014; Fernandez-Vicente *et al.*, 2016; Armillotta *et al.*, 2017; Chacón *et al.*, 2017) and is mentioned to be an ideal choice. But I-optimal design of experiment (DOE) approach was successfully used to investigate the effect of various FDM process parameters, on dynamic mechanical properties of PC-ABS components (Mohamed *et al.*, 2017). Moreover, I-optimal design has capability to reduce the prediction variance across the parameter space as well as its suitability for the development of second-order models which are critical for process parameter optimisation (Jones and Goos, 2012). Therefore, the objective of the study is to develop a predictive model between the key process parameters and mechanical strength of 3D printed parts in conjunction with I-optimal design in order to assess the impact of process parameters variations on the part strength. Moreover, the novelty of the study can be summarised below:

(1) This study utilises I-optimal design approach with a main focus on positional and infill design parameters (raster angle, number of contours, air gap and build orientation) which have not been employed so-far for examining their effects on mechanical strength of polycarbonate (PC) samples.

(2) In this study, process optimisation through ANN-GA modeling is performed for improvement of the tensile strength of the PC samples built by FDM 400mc printer, and tested as per ISO standards.

The rest of the paper is organised as follows: Section 2 discusses the previous works in the AM/FDM field. In Section 3, the research methodology followed in terms of sample design, DOE, printing and testing of samples is explained. Section 4 discusses development of empirical models along with analysis of results as well as development of regression model that relate the tensile strength of the part to the selected process parameters. This section also covers modelling of tensile strength with ANN technique and optimisation of process parameters for enhancement of the part performance by the GA solver. Section 5 deals conclusion of the study, research contributions and recommendations for future work.

2. Study background

AM technologies have emerged rapidly and progressively over the last two decades and they become well-received in several small and medium-sized industries such as automotive, healthcare, electronics and bio-medical for both the production of prototypes and the functional components. In this section a comprehensive review of related studies that deals characterisation of mechanical properties of 3D printed parts is presented. Further, this section focuses on identification of the key process parameters in mitigating the AM process with an emphasis on the tensile strength of FDM samples. A summary of literature highlighting the materials and performance measures used by various researchers along with categorisation of process parameters into infill, positional and other type can be seen in Table 1.

2.1 Characterisation of mechanical properties with an emphasis on the importance of key process parameters

Wu *et al.* (2015) conducted a conjoint experimental study to determine the influence of layer thickness and raster angle on the mechanical properties of FDM built polyether ether ketone (PEEK) samples and compared the mechanical performance of 3D printed PEEK with ABS parts. Geometric models of tensile, compressive and bending samples were created. From the results, it was confirmed that raster angle and layer thickness both have a substantial effect on tensile, compressive and three-point bending properties of PEEK samples. Layer

Study reference	Material (s) used	Performance measure(s) selected	Categorisation of parameters into †Infill design type	‡Positional type	Other parameter
Auffray *et al.* (2022)	PLA	Young's Modulus and Yield Strength	Infill Pattern, Layer Height, Infill Density Printing Velocity	Raster orientation	Outline Overlap and Extruder Temperature
Harpool *et al.* (2021)	PLA	Tensile Strength	Layer Thickness		Printing Temperature
Xue *et al.* (2021)	PLA	Vibration Properties	Layer Height and Deposition Speed	Raster Angle	Nozzle Temperature
Chowdaty and Bobb (2021)	PLA	Fatigue Life	Layer Thickness and Raster Width	Raster Angle	Number of Contours
Bardiya *et al.* (2021)	PLA	Tensile Strength, Flexural Strength and Manufacturing Time	Layer Height, and Infill Percentage	Part Orientation	
Chen *et al.* (2020)	Carbon Fibre, Kevlar and Fibre Glass	Tensile strength	Infill Percentage	Part Orientation	
Mallian and Chowdary (2020)	ABS	Build Time, Material Consumption and Torsional Stress	Raster Width, and Layer Thickness	Raster Angle and Part Orientation	
Aloyaydi *et al.* (2019)	PLA	Flexural Strength	Infill Density		
Ali and Chowdary (2019)	PC	Natural Frequency	Raster Angle, Air Gap, Build Orientation and Number of Contours	Raster Angle, and Build Orientation	Number of Contours
Porter *et al.* (2019)	PLA	Flexural Rigidity	Infill Percentage, and Member Thickness	Orientation	
Balderrama-Armendariz *et al.* (2018)	ABS	Ultimate Shear Strength, 0.2% Yield Strength, Shear Modulus and Fracture Strain		Orientation and Raster Angle	
Rajpurohit and Dave (2018)	PLA	Flexural Strength	Layer Height, and Raster Width	Raster Angle	
Abdullah *et al.* (2018)	ABS and PLA	Tensile strength and Flexural strength	Layer Thickness	Raster Angle	
Gebisa and Lemu (2018)	ULTEM 9085	Flexural Properties	Raster Width	Raster Angle	Air Gap Contour Number, and Contour Width

(*continued*)

Table 1.
Summary of literature in terms of materials, performance measures and process parameters used along with categorisation into infill, positional and other type

Study reference	Material (s) used	Performance measure(s) selected	Categorisation of parameters into †Infill design type	‡Positional type	Other parameter
Nugroho *et al.* (2018)	PLA	Flexural Strength	Layer Thickness		
Luzanin *et al.* (2017)	PLA	Flexural Force	Layer Thickness, Infill Pattern	Deposition Angle	Extrusion Speed and Extrusion Temperature
Fernandez-Vicente *et al.* (2016)	ABS	Tensile Strength	Pattern and Infill Density		
Alvarez *et al.*, (2016)	ABS	Tensile Strength, Impact Resistance and Printing Time	Infill Percentage		
Noon *et al.* (2015)	PC	Surface Roughness, Dimensional Accuracy	Layer thickness and Raster Width	Part Orientation	Air Gap, and Deviational Tolerance
Luzanin *et al.* (2014)	PLA	Flexural Force	Layer Thickness, and Infill	Deposition Angle	
Durgun and Ertan (2014)	ABS	Surface Roughness, Tensile Strength, Elongation and Flexural Strength	Raster Angle and Orientation	Raster Angle and Orientation	
Ali *et al.* (2014)	PC	Build Time, Material Consumption and Surface Roughness	Slice Height, Road Width	Raster Angle	Number of Contours, and Air Gap
Croccolo *et al.* (2013)	ABSplus430	Tensile Strength and Stiffness		Raster Angle	Number of Contours and Dimensions
Munguía *et al.* (2011)	ABS	Fatigue Life			Air Gap
Bagsik and Schöppner (2011)	Ultem*9085	Tensile Strength	Raster Width	Build Orientation, Raster Angle	Air Gap
Panda *et al.* (2009)	ABS P400	Tensile, Flexural and Impact Strength	Layer Thickness and Raster Width	Orientation and Raster Angle	Air Gap

Note(s): † Classification based on Pandzic and Holdzic (2021) and Porter *et al.* (2019)
‡ Classification based on Balderrama-Armendariz *et al.* (2018)
Source(s): Authors own work

Table 1.

thickness had a significant influence on tensile strength; however, it had little influence on bending and compressive strengths. Further, the study indicated that 3D printed PEEK samples were 108%, 114 and 115% superior to the ABS samples in terms of tensile, compressive and bending strengths respectively.

Alvarez *et al.* (2016) investigated the influence of the infill percentage on the mechanical properties of ABS parts and assessed the tensile strength. The study found that the tensile strength and impact resistance were attained at 100% infill. Moreover, the study showed that printing with an infill range between 50 and 98% is not suggested. Therefore, selecting infill design parameters is often pose a great challenge for practitioners, and thus required more empirical investigations.

Li *et al.* (2017) evaluated the impact of rheological properties of FDM built polyamide-12 and ABS parts on bonding quality and tensile strength. In this regard, liquefier temperature and raster orientation of the specimens were varied. Furthermore, injection moulded specimens were made using the same polyamide-12 and ABS materials and used as benchmarks for the thermal, mechanical and microscopic analyses. It was seen that rheological properties, in particular the melt viscosity, had substantial effect on the inter-filament bond quality. Accordingly, it was suggested that better bonding quality and higher tensile strength exhibited by FDM built polyamide-12 specimens when compared to FDM built ABS specimens, was due to lower melt viscosity of polyamide-12 at low shear rates. The results demonstrated that the FDM process is capable of producing semi-crystalline polyamide-12 parts with reasonable mechanical functionality and hence provides an alternative to traditional amorphous thermoplastics.

Benwood *et al.* (2018) studied the improvement of impact, tensile and flexural strength of PLA through alteration of nozzle temperature, bed temperature and raster angle orientation within the FDM process. Additionally, annealing treatment was performed and injection moulded samples were also prepared for reference and verification. It was reported that PLA's crystalline phase structure was critical to the mechanical response. Further, bed temperature was seen to have a significant impact on strength and modulus with elevated temperatures resulting in increased diffusion between the printed filament layers.

Abdullah *et al.* (2018) studied the effect of layer thickness and raster angle on tensile and flexural properties of ABS and PLA parts printed using FDM technique. The study concluded that the layer thickness and raster angle affected the flexural strength more than these variables shown influence on the tensile strength of the test specimen. Further, the study proven that the samples printed using PLA material had higher strength than the ABS material.

Dey and Yodo (2019) conducted a survey of FDM process parameter optimisation methods and the influence of process parameters on part mechanical characteristics. It was stated that the characteristics of FDM built components are impacted by various process parameters such as layer thickness, build orientation, raster width and print speed. In addition, the right selection of process parameter settings dependent on the type of FDM process in use. The study concluded that the optimisation of controllable parameters is deemed to enhance the performance of 3DP components and may lessen post-production costs.

Gonabadi *et al.* (2020), studied the impact of build orientation and infill density on the mechanical properties of PLA samples. The study concluded that the tensile strength and Young's modulus increased with increase in infill density. Further, the authors stated that the study provides an outline for systematic mechanical characterisation of thermoplastic materials and possible ways of choosing AM variables to maximise performance of PLA components.

Pandzic and Hodzic (2021) investigated the sample mechanical properties (tensile strength and elastic modulus) of PLA, tough PLA and PC materials using FDM technology with varying infill structure. The study results showed that infill pattern had a critical influence on tensile strength of the three selected materials. The study concluded that the AM technology offers several benefits such as reduced manufacturing time, product weight and reduction in the final product cost if the object is built with a correct infill structure.

Harpool *et al.* (2021) studied the effects of geometrical shapes of the infill on the 3D printed PLA samples mainly to assess the modulus of toughness, ultimate tensile stress, yield stress and percent elongation. The study noted a brittle behaviour for solid infill pattern, while rectangular, diamond and hexagonal infill patterns showed ductile-like behaviour. The study concluded that the brittleness may be due to the relatively higher infill density which led to the high bonding adhesion of the printed layers, whereas the infill size and thickness influence the solid substrate.

Auffray *et al.* (2022) examined the mechanical properties of PLA specimens' manufactured using FFF technology. The study noted that the infill density, infill pattern, printing velocity and printing orientation were the most critical parameters, whereas layer thickness, temperature and outline overlap had not much impact on Young's modulus and sample yield strength.

2.2 Gaps in the literature

Based on the review of literature, it can be concluded that even though AM technologies have been adopted in the modern industry for several years, the academic fraternity has just started conducting more studies on the influence of variations in FDM process parameters' effects on various mechanical properties of products such as tensile, compressive, flexural strengths (Almagharizet *et al.*, 2016; Fera *et al.*, 2018). In addition, the AM literature observed optimisation of process parameters (Mushtaq *et al.*, 2022) and material reinforcement (Statista, 2019) as two common strategies approved by most research pioneers for improvement of FDM part performance characteristics.

Further, it is clear that the most popular controllable process parameters researched were layer thickness, raster angle, infill percentage, printing speed, filling pattern, printing plane, position of the piece on the printing table surface, initial line thickness, raster width, bed temperature and extrusion temperature (Mendricky and Fris, 2020; Algarni and Ghazali, 2021; Mushtaq *et al.*, 2022). These were found to be highly dominant, individually and in some cases jointly, to enhance the part mechanical performance. Thus, the AM process involves a complicated system in fabricating parts and causes difficulty in understanding the conflicting nature of FDM parameters that influence the part quality significantly from material to material. Further, the key industrial sectors such as aerospace, bio-medical and electronics entail increasingly higher levels of part quality (Mohamed *et al.*, 2016). These issues can be overtaken if the I-optimality design approach combined with the machine learning ANN technique for optimisation of the conflicting process parameters as well as to address the shortcomings of the commonly used DOE schemes. Machine learning models are successfully applied for optimisation of the FDM process (Mahmood *et al.*, 2021; Giri *et al.*, 2021; Moradi *et al.*, 2020).

Moreover, the majority of studies focussed on ABS material as test specimens (Mushtaq *et al.*, 2022; Algarni and Ghazali, 2021; Singh *et al.*, 2019). However, some studies have shown the benefits of several industrial thermoplastics such as PLA (Torres *et al.*, 2016; Song *et al.* 2017; Benwood *et al.*, 2018; Mendricky and Fris, 2020; Algarni and Ghazali, 2021; Napolitano *et al.*, 2022), ULTEM (Gebisa and Lemu, 2018), PC-ABS (Mohamed *et al.*, 2017), PC (Domingo-Espin *et al.*, 2015) and carbon fibre reinforced plastics (Chen *et al.*, 2020). Other key observation from the literature review was the evolution of the machine learning predictive models for optimisation of FDM process parameters for manufacture of the functional components to fulfil the industrial needs. In summary, the gaps in the literature that motivated for conduct of this research are given below:

(1) PC is an industrial thermoplastic widely used in automotive, aerospace, bio-medical and many other applications. It presents superior mechanical properties to ABS and a number of other materials employed in FDM (Boschetto and Bottini, 2014; Noon *et al.*, 2015; Ali and Chowdary, 2019). Though considerable research has been done for improvement of FDM part quality by conducting extensive tests on tensile strength, flexural strength, impact strength, compressive strength, fracture toughness and dimensional accuracy, however, there is limited number of studies available on improvement of the tensile strength of FDM PC components.

(2) Predictive models assist AM users to determine the optimal process parameter settings that would result in the best response characteristics such as cost, time and

part quality (Boschetto and Bottini, 2014; Mohamed *et al.*, 2016; Porter *et al.*, 2019; Chowdary and Bobb, 2021) which in turn avoids unacceptable wastes and improves the process performance.

(3) Although the mechanical strength of various thermoplastics has already been studied, but there is limited literature on the tensile strength of the 3D printed PC with application of I-optimal design approach. The I-optimal design has capability to reduce the prediction variance across the parameter domain and is suitable for development of the second-order models which are critical for FDM parameter optimisation (Mohamed *et al.*, 2017).

(4) Build orientation and raster angle are critical positional parameters that need technician involvement for modification in the AM system. However, the later parameter contributes significantly for improvement of the part mechanical strength (Balderrama-Armendariz *et al.*, 2018). In addition, 3D print samples built with 0° raster angle exhibited the highest tensile strength compared to those of 45 and 90° (Afrose *et al.*, 2016). Air gap had direct influence on the mechanical properties of FDM parts (Balderrama-Armendariz *et al.*, 2018). Rayegani and Onwubolu (2014) shown that the tensile strength of the 3D printed part was at its maximum with a negative air gap value.

    Croccolo *et al.* (2013) study concluded that with an increase in the number of contours in the production of ABS components exhibit greater stiffness and superior strength.

(5) ANN led machine-learning technique has capability to carry out intricate pattern identification and develop a deterministic functional relationship which reduces the need to produce physical models (Giri *et al.*, 2021).

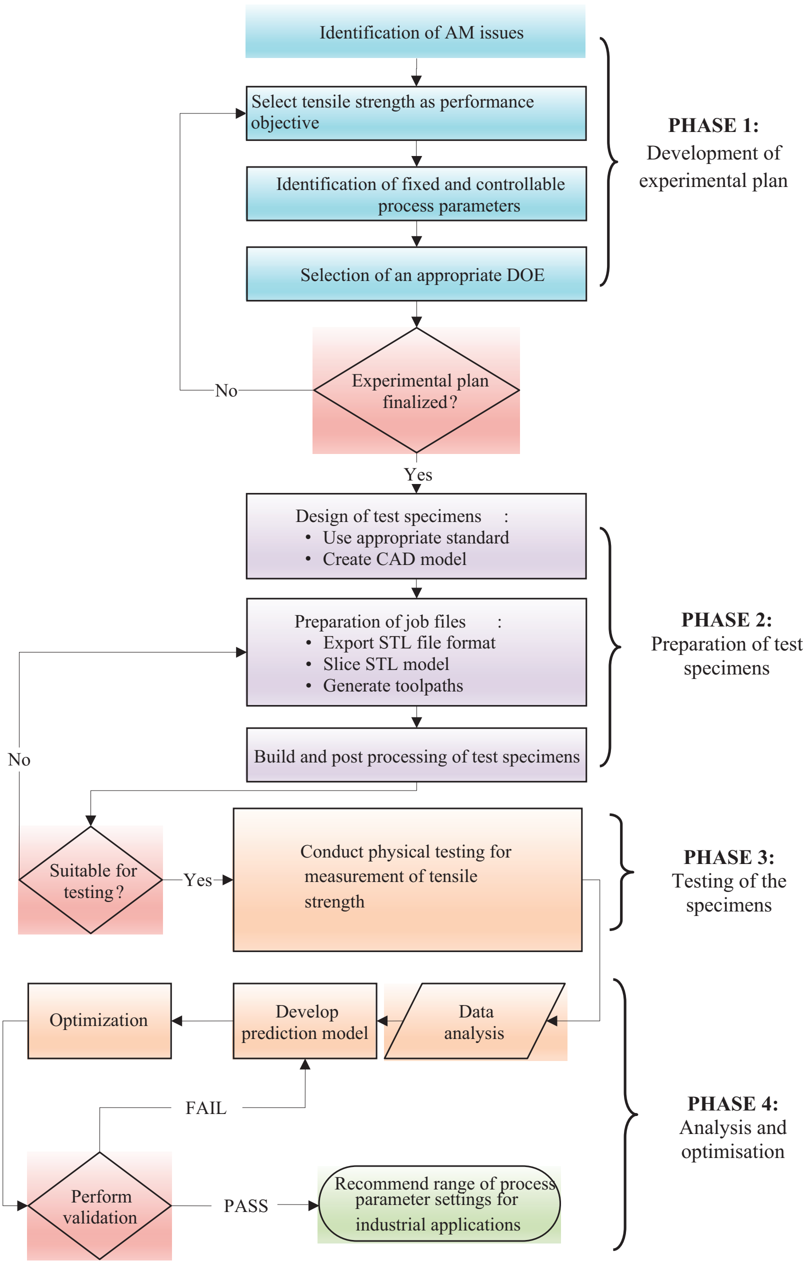
In summary, the literature evidenced several 3D printing process variables and their influence on mechanical strength of the FDM components built with various thermoplastics. In the current study, the key FDM process parameters such as raster angle (RA), raster to raster air gap (AG), build orientation (BO) and number of contours (NoC) are considered for improvement of the PC part tensile strength by deployment of ANN and GA techniques. Further, I-optimal approach is adapted for design of experiments. Accordingly, variation of these process parameters as per the selected experimental plan is performed to study the effects of their variation on tensile strength of the specimens built as per ISO standards using FDM 400mc. The next section expands on the research methodology adopted for execution of the study.

3. Research methodology

The methodology followed for conducting the research is outlined in Figure 1 which consists of four phases and each phase is explained in the following sections.

3.1 Phase 1 – development of experimental plan

Based on the literature review, one of the desired properties of a 3D printed object is tensile strength, thus it is considered as one of the key FDM issues. This research takes into account of the critical FDM process parameters such as, raster angle, air gap, build orientation and number of contours for analysis of the part mechanical properties. These process parameters are considered as controllable input parameters identified by authors through a preliminary study. Because these process parameters have a significant impact on part quality characteristics as well as productivity. On the other hand, build material, part interior style, visible surface style, support style, contour to raster air gap and contour to contour air gap are treated as fixed input parameters. These parameters are assigned as fixed input parameters



Note(s): AM- Additive manufacturing; DOE- Design of experiments
Source(s): Authors own work

Figure 1.
Proposed research methodology for enhancement of tensile strength

using the manufacturer's default settings. The details of the selected controllable and fixed process parameters of the study are shown in Tables 2 and 3.

I-optimal design of experiments is selected for generation of the experimental plan to investigate the effect of the input process parameters on tensile strength. This design approach was selected because of its capability to reduce the prediction variance across the parameter space as well as its suitability for the development of second-order empirical models which are essential for optimisation of process parameters (Mohamed *et al.*, 2016). With all four controlled factors at three levels, the resulted I-optimal experimental plan can be seen in Table 4. Accordingly, the experimental runs were scheduled such that those with zero build orientation would be printed first, followed by those with 9° and 12° respectively due to the progressive increase in build time.

3.2 Phase 2 – preparation of test specimens

Dogbone tensile specimen type-1B as per ISO 527–2:2012 is selected due to its small size which is conducive to time and material savings during experimentation (Ali *et al.*, 2014). The 3D CAD model of the specimen is developed using SolidWorks® software and is shown in Figure 2. Firstly, the CAD model of the specimen was saved as an STL file and then imported into Insight™ software. Afterwards, the STL model was rotated to the desired build orientation and then sliced in accordance with the layer thickness specified through selection of the relevant printing tip. Subsequently, the necessary support material was generated and the selected process parameters such as raster angle, air gap, build orientation and number of contours were specified. Then the specimens were printed using the Fortus FDM 400mc. A snapshot of the selected printer can be seen in Figure 3.

Table 2. Selected process parameters for investigation of tensile strength

Process parameter	Units	Level 1 Low (−1)	2 Centre (0)	3 High (1)
Raster angle (RA)	degree	0	45	90
Raster to raster air gap (AG)	mm	0	0.008	0.016
Build orientation Y axis (BO_y)	degree	0	9	12
Number of contours (NoC)	integer	0	4	8

Source(s): Authors own work

Table 3. Fixed process parameters for investigation of tensile strength

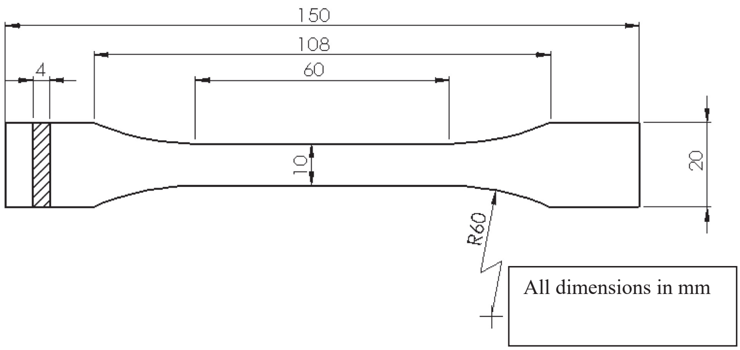
Process parameter	Unit	Value
Build material	–	PC white
Part interior style	–	Solid-normal
Visible surface style	–	Normal
Support style	–	Basic
Part XY shrink factor	–	1.0071
Part Z shrink factor	–	1.0070
Contour to raster air gap	mm	0.000
Contour to contour air gap	mm	0.000
Layer thickness	mm	0.1778
Raster width	mm	0.3556
Contour width	mm	0.3556

Source(s): http://www.3dprinterscanada.com/fdm-production-series-fortus-400mc.php

Experiment number	RA	AG	BO_y	NoC
1	45	0	9	8
2	0	0.008	0	8
3	90	0.008	0	0
4	0	0.016	0	0
5	0	0.008	9	8
6	0	0.008	0	4
7	45	0	0	4
8	45	0.008	9	0
9	90	0.008	9	4
10	45	0.016	0	4
11	0	0.008	12	4
12	45	0.016	12	8
13	45	0.008	0	0
14	90	0.008	9	4
15	90	0	12	0
16	90	0.008	0	8
17	0	0	9	0
18	0	0.016	12	0
19	45	0.008	9	0
20	0	0.016	9	4
21	45	0	12	4
22	0	0.016	9	4
23	45	0.008	9	0
24	45	0.016	0	4
25	90	0.016	12	0

Note(s): RA – Raster angle; AG – Raster to raster air gap
BO_y – Build orientation Y axis; NoC – Number of contours
Source(s): Authors own work

Table 4.
I-optimal experimental plan for investigation of tensile strength

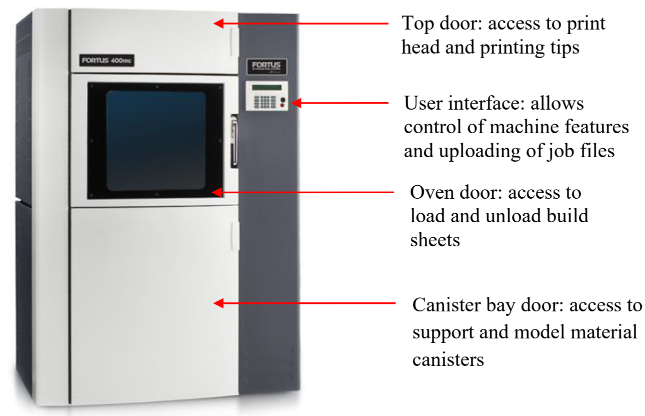


Source(s): Figure authors reproduced as per ISO 527-2:2012 tensile specimen

Figure 2.
Schematic representation of ISO 527–2:2012 tensile specimen

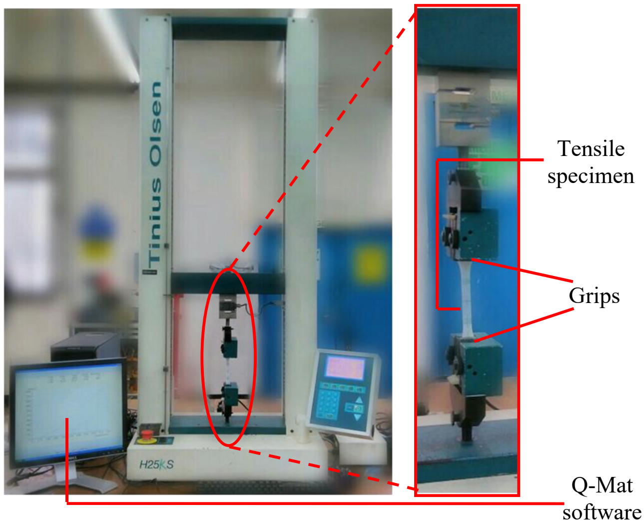
3.3 Phase 3 – testing of specimens

The setup of equipment used to measure tensile strength of the test specimens is shown in Figure 4. All specimens were marked to identify the initial distance between grips of 115 mm according to ISO 527–2:2012 testing conditions. Furthermore, the cross head was set to move at 1 mm/min to ensure a consistent speed of testing. Graphs that indicate force-extension



Source(s): http://www.3dprinterscanada.com/fdm-production-series-fortus-400mc.php

Figure 3.
Fortus 400mc FDM machine



Source(s): https://www.tiniusolsen.com

Figure 4.
Setup of apparatus used to measure tensile strength of test specimens

characteristic curves were plotted in real time and ultimate tensile strength values were recorded using the Q-Mat software synchronized with the Tinius Olsen tensile testing machine.

3.4 Phase 4 – analysis and optimization

3.4.1 Data analysis and development of predictive models. Data obtained from the tensile strength tests are then statistically analyzed using Design Expert and Minitab software. Process parameter relationships with the part tensile strength are determined with the aid of main effect plots. Additionally, surface plots are utilized for identification of process parameter interactions. Moreover, ANOVA results together with normal probability plots are generated to assess suitability of regression predictive model for predicting the sample strength. In addition, ANN technique is implemented for generation of predictive models and compared to the regression model in order to select an appropriate model for optimisation. Then the selected optimal process parameter set for improvement of the tensile strength is validated through confirmation experiments. The development of experimental models, analysis of results and discussion are presented in the following section.

4. Development of empirical models, discussion and interpretation of results

I-optimal design matrix as outlined in Table 4 was used to investigate the effect of raster angle, raster to raster air gap, build orientation and number of contours on the FDM built specimens. It can be noted that the build orientation process parameter focused in the study relates to Y axis only. Further, the Tinius Olsen tensile testing machine together with QMat software were used for the measurement of tensile strength of the specimens. The tensile strength results as per the I-optimal experimental plan can be seen in Table 5. The next section discusses development of regression and ANN predictive models, to see the impact of selected process parameters (RA, AG, BO_y and NoC) on tensile strength as well as optimisation and validation of the selected predictive model.

	Process parameters				Response
Expt. No.	RA (º)	AG (mm)	BO_y (º)	NoC	Tensile strength (MPa)
1	45	0	9	8	32.97
2	0	0.008	0	8	43.01
3	90	0.008	0	0	7.98
4	0	0.016	0	0	39.11
5	0	0.008	9	8	42.56
6	0	0.008	0	4	38.76
7	45	0	0	4	32.82
8	45	0.008	9	0	18.16
9	90	0.008	9	4	17.18
10	45	0.016	0	4	18.68
11	0	0.008	12	4	47.02
12	90	0.008	9	4	14.26
13	90	0	12	0	27.95
14	90	0.008	0	8	24.52
15	0	0	9	0	51.10
16	0	0.016	12	0	47.01
17	45	0.008	9	0	21.36
18	0	0.016	9	4	47.65
19	45	0	12	4	31.10
20	0	0.016	9	4	43.59
21	45	0.008	9	0	21.12
22	45	0.016	0	4	19.42
23	90	0.016	12	0	18.51

Note(s): Expt. No. – Experiment number; RA – Raster angle; AG – Raster to raster air gap BO_y – Build orientation about Y axis; NoC – Number of contours
Source(s): Authors own work

Table 5. I-optimal design with tensile strength results

4.1 Development of regression model

The quadratic regression model was developed in this study to represent the response surface. In view of that, the experimental data shown in Table 5 was used for the estimation of the regression coefficients by means of Design-Expert® software and the final regression equation for tensile strength was obtained as seen in equation 1.

$$\begin{aligned}\text{Tensile Strength (TS)} &= 50.9784 - 0.652977 * \text{RA} - 2355.26 * \text{AG} - \ldots - 0.67648 * \text{BO}_y \\ &+ 0.65595 * \text{NoC} + \ldots + 37.8725 * \text{AG} * \text{BO}_y \\ &+ 0.0040666 * \text{RA}^2 + \ldots + 96687 * \text{AG}^2 + 0.0627571 * \text{BO}_y^2.\end{aligned} \tag{1}$$

Moreover, ANOVA was conducted to verify the suitability of the regression model and the results are presented in Table 6. Overall, the model has a p-value less than 0.05 which suggests that the model terms significantly represent the tensile strength response. Further, it can be seen from Table 6 that co-efficient of determination (R^2) together with adjusted R^2 and predicted R^2 are close to 1, which indicate a good quality of fit for the regression model. In addition, the adequate precision of 19.9995 implies that the ratio of the predicted values for the experimental runs to the average prediction error is satisfactory since a ratio of 4 is desirable.

Another criterion used for evaluation of the regression model is the Lack of Fit test, which determines how well the model fits the response data by comparison of the residual error and pure error for replicated experimental runs. From Table 6 it can be seen that the p-value for Lack of Fit result is 0.1133 and thus considered to be not significant since $p > 0.05$.

Furthermore, the normal probability plot of residuals shown in Figure 5 was used as an indicator of skewed or biased predictions from the regression model due to outliers. Since, the residuals follow a straight line, it can be deduced that they are normally distributed and the model provides adequate predictions.

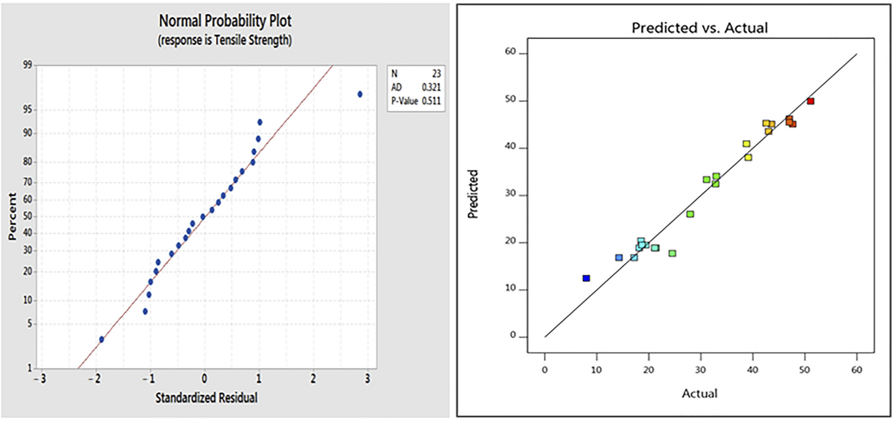
A comparison of the predicted and actual values of the experimental runs is displayed in Figure 5(b). Close agreement between the predicted and actual values is seen along the reference line which further supports satisfactory model predictions. Accordingly, the

Source	Sum of squares	Mean square	F-value	p-value	
Model	3485.62	435.7	48.55	<0.0001	significant
A	2130.79	2130.79	237.44	<0.0001	
B	201.54	201.54	22.46	0.0003	
C	48.71	48.71	5.43	0.0353	
D	68.72	68.72	7.66	0.0151	
BC	24.48	24.48	2.73	0.1209	
A^2	287.56	287.56	32.04	<0.0001	
B^2	170.65	170.65	19.02	0.0007	
C^2	10.87	10.87	1.21	0.2896	
Residual	125.64	8.97			
Lack of Fit	106.5	11.83	3.09	0.1133	not significant
Pure Error	19.13	3.83			
Corrected Total	3611.26				

$R^2 = 0.9652$, Adjusted $R^2 = 0.9453$, Predicted $R^2 = 0.9104$

Source(s): Authors own work

Table 6.
ANOVA results for tensile strength



Normal probability
(a)

Predicted vs. actual
(b)

Source(s): Authors own work

Figure 5.
ANOVA results for tensile strength

relationship between the process parameters and tensile strength response as described by the regression model is further explored in the next section.

4.2 Effect of process parameters on tensile strength: discussion and interpretation of results

Figure 6 shows the main effects plot that illustrates the effect of the selected FDM process parameters on tensile strength. From the figure it can be seen that raster angle had the most pronounced effect on tensile strength wherein lower raster angle resulted in higher tensile strength. This observation has been noted by previous studies (Durgun and Ertan, 2014; Ning *et al.*, 2016; Casavola *et al.*, 2016; Torres *et al.*, 2016) and was attributed to the production of longer and more effective rasters. Also, when the rasters are aligned parallel to the loading direction, greater resistance is exhibited thus resulting in superior tensile strength.

Further it can be noted that the zero air gap between rasters produced specimens with higher tensile strength which may be linked to the development of stronger bonds between adjacent rasters. Interestingly, a decrease in tensile strength followed by an increase was noticed as the air gap between rasters was enlarged. This can be due to heat dissipation being restricted for smaller air gaps which promotes the accumulation of stress thereby reducing resistance to tensile loading and ultimately lowering the strength. However, a larger positive air gap accommodates for material flow into the nearby layers and thus enhances the bonding between surfaces which leads to improved tensile strength.

Moreover, moderate increase in tensile strength was observed for larger build orientations about Y axis. In addition, examination through microscopic inspection of fractured surfaces of specimens, with varied build orientation can be seen in Figure 7. A rough staggered pattern along the fractured surface is observed for the specimen oriented 9° about the Y axis whereas a flat uniform cross-section is noted for the specimen with 0° orientation. This suggests that increase in build orientation about Y axis produced more compact structures which facilitated greater resistance to the continuous pulling and rupturing of rasters.

Further, from Figure 6 it can be seen that an increase in the number of contours resulted in enhanced tensile strength. This observation may be due to increased stiffness of the specimens thereby offering improved fracture resistance which concurs with the previous studies (Croccolo *et al.*, 2013; Torres *et al.*, 2016). Since the FDM process involves large number

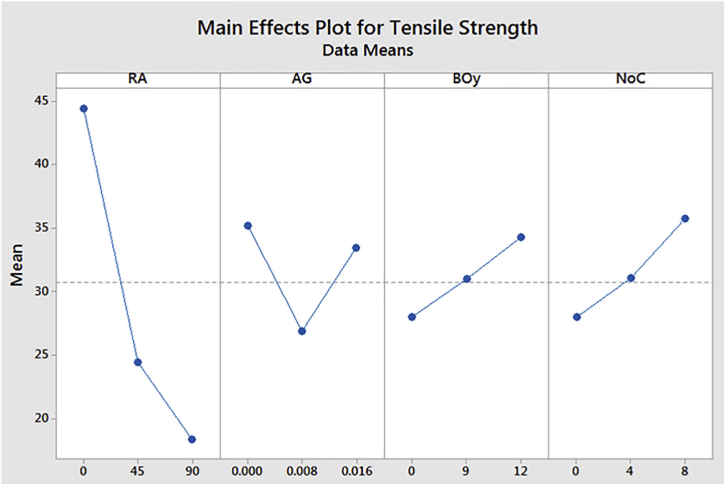


Figure 6. Influence of FDM process parameters on tensile strength

Note(s): RA – Raster angle (°); AG – Raster to raster air gap (mm); BO_y – Build orientation about Y axis (°); NoC – Number of contours
Source(s): Authors own work

of conflicting factors and complex phenomena for building a part, thus an alternative method for development of a predictive model is explored through ANN in the next section.

4.3 Modelling of tensile strength with ANN

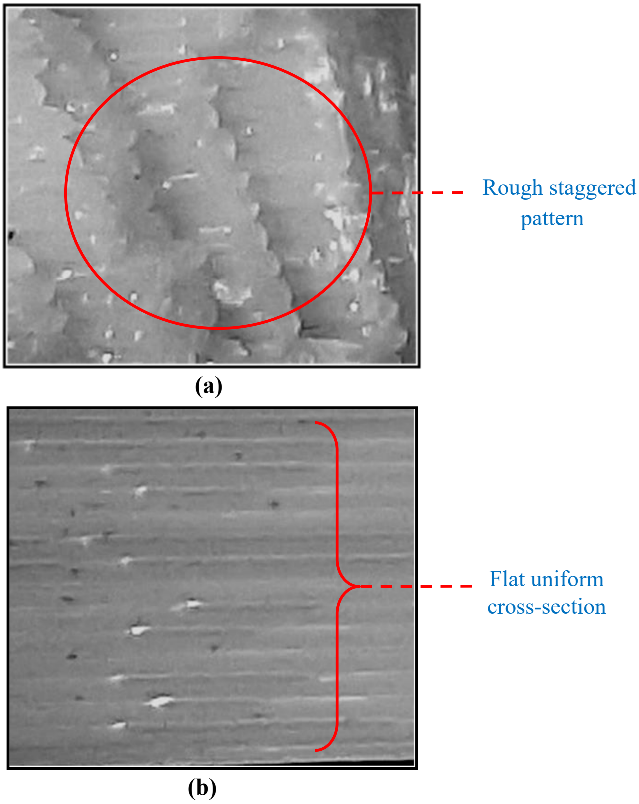
A multilayer feed forward back propagation ANN was used for this study which comprised of 4- neurons in the input layer, 10 neurons in the hidden layer and 1 neuron in the output layer. The network was trained using the Levenberg–Marquardt back propagation algorithm within MATLAB® version 2017b software.

This algorithm supports training with validation so that if network performance fails to improve or remains constant, training will be stopped early. Moreover, testing is done to further check that the network is generalizing well. The performance of the ANN model is shown in Figure 8 and demonstrates good agreement between the predicted and experimental values.

4.4 Comparison of regression and ANN predictive model

A confirmation run was performed to validate the I-optimal regression model as well as the ANN model. In view of that, a process parameter set outside of the experimental domain was selected for the confirmation run in order to evaluate autonomy of the predictive models. Accordingly, the actual tensile strength measured for the built specimen together with the calculated tensile strength values from both predictive models are presented in Table 7. In addition, Figure 9 illustrates a comparison of the I-optimal regression model and ANN model in terms of prediction error for the confirmation and experimental runs respectively.

From Figure 9, it can be seen that for the confirmation run both models provided reasonable predictions having prediction errors <5%. However, the ANN model showed better prediction capability upon comparison of the prediction error for the experimental runs. Taking this into account together with having lower prediction error for the confirmation run, the ANN model was selected for optimisation.



Note(s): Scale = 1: 0.012 (Image: Specimen) Unit is in millimetre
Source(s): Authors own work

Figure 7. Microscopic inspection of fractured surfaces with build orientation

4.5 Optimisation of ANN predictive model: discussion and interpretation of results

The GA solver was used for optimisation of the ANN model within MATLAB® version 2017b software. Firstly, a fitness function was created to reference the trained ANN. Thereafter, the number of process variables was defined along with their upper and lower bounds. Finally, the GA solver was utilized with default settings, as shown in Table 8 for determining maximum tensile strength and the result is presented in Table 9.

It can be seen from Table 9 that $BO_y = 8°$ is suggested for optimal tensile strength which supports the significance of increased BO_y for improvement of tensile strength. However, AM practitioners should consider the impact on build time when increasing the BO_y. Moreover, the predicted value of tensile strength for default machine settings was compared to the predicted maximum tensile strength in Figure 10 in order to assess the effectiveness of the optimisation of ANN predictive model. Further, it is clear from Figure 10 that a PC specimen with tensile strength of 51.10 MPa can be produced by FDM with the use of optimal settings, which is approximately 65% greater than the tensile strength achievable with default machine settings. Hence this confirms the efficacy of the selected ANN predictive model for improvement of tensile strength.

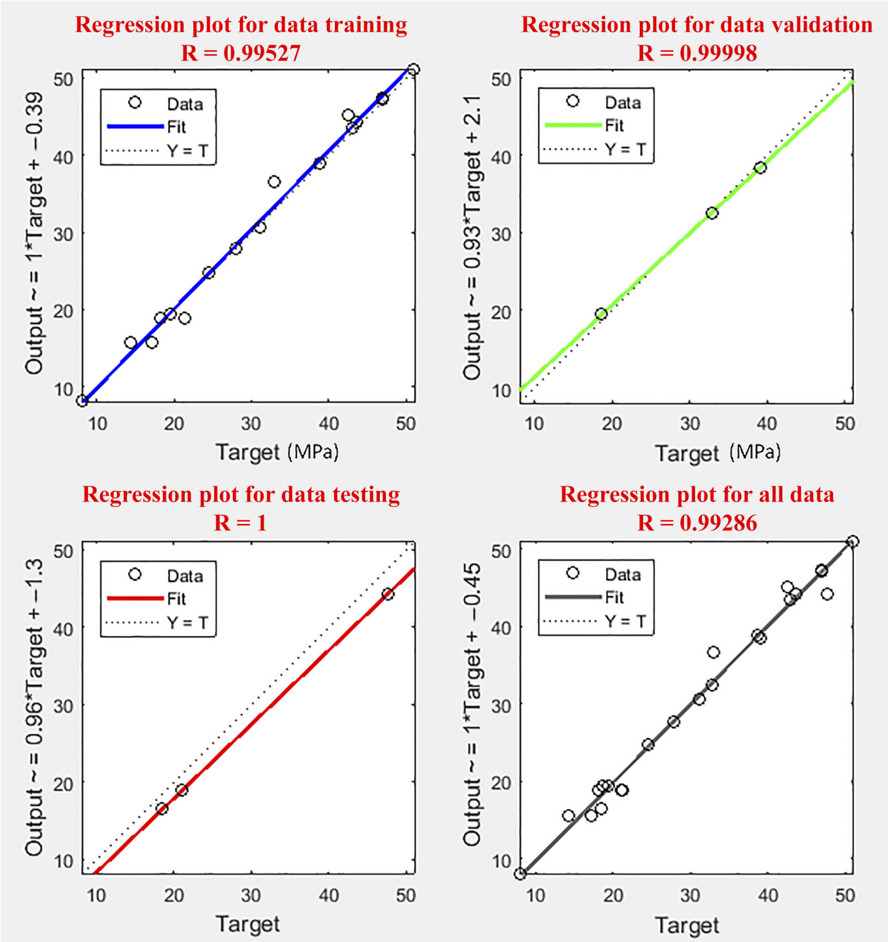


Figure 8.
Regression analysis of ANN model

Source(s): Authors own work

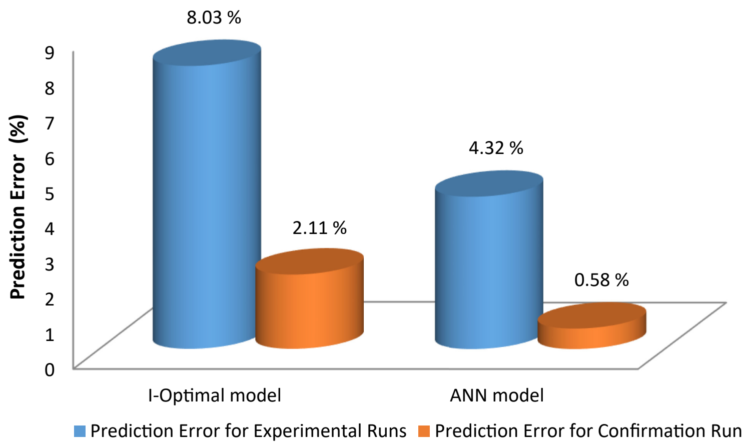
Process parameters				Tensile strength (MPa) Predicted values		Actual value
RA	AG	BO_y	NoC	I-optimal	ANN	50.80
0	0	12	0	51.90	51.09	

Note(s): RA – Raster angle (°); AG – Raster to raster air gap (mm)
BO_y – Build orientation about Y axis (°); NoC – Number of contours
Source(s): Authors own work

Table 7.
Results of confirmation run for tensile strength

5. Conclusion

As per the objective, this study presented an experimental investigation in establishing the relationship between FDM process parameters and tensile strength utilising the I-optimal



Source(s): Authors own work

Figure 9. Comparison of ANN and I-optimal models for confirmation and experimental runs

Table 8. Default genetic algorithm solver settings

Population	Population type: Double vector Population size: 200 Creation function: Constraint dependent Initial range: [−10; 10]
Fitness scaling	Rank
Selection	Stochastic uniform
Reproduction	Elite count: 10 Crossover fraction: 0.8
Mutation	Constraint dependent
Crossover	Constraint dependent
Migration	Direction: Forward Fraction: 0.2 Interval: 20
Constraint parameters	Initial penalty: 10 Penalty factor: 100
Hybrid function	None
Stopping criteria	Generations: 600 Time limit: Inf Fitness limit: -Inf Stall generations: 50 Stall time limit: Inf Function tolerance: 1e-6 Constraint tolerance: 1e-3
Plot functions	Plot interval: 1
Output function	None specified
Display to command window	Off
User function evaluation	In serial

Source(s): https://www.mathworks.com/help/gads/genetic-algorithm-options.html

design approach. Further, response surface methodology was implemented and the fitted regression model was checked for adequacy using ANOVA and residual plots. The various relationships between the significant process parameters and tensile strength were analyzed.

Additionally, an ANN predictive model was developed and compared to the regression model in order to select an appropriate model for optimisation. Finally, improvement result of tensile strength was validated.

It was seen that the selected process parameters (raster angle, raster to raster air gap, build orientation about Y axis and the number of contours) had significant effect on tensile strength with raster angle being the most influential factor. Increasing the build orientation about Y axis built specimens with compact structures that resulted in improved fracture resistance. Fluctuations in tensile strength were attributed to constricted heat dissipation and increased material flow when the raster to raster air gap was varied. Moreover, it was suggested that larger number of contours contributed to greater stiffness of specimens. Additionally, it was noted that the ANN model was more appropriate to establish the non-linear relationship between the process parameters and tensile strength. From the optimised ANN-GA model, raster angle = 0°, raster to raster air gap = 0 mm, build orientation about Y axis = 8° and number of contours = 0 seem to be the favourable process setting for improvement of tensile strength of FDM built PC part.

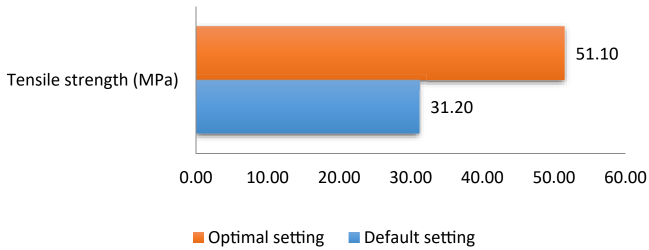
Despite its advantages, building FDM parts for end-use is still a challenging task because of the inherent multitude of process parameters which affect the part's, mechanical strength, build time and dimensional accuracy (Sheoran and Kumar, 2020). Accordingly, proper knowledge of FDM process parameters is necessary in order to specify appropriate conditions for part manufacture depending upon its application. Hence, determination of optimal process parameter sets for improvement of part quality characteristics is essential to the growth of FDM applications in industry as well as its suitability for customised mass production.

In this direction, the present work has investigated the impact of FDM process parameters on part tensile strength. I-optimal design along with statistical analyses was adopted to assess the influence of the process parameters variations on the part tensile strength. Furthermore, prediction model for the part strength was developed with the use of regression and ANN models. For optimisation purpose, GA approach was implemented to determine the preferred process parameter sets for enhancement of the PC part strength.

Table 9. Optimised tensile strength result

Optimal parameter settings RA	AG	BO_y	NoC	Tensile strength (MPa)
0	0	8	0	51.10

Note(s): RA – Raster angle (º); AG – Raster to raster air gap (mm)
BO_y – Build orientation about Y axis (º); NoC – Number of contours
Source(s): Authors own work



Source(s): Authors own work

Figure 10. Comparison of tensile strength for optimal and default settings

5.1 Major findings of the study

The study found that smaller raster angles were conducive to achieve higher tensile strength by formation of longer and effective rasters which offered greater resistance to the applied load. In addition, variation of air gap resulted in fluctuations of tensile strength. Further, higher values as well as no air gap favoured greater part strength due to increased material flow and stronger bonds between adjacent layers respectively. However, for smaller air gaps heat dissipation was restricted which led to stress accumulation and lower tensile strength. Additionally in this study, it was observed that an increase in the build orientation about Y axis produced more compact structures which demonstrated superior tensile strength. Further, a larger number of contours contributed to higher stiffness thereby resulting in enhanced tensile strength. Finally, the study observed that raster angle of 0°, no air gap, build orientation about the Y-axis of 8° and no contours can be used to improve the tensile strength of FDM built PC part.

5.2 Recommendations for future work

With continued advancement of FDM technology, there exists wide scope for further investigations. Some suggestions for future research include more studies on investigating the effects of FDM process parameters on part quality and functionality for other materials such as synthetic and natural fibre-reinforced thermoplastic composites are beneficial to the AM industry. Further use of finite element study for the simulation and prediction of various quality characteristics of AM built parts will benefit the practitioners in terms of reduction in material wastage and part production cost. In addition, further investigations on influence of environmental conditions such as humidity on the mechanical characteristics of AM built parts will be beneficial to the contemporary industrialists.

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