Experimental Characterization, Black-box Modeling, and Optimization of The Fused Deposition Modelled Acrylonitrile Butadiene Styrene

by

Ronak Vahed Mohammad Ghasemloo
B.A.Sc., In Mechanical Engineering, Amirkabir University of Technology, Iran, 2015

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF APPLIED SCIENCE
in
THE COLLEGE OF GRADUATE STUDIES
(Mechanical Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA
(Okanagan)

June 2018

© Ronak Vahed Mohammad Ghasemloo, 2018
The following individuals certify that they have read, and recommend to the College of Graduate Studies for acceptance, a thesis/dissertation entitled:

Experimental Characterization, Black-box Modeling, and Optimization of The Fused Deposition Modelled Acrylonitrile Butadiene Styrene

submitted by Ronak Vahed Mohammad Ghasemloo in partial fulfillment of the requirements of

the degree of Master of Applied Science

Dr. Abbas. S. Milani, School of Engineering, UBCO

Supervisor

Dr. Dimitry Sediako, School of Engineering, UBCO

Supervisory Committee Member

Dr. Rudolf Seethaler, School of Engineering, UBCO

Supervisory Committee Member

Dr. Mehdi Maadooliat, Marquette University, USA

External Examiner
Abstract

Additive manufacturing (AM) is becoming a mainstream manufacturing process in different engineering applications, owing to its capability to build 3-dimensional parts with complex geometries, while maintaining high production speed, low cost and a minimal material waste. Fused Deposition Modeling (FDM), as one of the AM techniques, is frequently used in industries and research laboratories to print parts from different thermoplastic filaments. The properties and quality of the FDM processed thermoplastic parts, however, is highly restricted by the proper selection of process parameters, and it remains as a challenging task for producing defect-free 3D printed parts. On the other hand, owing to the large number of FDM process parameters with highly nonlinear and interacting effects, the experimental optimization of FDM is costly and requires mathematical predictive models.

This thesis presents an integrated experimental-black box modeling and optimization framework to study the viscoelastic and tensile properties of FDM processed Acrylonitrile Butadiene Styrene (ABS). The effect of selected process parameters (including nozzle temperature, layer height, raster orientation and deposition speed) as well as their interaction effects are studied. Specifically, in the first step, a Taguchi orthogonal array was employed to design the experiments with a minimal number of runs, while considering different working conditions (temperatures) for the final prints. The Dynamic mechanical analysis (DMA) as well as tensile testing were carried out to investigate the significance of the process parameters, measured by statistical hypothesis testing methods. Due to the observed complex nature of the interacting effects of the FDM parameters, a series of artificial neural networks were developed and employed to predict the properties of the 3D printed samples, and consequently the process parameters were optimized via a particle swarm optimization (PSO). The percent contribution and ranking of the process parameters were identified and linked to the underlying meso/micro level mechanisms, through visual inspections of the samples and a Raman spectroscopy analysis.
Lay Summary

Nowadays, the fused deposition modelling (FDM), generally known as 3D-printing, is of high interest to numerous manufacturing sectors as a promising cost-effective substitution for traditional fabrication methods. Although FDM is ideally capable to build complex three-dimensional parts with low cost and low material waste, the mechanical performance of parts made of this process is still perceived to be lower than that of conventional fabrication techniques. This MASc dissertation aims to find some new guidelines to improve the mechanical properties of FDM processed plastic parts by means of integrating material testing and mathematical modeling, and eventually finding optimum sets of process parameters that may be used by designers to print high quality parts for applications with different working temperatures.
Preface

A version of this study was presented as part of a poster presentation as follows.


A portion of Chapter 4 has been published (cited below) based on a collaborative work conducted in the Composites Research Network Laboratory at UBC Okanagan by the author and Dr. Hamid Reza Zareie Rajani from Global Heat Transfer Ltd, who helped on experimental work and writing the manuscript. The performed analysis and the written manuscript further reviewed by Dr. Milani.


It should be added that other portions of Chapter 4 and Chapter 5 are under submission as two separate articles to peer-reviewed journals related to materials science and manufacturing.
# Table of Contents

Abstract ........................................................................................................................................ iii
Lay Summary ................................................................................................................................ iv
Preface ............................................................................................................................................ v
Table of Contents .......................................................................................................................... vi
List of Tables .................................................................................................................................. ix
List of Figures ............................................................................................................................... x
List of Symbols .............................................................................................................................. xvi
List of Abbreviations .................................................................................................................... xix
Acknowledgements ....................................................................................................................... xx
Dedication ........................................................................................................................................ xxi

## Chapter 1: Background and thesis organization ........................................................................ 1
  1.1 Introduction .......................................................................................................................... 1
  1.2 Motivations and objectives ................................................................................................. 1
  1.3 Thesis framework ................................................................................................................ 2

## Chapter 2: Literature review ..................................................................................................... 4
  2.1 Additive manufacturing ....................................................................................................... 4
  2.2 Fused deposition modelling (FDM) ................................................................................... 6
  2.3 The FDM process parameters ............................................................................................ 8
  2.4 Towards understanding the influence of FDM process parameters .................................... 10
    2.4.1 Experimental approaches ............................................................................................ 10
    2.4.2 Empirical approaches ................................................................................................. 15
    2.4.3 Numerical approaches ............................................................................................... 17
2.5 Summary of chapter ................................................................. 17

Chapter 3: Materials and methods ......................................................... 18

3.1 Overview ....................................................................................... 18
3.2 Test Material ............................................................................... 18
3.3 FDM set-up ................................................................................... 21
3.4 Design of experiments ................................................................. 22
3.5 Tensile test set-up ........................................................................ 25
3.6 Dynamic Mechanical Analysis (DMA) ........................................... 25
3.7 Raman spectroscopy ..................................................................... 27
3.8 Artificial neural network ............................................................... 29
3.8.1 Neural network design .............................................................. 29
3.9 Particle Swarm Optimization ......................................................... 35
3.10 Summary of chapter ................................................................. 37

Chapter 4: Dynamic mechanical analysis ................................................. 38

4.1 Overview ....................................................................................... 38
4.2 Experimental ............................................................................... 38
4.2.1 DMA test under dual cantilever bending .................................... 38
4.2.2 Sample shape and geometry ..................................................... 39
4.2.3 Loading and operating conditions ............................................. 40
4.3 Results and discussions ................................................................ 41
4.4 Summary of findings .................................................................... 73

Chapter 5: Characterization of the tensile properties .................................. 74

5.1 Overview ....................................................................................... 74
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.2 Experimental</td>
<td>74</td>
</tr>
<tr>
<td>5.2.1 Sample shape and geometry</td>
<td>75</td>
</tr>
<tr>
<td>5.3 Results and discussions</td>
<td>76</td>
</tr>
<tr>
<td>5.4 Microscopic Inspections and Raman Spectroscopy</td>
<td>100</td>
</tr>
<tr>
<td>5.5 Summary of findings</td>
<td>105</td>
</tr>
<tr>
<td>Chapter 6: Conclusions and Future Work Recommendations</td>
<td>107</td>
</tr>
<tr>
<td>6.1 Summary</td>
<td>107</td>
</tr>
<tr>
<td>6.2 Contributions to knowledge</td>
<td>111</td>
</tr>
<tr>
<td>6.3 Future Work</td>
<td>111</td>
</tr>
<tr>
<td>Bibliography</td>
<td>113</td>
</tr>
<tr>
<td>Appendices</td>
<td>123</td>
</tr>
<tr>
<td>Appendix A</td>
<td>123</td>
</tr>
<tr>
<td>Appendix B</td>
<td>127</td>
</tr>
</tbody>
</table>
List of Tables

Table 3-1 Properties of the used ABS filament .......................................................... 20

Table 3-2 Assigned values to the fixed FDM process parameters and .................................. 22

Table 3-3 Control factors to be used in the experimental procedures with their assigned levels. 23

Table 3-4 The L16 orthogonal array used to design the experimental layout .......................... 24

Table 4-1 Values of glass transition temperature measured by DMA technique .................... 45

Table 4-2 Lenth's method of factor analysis for glass transition temperature; the values for
factor levels correspond to the average of response under each corresponding level
according to 4-1; the physical values of factor levels are given in Table 3-3........... 48

Table 4-3 The obtained optimum values of the process parameters using PSO on E’ at each under
each working temperature .................................................................................................. 67

Table 4-4 The obtained optimum values of the process parameters using PSO on E’’ at each
working temperature ........................................................................................................ 70

Table 5-1 The experimental results of FDM- ABS parts under experimental layout described in
Table 3-4 .................................................................................................................................. 78

Table 5-2 The Lenth's method effect analyses of the simulated stress to expansion ratio for FDM
printed samples with 39mm gauge length; the values for factor levels correspond to
the average of response under each corresponding level according to neural network
response per Figure 5-8 to Figure 5-10the physical values of factor levels are given
in Table 3-3.3-3......................................................................................................................96

Table 5-3 ANOVA results for the simulated tensile behavior of FDM processed ABS parts
(assuming a confidence level of 95%) .................................................................................. 99
List of Figures

Figure 1-1 Organization of the thesis ................................................................. 3

Figure 2-1 Schematic view of additive manufacturing ........................................ 5

Figure 2-2 General layout of additive manufacturing techniques: (a) SLS[18], (b) SLA[19], (c) Polyjet [20], and (d) FDM ................................................................. 6

Figure 2-3 A schematic of Fused Deposition Modelling .................................... 7

Figure 2-4 The process parameters in FDM ........................................................ 9

Figure 3-1 Acrylonitrile Butadiene Styrene molecular components; a) acrylonitrile b) butadiene c) styrene ................................................................. 19

Figure 3-2 ABS 1.75 mm filament manufactured by makegear [63] ...................... 20

Figure 3-3 The modified Makegear M2 3D printer ............................................. 21

Figure 3-4 A schematic representation of stress and stress curve for elastic, viscous and viscoelastic material for a) Pure elastic response (similar to spring behavior) b) Pure viscous response c) Viscoelastic response ...................................................... 26

Figure 3-5 Part of a Raman spectrum showing peaks related to styrene, butadiene and acrylonitrile [73] .................................................................................. 28

Figure 3-6 Schematic view of an artificial neuron (a) in ANN method .................. 29

Figure 3-7 Symbolic configuration of an artificial neural network with one hidden layer .......... 31

Figure 3-8 General representation of data propagation in a multilayer feedforward neural network ......................................................................................... 32

Figure 3-9 Movement of each particle toward its best position in particle swarm optimization .. 36

Figure 4-1 The dual cantilever clamp used to characterize the dynamic mechanical response of the ABS samples ........................................................................... 39
Figure 4-2 The designed CAD model for DMA test coupons (dimensions are in mm) ............ 39
Figure 4-3 Prepared FDM fabricated ABS samples to perform DMA characterization. .......... 40
Figure 4-4 The variation of the storage modulus versus temperature for the test specimens ....... 42
Figure 4-5 The variation of the loss modulus versus temperature for the test specimens .......... 43
Figure 4-6 The variation of tan delta versus temperature for the test specimens, with the more
detailed view of the variation in the range of 110°C to 130°C .................................. 44
Figure 4-7 The variation of glass transition temperature of FDM processed ABS as a function of:
(a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed
............................................................................................................................................. 47
Figure 4-8 Percentage of reduction in storage modulus as a function of FDM process parameter:
(a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed. The black line and grey line represent the average reduction in storage modulus at 40 °C and 100 °C respectively. The values for factor levels correspond to the average of response under each corresponding level according to Figure 4-4; the physical values of factor levels are given in Table 3-3 ........................................ 51
Figure 4-9 Percentage of reduction in loss modulus as a function of FDM process parameter: (a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed. The black line and grey line represent the average reduction in loss modulus at 40 °C and 100 °C respectively. The values for factor levels correspond to the average of response under each corresponding level according to Figure 4-5; the physical values of factor levels are given in Table 3-3 ........................................ 52
Figure 4-10 The developed neural network architectures to predict the viscoelastic properties of FDM processed ABS plates under various thermal ambient (working) conditions:
(a) 5-9-1 architecture to approximate storage modulus (b) 5-7-1 architecture to approximate loss modulus

Figure 4-11 The performance of the developed 5-9-1 neural network to approximate the storage modulus of 3D printed parts

Figure 4-12 A graphical comparison between actual and predicted values of storage modulus under run 9

Figure 4-13 The performance of the developed 5-7-1 neural network to approximate the loss modulus in training, validation and testing

Figure 4-14 A graphical comparison between actual and predicted values of loss modulus under run 9

Figure 4-15 Simulated response of the storage modulus numeral network at working temperature of 40 °C and fixed nozzle temperature (shown by different colors): (a) at 0º raster orientation, (b) at 90º raster orientation, (c) at 45º raster orientation, (d) at ±45º raster orientation; the yellow surface represents the lowest level of the nozzle temperature and the pink surface represents the nozzle temperature highest level.

Figure 4-16 Simulated response of the storage modulus network at fixed layer heights (varying from 50 μm to 300 μm and categorized by different colors): (a) at 0º raster orientation, (b) at 90º raster orientation, (c) at 45º raster orientation, (d) at ±45º raster orientation; the yellow surface represents the lowest level of the layer height and the pink surface represents the layer height highest level.

Figure 4-17 Simulated response of the storage modulus by neural network at working temperature of 40 °C and at fixed deposition speed (varying from 1000 mm/min to 4000 mm/min and categorized by different colors): (a) at 0º raster orientation, (b) at
90° raster orientation, (c) at 45° raster orientation, (d) at ±45° raster orientation; the yellow surface represents the lowest level of the nozzle temperature and the pink surface represents the nozzle temperature highest level. ............................................ 65

Figure 5-1 The CAD model corresponding to the tensile test specimens; (a) Dimensions (in mm) and geometric specifications (b) the final shape of the sample ................................. 75

Figure 5-2 The 3D printed ABS sample for tensile testing ............................................................. 76

Figure 5-3 The relationship between the normal stress and normal strain for three replications of a FDM fabricated ABS part under experimental run (condition) #14. ....................... 77

Figure 5-4 The effect of process parameters on; (a) Nominal tensile strength, (b) Percent elongation at break, and (C) the Young’s modulus of FDM fabricated ABS parts; for physical levels of factors, see Table 3-3. ........................................................................... 79

Figure 5-5 The artificial neural network designed to approximate mechanical properties of FDM fabricated ABS samples ......................................................................................... 81

Figure 5-6 The performance of the developed neural network to predict the tensile behavior of FDM fabricated ABD samples as a function of FDM process parameters in: (a) training, (b) testing, and (c) validation......................................................................................................................... 82

Figure 5-7 Comparison of the actual and predicted tensile behavior of the FDM fabricated part under process condition #9 .......................................................................................... 83

Figure 5-8 The simulated response of FDM fabricated parts under tensile loading with: (a)R= 0° and Lh=50 μm, (b) R= 0° and Lh=130 μm, (c) R= 0° and Lh=210 μm, (d) R= 0° and Lh=300 μm, (e) R= 90° and Lh=50 μm, (f) R= 90° and Lh=130 μm, (g) R= 90° and Lh=210 μm, (h) R= 90° and Lh=300 μm, (i) R= 45° and Lh=50 μm, (j) R= 45° and Lh=130 μm, (k) R= 45° and Lh=210 μm, (l) R= 45° and Lh=300 μm, (m) R= ±45°
and \( Lh = 50 \, \mu m \), (n) \( R = \pm 45^\circ \) and \( Lh = 130 \, \mu m \), (o) \( R = \pm 45^\circ \) and \( Lh = 210 \, \mu m \), (p) \( R = \pm 45^\circ \) and \( Lh = 300 \, \mu m \)

Figure 5-9 The simulated response of FDM fabricated parts under tensile loading with: (a) \( R = 0^\circ \) and speed=1000 mm/min, (b) \( R = 0^\circ \) and speed=2000 mm/min, (c) \( R = 0^\circ \) and speed=3000 mm/min, (d) \( R = 0^\circ \) and speed=4000 mm/min, (e) \( R = 90^\circ \) and speed=1000 mm/min, (f) \( R = 90^\circ \) and speed=2000 mm/min, (g) \( R = 90^\circ \) and speed=3000 mm/min, (h) \( R = 90^\circ \) and speed=4000 mm/min, (i) \( R = 45^\circ \) and speed=1000 mm/min, (j) \( R = 45^\circ \) and speed=2000 mm/min, (k) \( R = 45^\circ \) and speed=3000 mm/min, (l) \( R = 45^\circ \) and speed=4000 mm/min, (m) \( R = \pm 45^\circ \) and speed=1000 mm/min, (n) \( R = \pm 45^\circ \) and speed=2000 mm/min, (o) \( R = \pm 45^\circ \) and speed=3000 mm/min, (p) \( R = \pm 45^\circ \) and speed=4000 mm/min.

Figure 5-10 The simulated response of FDM fabricated parts under tensile loading with: (a) \( R = 0^\circ \) and \( T = 250^\circ C \), (b) \( R = 0^\circ \) and \( T = 270^\circ C \), (c) \( R = 0^\circ \) and \( T = 290^\circ C \), (d) \( R = 0^\circ \) and \( T = 310^\circ C \), (e) \( R = 90^\circ \) and \( T = 250^\circ C \), (f) \( R = 90^\circ \) and \( T = 270^\circ C \), (g) \( R = 90^\circ \) and \( T = 290^\circ C \), (h) \( R = 90^\circ \) and \( T = 310^\circ C \), (i) \( R = 45^\circ \) and \( T = 250^\circ C \), (j) \( R = 45^\circ \) and \( T = 270^\circ C \), (k) \( R = 45^\circ \) and \( T = 290^\circ C \), (l) \( R = 45^\circ \) and \( T = 310^\circ C \), (m) \( R = \pm 45^\circ \) and \( T = 250^\circ C \), (n) \( R = \pm 45^\circ \) and \( T = 270^\circ C \), (o) \( R = \pm 45^\circ \) and \( T = 290^\circ C \), (p) \( R = \pm 45^\circ \) and \( T = 310^\circ C \).

Figure 5-11 Normal probability distribution of model residuals

Figure 5-12 The microscopic inspections of the cut cross section of ABS parts fabricated by FDM under process conditions 1 to 16 per Table 3.

Figure 5-13 The graphical illustration of the points characterized via Raman spectroscopy; \( R1 \) and \( R2 \) represent two adjacent roads separated by the interface boundary region.
Figure 5-14 The Raman spectrum obtained for five different points of 3D printed sample 1; (a) to (e) are respectively representing the spectrum obtained for points 1 to 5 illustrated in Figure 5-12.......................... 104

Figure 6-1 Graphical comparison between the effect of process parameters on changing glass transition temperature and Young's modulus......................................................... 110
List of Symbols

$LH$  
Printed layer height

t  
Layer thickness

$NT$  
Nozzle temperature

$\vec{V}$  
Deposition speed

$\theta$  
Raster orientation

d  
Nozzle diameter

$\sigma(t)$  
Applied sinusoidal stress over time

$\sigma_0$  
The maximum stress

$\omega$  
Frequency of oscillation

$\delta$  
Phase angle

$E'$  
Storage modulus

$E''$  
Loss Modulus

$E^*$  
Complex modulus

$T_g$  
Glass transition temperature

$\Delta\omega$  
Raman shift

$\lambda_0, \lambda_1$  
Raman pre and post excitation wavelength

$W_i$  
Connection weight in neural network
$x_i$  Input of neuron $i$

$a$  Scalar output of neuron

$f$  Transfer function

$E$  Error of neural network

$t_i$  Desired output

$s_j^{(n)}$  Sensitivity of network

$b$  Bias term

$\overrightarrow{X_i(t)}$  Position of particle $i$

$\overrightarrow{X_i(t+1)}$  Next position of particle $i$

$\overrightarrow{V_i(t)}$  Velocity of particle $i$

$g(t)$  The best experience of the whole swarm

$P_i$  Best position of particle $i$

$W$  Real value coefficient

$C_1$ and $C_2$  Acceleration coefficient

$c_1,...,c_m$  Factors effects in Lenth’s approach

$PSE$  Pseudo Standard Error

$ME$  Margin of error

$t_{\alpha}^{d}$  $t$-distribution with the significance level of $\alpha$ and degree of freedom of $d$
\( n \)  Number of runs in ANOVA analysis

\( y_i \)  The \( i \) -th response

\( \bar{y}_T \)  Total average

\( SS_T \)  Total sum of squares

\( SS_x \)  Sum of squares corresponding to Factor \( x \)

\( SS_{Error} \)  Sum of squares corresponding to Error

\( MS_{Error} \)  Mean squared error

\( SS'_x \)  Adjusted sum of square for factor \( x \)
List of Abbreviations

CAD      Computer Aided Design
CRN      Composites Research Network
AM       Additive Manufacturing
FF       Freeform Fabrication
RP       Rapid Prototyping
RM       Rapid Manufacturing
FDM      Fused Deposition Modelling
SLA      Stereolithography
UV       Ultra violet
SLS      Selective laser sintering
ABS      Acrylonitrile Butadiene Styrene
ANN      Artificial Neural Network
PSO      Particle Swarm Optimization
Acknowledgements

First of all, I owe my sincere gratitude to my supervisor, Dr. Abbas S. Milani, for all of his patient guidance, encouragement, and expertise throughout this project. Dr. Milani played an influential role in broadening my knowledge in manufacturing science, modelling and optimization, and delivered coherent answers to my questions and queries. Without his encouragement and support, this project would not be completed.

I would also like to deeply appreciate Dr. Hamid Reza Zareie Rajani from Global Heat Transfer Research and Technology Center for his endless support and insightful suggestions throughout my Master’s project. In addition, I would like to sincerely appreciate the time and valuable guidance provided by my committee members, Drs. Rudulf Seethaler and Dimitry Sediako.

I wish to pass on many special thanks to my colleagues and friends at CRN Okanagan laboratory, Armin Rashidi, Kurt Yesilcimen, Bryn Crawford, Hossein Montazerian, Connor Keegan, Milad Ramezankhani, Tina Olfatbakhsh, and Behnaz Khatir, who made this journey an enjoyable one.

I must express my gratitude to all my other friends in Kelowna for their day-to-day- support, countless laughs and memorable times over the past two years.

Finally and most importantly, special thanks are due to my beloved family for supporting me endlessly throughout my academic career. Their unlimited love, encouragement, and care make it all worthwhile!
To my ever-caring parents,

*Shahla and Reza,*

&

My beloved brother,

*Ali,*

Without whom none of my success would be possible.
Chapter 1: Background and thesis organization

1.1 Introduction

Additive Manufacturing (AM), often known as 3D printing, is increasingly becoming a popular manufacturing method that can allow manufacturers to rapidly fabricate highly complex three-dimensional (3D) parts while producing a minimal material waste [1], as opposed to subtractive manufacturing methods [2][3]. In AM, Computer Aided Design (CAD) files containing 3D part models are employed as input. The 3D CAD model is sliced into several 2D layers and then transmitted to a 3D printer, which then fabricates each 2D layer and joins them one upon another to make the final part. Owing to the various methodologies employed to deposit and consolidate the material layers, AM today includes a large variety of techniques [4]. Among these, Fused Deposition Modelling (FDM) is one of the most commonly used AM technologies, which is traditionally based on extrusion and deposition of thermoplastics [5].

Owing to the relatively low processing time and cost associated to the fabrication of 3D parts using FDM, it has been considered as a preferred prototyping tool by various industries. In particular, over the past twenty years of research on the additive manufacturing techniques [6], researchers from mainstream industries such as automotive, aerospace and tissue engineering have aimed to improve the properties of FDM printed parts by means of development of new software and hardware as well as optimization processes [6].

1.2 Motivations and objectives

Fast evolution of additive manufacturing (AM) methods suggests that it is becoming a highly viable alternative to most conventional subtractive manufacturing techniques. One of the current, principal challenges that researchers confront in using AM techniques, however, is the lowered mechanical properties of AM fabricated parts compared to their conventionally built counterpart e.g. using injection molding [6]. In particular, the effect of process parameters on the behavior of
FDM processed thermoplastics has not been fully addressed yet. Theoretically, this is owing to the highly complex relationships between the process parameters and viscoelastic properties of the 3D printed parts (i.e. processing-properties relationships), whereby full experimental optimization of the process is very time-consuming and costly. Accordingly, employing advanced black-box techniques along with intelligent sampling methods are deemed beneficial to predict the process at low costs, and in turn, to find the optimum sets of process parameters for different working conditions of the end-use parts.

With the above motivation, the specific objectives of this research are defined as follows:

1. Perform a comprehensive characterization of the tensile and viscoelastic behavior of FDM fabricated ABS thermoplastic samples by means of a Taguchi design of experiment (DOE) on selected process parameters (nozzle temperature, layer height, raster orientation, and deposition speed).
2. Model the relationship between the FDM process parameters and the above mechanical properties of the 3D printed ABS parts via a series of neural networks.
3. Statistically analyse and optimize the FDM process parameters using the developed neural networks, while considering different working (temperature) conditions for end-use applications.
4. Perform visual inspections and a Raman spectroscopy analysis to gain a more in-depth understanding of the effect of process parameters on the quality of the printed parts.

1.3 Thesis framework

This thesis has been arranged in six chapters. Chapter 2 reviews the background research conducted on the additive manufacturing techniques, including studies concerning material characterization and optimization. Chapter 3 discusses the materials and methods employed to fulfill Objectives 1-3. Chapters 4 and 5 form the main body of the research results. Specifically, chapter 4 is dedicated to the characterization of viscoelastic properties of the FDM fabricated ABS samples. The chapter includes the Dynamic Mechanical Analysis (DMA) results as well as finding the optimum level of FDM process parameters. Chapter 5 is devoted to the effect of process
parameters on the tensile behavior of the printed ABS parts. Finally, the chapter validates the observed mechanical behaviors using microscopy and a Raman spectroscopy analysis. Chapter 6 summarizes the main findings of the thesis and outlines some recommendations for future work. Figure 1-1 summarizes the organizational framework of the thesis.
Chapter 2: Literature review

2.1 Additive manufacturing

Today, manufacturing parts with minimum time and cost while enhancing their quality is the major concern of manufacturers. Freeform fabrication (FF), rapid prototyping (RP), rapid manufacturing (RM) and additive manufacturing (AM) are different terms commonly used for the same concept to address the above concern [7].

Generally, additive manufacturing is a technique used to make structures by adding multiple (sometimes thousands) of thin 2D layers. The first roots of additive manufacturing go back to topography and photosculpture techniques. Topography is the process of adding a stack of counter cut papers on top of each other, which was first developed by Blanther [8]. Photosculpture is the technique introduced by a French artist, Francois Willeme [9], in 19th century to build the three-dimensional facsimile of an object. Despite all the mentioned historical efforts in the area of 3D fabrication, the first comprehensive step to manufacture 3D parts was taken by Mitsubishi Motors in 1972 [10]. In this technique, Matsubara employed particles coated by photo hardening materials to form each layer of the part.

More modern face of AM started in 1951 based on the solidification of photo-sensitive materials [11]. The fast development of additive manufacturing techniques which was historically started in 1960s never stopped. Researchers worldwide have patented multiple techniques to fabricate parts with the concept of adding desired material instead of removing unneeded material. For example, in 1968, Swanison suggested a system based on the photopolymerization to make the plastic parts [12]. In 1979, the first steps to use laser sintering powder to solidify the part was taken by Housholder [13].

Generally defining, additive manufacturing is “the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies”[3], (see Figure 2-1). In additive manufacturing, Computer Aided Design (CAD) files that contain 3D geometrical models are used as input data. Specifically, a 3D CAD model is
first sliced into several 2D layers and then sent to a 3D printer where a processing method like FDM is employed to build each of the 2D layers and consequently construct the entire 3D model.

Today, the most common AM technologies can be listed as follows [14]:

- Selective Laser Sintering (SLS) in which powders are consolidated layer-by-layer through a laser beam [15] (Figure 2-2 (a))
- Stereolithography (SLA) that is based on UV curing of photo-sensitive resins [16] (Figure 2-2(b))
- Polyjet that uses polymer ink jet to deposit each layer of the model [17] (Figure 2-1 (c))
- Fused Deposition Modeling (FDM) (Figure 2-2 (d))
2.2 Fused deposition modelling (FDM)

As shown in Figure 2-3, FDM technology is traditionally based on extrusion and deposition of the thermoplastic materials. In this technology, a relatively thin filament of thermoplastic is fed into a printer where the filament melts by passing through a hot print head. In a 3-axis configuration, a nozzle attached to the print head deposits the molten material in fine roads (beads), in order to form a 2D layer, usually on the X-Y surface. Once the first layer is completed, a relative movement between the model and nozzle along the Z axis will allow for the deposition of the second layer. The same procedure is repeated to build the entire 3D model through stacking 2D consolidated layers.
Today, FDM is recognized as one of the most popular AM technology due to its availability, simplicity, and affordability [5]. Although FDM is mainly used for rapid prototyping, a series of attempts have recently been made to manufacture end-use parts through FDM technology [21]. Using high-performance consumables such as Poly Ether Ether Ketone (PEEK) [22] and Acrylonitrile Butadiene Styrene (ABS) [23], and also improving the quality of prints [24], are the main themes of these attempts. It is already shown that the quality of print in FDM is closely linked to the choice of process parameters [25]. A defect-free FDM print requires a careful optimization routine through understanding the role of each process parameters and their interactions in the resulting mechanical properties of 3D printed objects.
2.3 The FDM process parameters

The biggest challenge in the field of additive manufacturing is yet to build high-quality parts with minimal waste while maintaining a high rate of production. The literature review reveals that several studies have been conducted to investigate the effect of FDM process parameters as follows [26] [27] (see also Figure 2-4):

- Road width ($w$) that is the width of a road deposited through the nozzle.
- Layer height ($LH$) (a.k.a Layer thickness ($t$)) that is the thickness of each 2D layer made upon the previously deposited layer.
- Deposition speed ($v$) that is the pace at which the 3D printer head moves with respect to the bed.
- Feeding rate that is the rate at which the thermoplastic filament is fed into the nozzle. Note that the feeding rate is different from the speed.
- Nozzle temperature ($NT$) that is the temperature of the nozzle prior to extrusion. This elevated temperature will result in melting the thermoplastic. This parameter should be selected based on the characteristics of the given thermoplastic filament and the capabilities of the given 3D printer.
- Bed temperature is the temperature of the printing bed. Wrong selection of this parameter can lead to dimensional inaccuracies.
- Raster orientation ($\theta$) that is the orientation of roads in each 2D layer.
- Overlap ($b$) that is the horizontal distance between two adjacent roads. As it is shown in Figure 2-4, it could be negative or positive or zero.
- Infill degree which represents how the model would be filled with the material when it is printed. Expectedly, the higher infill degree would lead to higher part strength. Usually, for prototyping purposes, where the strength of the part does not matter, the infill degree is selected as low as 20 %-30 %.
- Nozzle diameter ($d$) which is the diameter of the printer nozzle.
- Stand- off distance which is the distance between the nozzle tip and the deposited layer.
Next to the above mentioned FDM process parameters, there are few more operating conditions that are potentially effective in controlling the quality of fabricated parts. For example, the adhesion of the first printed layer to the bed could influence the accuracy of fabrication. The role of the first 3D printed layer with respect to the whole model would be very similar to the foundation of a building. It is not possible to build a strong building on an unstable foundation. Unique studies on bed treatment solutions can be found in the previous literature addressing this challenge [28]. The distance between the nozzle and the bed is also another important factor controlling the adhesion of the deposited layers to each other.
2.4 Towards understanding the influence of FDM process parameters

In order to employ the FDM as a fully functional manufacturing technique to build end-use parts rather than prototypes, the improvement of the properties of fabricated parts is necessary. As previously mentioned in section 2.3, there is a large variety of building parameters to control the final quality of parts fabricated by FDM. Moreover, due to the complexity of the FDM process, there are conflicts in the literature regarding selecting the most effective process parameters [33-43]. Consequently, it is deemed crucial to continue establishing more in-depth understanding of processing-properties relationship in FDM process.

Assessment of FDM fabricated parts could be performed using several quality measures such as processing time, durability and mechanical performance of the part, and manufacturing accuracy. Generally, each process parameter could affect each quality measure differently. For example, increasing one process parameter could improve one quality measure while adversely affect the others. Thus, the majority of performed studies in the field of additive manufacturing have focused on a specific property such as processing time, dimensional accuracy, surface finishing, mechanical strength and dynamic mechanical properties of 3D printed parts [29-40].

Although studying the FDM process parameters and finding their effects on the properties of fabricated parts is highly important for designers, their optimization is not an easy task. That is, the FDM process parameters are often interacting with each other and as a result, highly nonlinear and global optimization techniques (specifically multi-objective methods) are required. In the subsections to follow, some experimental approaches, analytical techniques and theoretical studies for improving FDM applications are reviewed.

2.4.1 Experimental approaches

Experimental analysis is perhaps the most common approach to identify the potentially effective FDM process parameters for a given application. Van Weeren et al. [29] conducted one of the earliest investigations under this category to differentiate defects caused by fused deposition of
ceramic parts. They claimed that by assigning proper values to the process parameters, the occurrence of the defects could be minimized.

In 1996, Agarwala Mukesh et al. [24] stated that due to the nature of fused deposition modelling both internal and external defects may be occurring. They also emphasized that this phenomenon is not limited to a specific type of material. In fact, these defects can happen in the fused deposition of metals, plastics as well as ceramics. Owing to the ease of removing external defects by post-processing techniques, most studies have focused on the reduction of internal imperfections. As a main conclusion in the study [24], the process optimization was identified as a key to cope with internal defects in 3D printed parts.

The enthusiasm to find the influential parameters of fused deposition technique has led to several other novel experimental studies. For example, in 1998, Bosett et al. [30] designed a real-time microscopy system to monitor the process of deposition of material. Their study could successfully quantify the imperfections and showed that a smart selection of process parameters could result in building void-free FDM processed parts.

In 1998, another influential investigation was performed [31] which focused on the elastic behavior of crystalline reinforced PP (Polypropylene) parts fabricated by FDM as a function of lay-down pattern. The study concluded that a suitable adjustment of laydown pattern, with respect to the final application of the processed part, could result in obtaining a satisfying part.

Rodriguez et al. [32] investigated the change in elastic moduli of FDM fabricated ABS. They showed that in comparison to ABS filament, the elastic modulus and strength of 3D printed ABS samples were reduced between 11 to 37 percent and 22 to 57 percent, respectively. They believed that the porous structure of 3D printed parts caused this reduction in mechanical properties. The influence of raster orientation on the strength of ABS parts processed by FDM has been also previously studied by Es-said et al. [33] through a series of experiments. They showed that unidirectional 0° raster orientation would result in maximum ultimate and tensile strengths and for all tested samples, the fracture happened along the interface of two adjacent layers. The 0° raster orientation also showed the best performance during Izod impact test and rupture test.
The influence of selected process parameters on the tensile strength of FDM processed ABS was also characterized by Montero et al [23]. In this research, raster orientation, air gap, road width, color of filaments and nozzle temperature were selected as the controlling factors. The tensile strength of 3D printed samples was characterized and compared to the similar properties of injection-molded parts. They reported that the strength of the 3D printed samples ranged from 65 to 72% of the strength of molded samples.

Characterization of tensile properties of FDM fabricated parts has not been limited to the above-mentioned investigations. Ahn et al. [34] investigated the impact of few factors similar to parameters selected by Montero et al [23], except the color of filaments, on the tensile and compression strengths of ABS models printed by FDM. Their study suggested that overlap and raster orientation can have the strongest influence on both the strengths of the parts. Also, through a comparison with injection molded ABS parts, Ahn et al. [34] concluded that FDM compromises the static strength of ABS by 28%-35% and 10%-20% for the tensile and compression elastic moduli, respectively.

In another study, Lee et al. [35] used the unidirectional tensile tests to examine the effects of overlap, raster orientation, road width, and layer thickness on the elastic modulus of FDM processed ABS parts. Their study indicated that increasing the overlap along and decreasing the layer thickness would improve the elastic modulus of 3-D printed ABS parts. In addition, in their study, the optimum raster orientation was reported to be 30°/60°.

In 2010, Sood et al. [36] not only studied the tensile properties of FDM processed parts but also they characterized their flexural and impact strength. Layer thickness, raster orientation, road width, and overlap were considered as the independent (control) factors and it was concluded that for small layer thicknesses, using small raster angles and large overlaps can increase the tensile and flexural strengths of fabricated parts. However, at higher levels of layer thickness, the smaller overlaps and larger raster angles would increase the tensile and flexural strengths of FDM processed ABS. This clearly indicated the existence of interactions between the FDM process parameters.
Onwubolu and Rayegani [37] studied the change in the tensile strength of 3D printed parts as a function of layer thickness, part orientation, raster angle, raster width, and air gap. Liu Xinhua et al. [38] attempted to characterize these properties through an experimental approach. In addition to the factors studied by Sood et al. [36], they measured the effect of air gap and deposition style. A L27 Taguchi orthogonal array was used to design the experimental layout and the obtained results were optimized comprehensively with the gray relational method. Finally, they indicated that raster orientation is the most influential factor, which is following by layer thickness and deposition style.

Most recently, in addition to the tensile properties, investigations on the impact of FDM process parameters on the other properties of fabricated parts including surface finish and viscoelastic behavior have been launched [27, 39, 40].

In 2006, Chin Ang et al. [41] focused on the dynamic mechanical properties of FDM processed parts with respect to the porosity of fabricated parts. They selected few process parameters including air gap, raster width, raster orientation, deposition profile, and layer height, and studied the dependency of complex strength and complex modulus of fabricated samples through a series of designed experiments. Consequently, they reported air gap and raster width as the most effective process parameters to control porosity and strength of processed parts. Furthermore, they claimed that there is a logarithmic relationship between mechanical properties and porosity, which meant that the 3D printed scaffold parts with a lower porosity should show a higher strength.

Later, Arivazhagan et al. [27] used a Dynamic Mechanical Analyzer (DMA) to examine the effects of road width, raster orientation, and nozzle temperature on the viscosity and dynamic moduli of FDM processed ABS samples. They showed that a raster orientation of 30°/60° and a road width of 0.454 mm improves the dynamic moduli of 3D printed ABS.

Mohamed et al. [39] considered layer thickness, overlap, raster angle, raster orientation, and road width as control factors to investigate the dynamic mechanical properties of FDM processed ABS. The results of their study indicated that the overlap and layer thickness are the most effective process parameters. Specifically, it was shown that a layer thickness of 0.3302 mm, a road width
of 0.4572 mm, and an overlap of 0 mm with a raster angle of 0° can increase the dynamic moduli of ABS.

As reviewed above, there have been several experimental studies on the FDM process parameters and finding their optimum values. However, lack of systematic experimental designs often does not allow for parametric studies to account for a statistically-informed selection of factor combinations. This can potentially lead to errors in interpreting the role of each process parameter and their interactions. Owing to the growth of experimental tools, the design of experiments techniques have been used widely in the field of additive manufacturing to cope this challenge. For example, similar to the work of Liu Xinhua et al. [38], Laeng et al. [42] investigated the effect of air gap, raster angle, road width and layer thickness on the elastic behavior of FDM fabricated parts using the Taguchi design of experiments technique. In the latter work, the statistical analysis was carried out via ANOVA and finally the optimum values for the process parameters were estimated to improve the elasticity of the printed parts.

Devika and Gupta [43] developed a series of experiments to evaluate the porosity, surface finish and dimensional accuracy of PC-ABS materials processed by FDM. According to ANOVA and surface response methodologies, a 0.1270 mm of layer height, 0.6096 mm of raster width, 0 mm of air gap and unidirectional raster orientation of 0° led to the best results and minimum imperfections.

Torres et al. [44] also employed a Taguchi design of experiments to perform their investigation. An L8 orthogonal array, which included 6 factors, including the layer height, infill percentage, nozzle temperature, speed, raster orientation and loading orientation were used as the controlling factors to study their influence on the stiffness, strength and ductility of 3D printed PLA parts. They concluded that regardless of the value assigned to the raster orientation, infill percentage is the most effective factor following by layer thickness and nozzle temperature. This study revealed that due to the containing more boundary regions, decreasing infill degree and layer height increases the probability of containing numerous defects in the microstructure of 3D printed part.

Ductility of unidirectional 3D printed PLA has also received attention by Song et al. [45] who studied tension, compression and fracture characteristics of FDM processed parts. Based on their
experimental research, the ductility of printed parts was lower than the same ones prepared by other techniques. The decrease in ductility would result in lower fracture toughness and more sensitivity to strain rates.

2.4.2 Empirical approaches

Generally, physics-based modelling approaches focus on the explicitly formulated response of the AM process with respect to the process parameters. However, empirical (black-box) modelling techniques could be employed for prediction purposes even with an incomplete understanding of the nature of a given process [46-48]. In general, these methods are developed based on available experimental datasets and observations. Due to the high complexity of FDM, artificial neural network (ANN) and regression are the two most common empirical techniques that have been used to model the process.

Artificial neural network (ANN) is known as a dominant black-box technique to predict non-linear relationships between inputs (process parameters in the case of FDM optimization) and outputs (characteristics of fabricated parts). The robustness of this technique, which is inspired by the biological neural systems, to work with incomplete datasets, had made it a powerful optimization tool for numerous applications.

One of the first attempts that employed empirical modelling approaches for FDM was the work of Anitha et al. [49]. They developed a regression model to investigate the influence of layer thickness, road width and deposition speed on the surface roughness of FDM fabricated parts. The capability of the developed regression model to fit the experimental results was a revolutionary conclusion of their research, which led other researchers to use further empirical models in the field of additive manufacturing. The performed analysis on their developed regression model proved that the layer thickness is the only significant factor amongst the studied factors to control surface roughness.

Regression models have been used in other studies of additive manufacturing. For example, Ang et al. [50] employed quadratic regression models and logarithmic curve fitting tools to explore the
effect of air gap, raster width, raster orientation, build layer and build profile on the porosity and mechanical properties of FDM processed parts.

Reddy et al. [51] also employed the regression technique to examine the effect of four FDM process parameters including nozzle temperature, chamber temperature and air gap on the surface roughness of fabricated parts. They reported that only the air gap has a significant influence on the surface roughness.

Artificial neural network, as mentioned before, is another powerful modeling tool to explore the FDM process parameters. In a black-box investigation by Sood et al. [52] layer thickness, raster orientation, raster angle, raster width and air gap as have been considered as five input neurons connecting through seven hidden neurons to one output node in an artificial neural network (the basics of neural network design will be described in more details in chapter 3). Their study showed that the optimal dimensional accuracy of 0-3.5 percent could be achievable with the optimum values obtained by the neural network. In another study, Sood et al. [53] considered the same inputs to predict the dimensional accuracy of the FDM fabricated parts in three independent dimensions (width, length and thickness). Consequently, they developed a feed forward-back propagation neural network with 5-7-3 architecture and proved that the predicted results of the network had only 0.012 percent difference with the actual values.

Later, other researchers aimed to employ the neural network technique to investigate other specifications of FDM processed parts. For example, Sood et al. [54] considered the compressive strength of 3D printed parts as the dependent variables and developed a 5-8-1 ANN model to determine the significance of layer thickness, orientation, raster angle, raster width and air gap. Their study revealed that the above-mentioned factors and their interactions can closely affect the compressive strength of the final parts.

A more recent study accomplished by Panda et al. [55], compared three promising numerical methods including Neural network, Genetic programming and response surface regression. All of the employed methods were used to formulate an unknown relationship between selected process parameters and two mechanical properties of honey comb structures made via FDM. Consequently, they concluded that the neural network technique and response surface regression
have respectively the highest and lowest compatibility with the obtained experimental observations.

### 2.4.3 Numerical approaches

The extensive need to employ virtual tools to evaluate the properties of FDM fabricated parts prior to fabrication has led researchers to consider finite element methods. Results obtained by numerical simulations have been shown to be compatible with the experimental results in most cases. For example; Hambali et al. [56] compared the properties of FDM processed ABS parts obtained from experimental data to the FEA simulated results and reported that the simulated results were reliable enough to be used for process optimization instead of experimental analysis. In 2013, Croccolo et al. [57] achieved an error level as low as 4% in predicting the tensile properties of FDM fabricated ABS using an FEM model. Moreover, in independent studies performed by Bellini and Selcuk [58] and Zhang and Chou [59], the effect of process parameters and compatibility of simulated and experimental results were explored.

### 2.5 Summary of chapter

In this chapter, the basics of additive manufacturing (AM) techniques were outlined and subsequently with a focus on the FDM type of AM, a series of past experimental, empirical and numerical modeling approaches were reviewed. Accordingly, it was shown that there are no consensus on identifying the most effective FDM process parameters that could work for different types of thermoplastics and all part performance measures, mainly due to the presence of highly complex interactions between the process parameters. Accordingly, the use of high fidelity black-box modeling techniques such as artificial neural networks was deemed to be beneficial in the field. However, there has been no unified study to integrate the ANN with both statistic and dynamics properties of FDM process parts while statistically testing the significance of process parameters and their complex interactions, and eventually optimizing the process parameters using global optimization techniques. Moreover, regardless of the employed approach to study the FDM process in previous investigations, the conclusions have not been verified using micro/meso level inspections (such as microscopy or spectroscopy techniques etc).
Chapter 3: Materials and methods

3.1 Overview

The main goal of this thesis investigation has been to perform a comprehensive characterization and optimization of the FDM process on a typical thermoplastic. This chapter discusses the employed materials and methods by which the investigation has been performed in the subsequent chapters. Specifically, the characteristics of the raw material, the characterization methods, and the employed FDM fabrication system will be presented in sections 3.2 to 3.7. The following sections, including 3.8 and 3.9, will overview the mathematical methods adapted to analyze the collected experimental results. Namely, Artificial neural network (ANN) and particle swarm optimization (PSO) methods will be coupled to perform the optimization of the FDM process.

3.2 Test Material

ABS (Acrylonitrile Butadiene Styrene) was chosen as a typical material commonly used in 3D printing industries. It is a terpolymer consisting of acrylonitrile, polybutadiene, and styrene as depicted in Figure 3-1. These components provide a two-phase material composition, including a rubbery phase (butadiene) spreading in a viscoelastic matrix of styrene- acrylonitrile (SAN) [60]. In recent years, ABS has been known for its good rigidity coupled with a high toughness [60]. High thermal and electrical resistance and low absorption of liquids are among other superior characteristics that have made ABS as a best-selling engineering thermoplastic [61].

The material properties of ABS are highly dependent on the micro-structural parameters such as particle size, ratio and distribution, and molecular weight of the constituent monomers. In fact, each of the mentioned monomers is providing a specific characteristic to the ABS.
Owing to the polar bonding in the nitrile monomer, ABS molecules can achieve a strong bonding where styrene monomer brings a shiny surface to it. Despite the fact that ABS is mechanically a strong thermoplastic, it is tough enough even at low working temperatures, which comes from the presence of polybutadiene monomer [62].

The ABS thermoplastic material that used in experiments of this thesis (Figure 3-2) was produced by Makergear, in the form of filaments a nominal diameter of 1.75 mm and with a purity of >98%. According to Makergear [63], the filaments were extruded out of ABS POLYLAC® manufactured by CHIMEI Corporation. A summary of the specifications of this test material is provided in Table 3-1.
Figure 3-2 ABS 1.75 mm filament manufactured by makergearr [63]

Table 3-1 Properties of the used ABS filament

<table>
<thead>
<tr>
<th>Commercial code</th>
<th>CHIMEI PA-747S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purity</td>
<td>&gt;98%</td>
</tr>
<tr>
<td>Nominal Young’s modulus (GPa)</td>
<td>2</td>
</tr>
<tr>
<td>Relative density - $H_2O \left( \frac{g}{cm^3} \right)$</td>
<td>1.03-1.10</td>
</tr>
<tr>
<td>Decomposition temperature (°C)</td>
<td>&gt; 310</td>
</tr>
</tbody>
</table>
3.3 FDM set-up

Fused deposition modelling, as a rigorous AM process, needs a reliable machine with a high degree of controllability. In this research, a Makergear M2 FDM 3D printer, depicted in Figure 3-3, was employed to fabricate the parts. It should be noted that, the printer bed and heating cartridge of the original 3D printer was modified by the research team at CRN Okanagan laboratory to achieve higher temperature ranges (500°C).

![Figure 3-3 The modified Makergear M2 3D printer](image)

As outlined in chapter 2, there are several process parameters potentially controlling the properties of FDM parts for each given material. However, planning an experimental layout considering all the parameters would be highly time and cost consuming. Therefore, this research aimed to find the effect of four selected process parameters based on past literature [37, 39, 53, 64, 65] including nozzle temperature, layer height, raster orientation and deposition speed. Other process parameters kept constant at their fixed levels, as shown in Table 3-2.
Table 3-2 Assigned values to the fixed FDM process parameters and

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infill degree</td>
<td>100%</td>
</tr>
<tr>
<td>Bed temperature</td>
<td>100℃</td>
</tr>
<tr>
<td>Nozzle diameter</td>
<td>0.35mm</td>
</tr>
<tr>
<td>Nominal Overlap</td>
<td>0mm</td>
</tr>
</tbody>
</table>

3.4 Design of experiments

Despite the fact that employing an experimental strategy to evaluate all the possible combinations of FDM process parameters would be useful, it is highly time and cost consuming. As a result, employing Design of Experiments (DOE) techniques is seemed most efficient to plan and analyze the AM experiments to collect a sufficient amount of data along with performing a minimal number of experiments. Based on initial trial and errors (to ensure the prints are of minimum acceptable quality with no visible large defects) and our industrial partner recommendations, four corresponding levels (presented in Table 3-3) were assigned to each of the four selected process parameters (Table 3-3). For this case, the total (full-factorial) number of experiments would be $4^4$ or 256.
Table 3-3 Control factors to be used in the experimental procedures with their assigned levels

<table>
<thead>
<tr>
<th>Control factors</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raster orientation</td>
<td>0˚</td>
<td>90˚</td>
<td>45˚</td>
<td>±45˚</td>
</tr>
<tr>
<td>Layer height (μm)</td>
<td>50</td>
<td>130</td>
<td>210</td>
<td>300</td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>250</td>
<td>270</td>
<td>290</td>
<td>310</td>
</tr>
<tr>
<td>Feeding rate (mm/minute)</td>
<td>1000</td>
<td>2000</td>
<td>3000</td>
<td>4000</td>
</tr>
</tbody>
</table>

The Taguchi approach meets the need of designers to reduce the number of costly experimental runs by means of using orthogonal arrays, at the cost of assuming ‘the factor interactions are negligible’ [66]. Taguchi orthogonal arrays are often shown by “L_n(x^y)”. Where, n stands for total number of experiments, x representing the levels, and y is the number of controlling factors. In the current research, the L_{16}(4^4) design has been used (Table 3-4).
<table>
<thead>
<tr>
<th>Experiment</th>
<th>Raster orientation</th>
<th>Layer Height (μm)</th>
<th>Temperature (˚C)</th>
<th>Velocity (mm/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>10</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>11</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>4</td>
<td>1</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>14</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>16</td>
<td>4</td>
<td>4</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>
3.5 Tensile test set-up

Tensile testing is a well-known, fully standardized set-up to characterize mechanical properties of materials, owing to its simplicity and economic efficiency. An Instron 5969 tensile machine was used in this research with a crosshead speed of 1 mm/min. The force accuracy of the machine was up to 0.001N with a precision of 0.057 micron for displacement and up to 0.001 N for force measurement. The dimension of the samples will be discussed in more details in chapter 5.

3.6 Dynamic Mechanical Analysis (DMA)

Dynamic mechanical analysis, or DMA, is a well-known technique to characterize the polymeric materials, specifically the Storage Modulus ($E'$), Loss Modulus ($E''$), Complex Modulus ($E^*$), and tan $\delta$. Through application of an oscillatory force (stress) and measuring the displacement (strain) response, the DMA is capable to characterize the viscoelasticity of the material by means of the aforementioned material properties. Briefly, viscoelasticity represents both viscous and elastic behavior of a material under loading. Elasticity shows the ability of the material to return to its original shape after the release of the force. However, viscosity is defined as the resistance of a liquid to flow. Most real-world materials, exhibit neither pure elastic nor pure viscous behavior [67]. In fact, materials such as wood, polymers, body tissues and etc. fall between the two aforementioned material behavioral extremes, which is known as viscoelastic. As depicted in Figure 3-4, an ideal elastic material would show a fully in-phase response (i.e. whit zero phase delay); whereas, pure viscous materials would show a fully out-of-phase response (i.e. with 90° phase delay) [68].
Figure 3-4. A schematic representation of stress and stress curve for elastic, viscous and viscoelastic material for a) Pure elastic response (similar to spring behavior) b) Pure viscous response c) Viscoelastic response

DMA conducts the analysis by applying an oscillatory or pulsing stress, described by the equation 3-1. Where $\sigma$ is representing stress at time $t$, $\sigma_0$ is the maximum stress, and $\omega$ is showing the frequency of oscillation.

$$\sigma = \sigma_0 \sin(\omega t) \quad (3-1)$$

Owing to the viscoelasticity of the material sample, the response would follow the equation 3.2.

$$\varepsilon(t) = \varepsilon_0 \sin(\omega t - \delta) \quad (3-2)$$

In these equations, phase angle, $\delta$, shows the damping ability of the material, which is 0 for pure elastic and 90° for pure viscous states. The latter equation could be rewritten as 3.3:

$$\varepsilon(t) = \varepsilon_0 [\sin(\omega t) \cos \delta + \cos(\omega t) \sin \delta] \quad (3-3)$$

Which represents the fact that the material viscoelastic response could be separated into two in-phase and one out-of-phase components. Symbolically, the in-phase and out-of-phase material behaviors could be written as a function of storage modulus and loss modulus, respectively, as follows.
\[ E' = \frac{\sigma_0}{\varepsilon_0} \cos \delta \]  

(3-4)

\[ E'' = \frac{\sigma_0}{\varepsilon_0} \sin \delta \]  

(3-5)

The elastic or storage modulus \( E' \) shows the material’s ability to store energy (elastic behavior). The loss or imaginary modulus \( E'' \) represents the ability of the material to lose energy (viscose behavior) e.g. through dissipating heat. The vector summation of the two moduli gives the complex modulus as:

\[ E^* = E' + iE'' \]  

(3-6)

The ability of the sample to dissipate energy is known as damping. Damping is a dimensionless property and is equal to ratio of the loss modulus to the storage modulus [69]:

\[ Damping = \frac{E''}{E'} = \tan \delta \]  

(3-7)

The DMA results of the FDM fabricated ABS parts in this research will be provided in chapter 4.

### 3.7 Raman spectroscopy

Raman spectroscopy is a spectroscopic technique used to characterize chemical structures and identify the chemical fingerprints of materials and objects. The method is historically established based on the well-known Raman scattering effect [70]. Briefly, depending on the micro-structure of a given material, the energy level of an absorbed laser photon in a sample will increase or decrease. Raman scatter theory states that, as a result of interaction between electrons in the sample and electrical field of the laser beam, a shift occurs in the energy level, which is directly related to the molecular vibrations. Thus, investigation of this shift, and consequently the frequency of light, can provide information about the chemical structure of the excited material sample and its molecular bonding [70].
The Raman shift is directly reflected to the frequency and the wavelength of excitation and reflection of laser photon. The shift value can be calculated based on the pre- and post-excitation wavelengths [71] as:

$$\Delta \omega = \left( \frac{1}{\lambda_0} - \frac{1}{\lambda_1} \right)$$  \hspace{1cm} (3-8)

Where $\Delta \omega$ is the Raman wave number, $\lambda_0$ is the excitation wavelength and $\lambda_1$ is standing for the Raman spectra wavelength [72]. Chemical structure, molecular bonding, residual stress, change in crystallinity, and the variation in homogeneity are among the main accessible information through analysis of a Raman diagram. Raman diagram is a distribution plot scheming the light intensity versus Raman wave number.

For ABS, owing to the presence of 3 monomers including Acrylonitrile (A), Butadiene (B) and Styrene (S), the Raman diagram is expected to give three corresponding peaks (Figure 3.5).

![Figure 3-5 Part of a Raman spectrum showing peaks related to styrene, butadiene and acrylonitrile](image-url)
3.8 Artificial neural network

Artificial neural network (ANN) technique, which is inspired by the neurologic system of brain, has received increasing attention in recent years. High capability to approximate complex non-linear relationships between input and output parameters of large systems is the key that has made this method a powerful predictive modeling tool in numerous applications [74]. Moreover, ANN is able to provide the predictions with minimal prior assumptions and understanding of the nature of the given system, hence making it a black-box modeling tool as compared to more explicit e.g. regression modelling techniques with pre-defined assumptions [75]. The basic methodology of the ANN is reviewed in the following sub-sections.

3.8.1 Neural network design

A neural network is a composition of neurons connected to each other by numerically assigned connections, known as weights ($W_i$). An artificial neuron receives one or more inputs ($x_i$) and produces one output. Figure 3-6 represents the structure of an artificial neuron and the output calculation process.

![Figure 3-6 Schematic view of an artificial neuron (a) in ANN method](image)

Figure 3-6 Schematic view of an artificial neuron (a) in ANN method
Equation 3-9 demonstrates the mathematical formulation of an artificial neuron, where \( a \) is the scalar output of the neuron. In a neural network, the summation of the weighted inputs and the bias term \( (b) \) is passed to a transfer function \( (f) \) to calculate a neuron’s output. The bias term acts similar to an input with the value of 1 and its existence in a network is not mandatory. However, it can improve the performance of the network [76].

\[
a = f(\sum_{i=1}^{n} w_i x_i + b)
\]  

(3-9)

Generally, the transfer function would limit the output of neuron and it does not have a fixed formulation. Based on the given dataset and the desired output form, the modeler could choose the appropriate function to be used. There are few functions that have been used commonly in several studies such as hard limit, symmetrical hard limit, linear, saturating linear, symmetric saturating linear, log sigmoid, hyperbolic tangent sigmoid, and positive linear [77].

Formerly described, artificial neurons are the basic single units in an artificial neural network. However, these units are not working solely. In fact, neurons are laying in parallel levels a.k.a. layers. In each layer, all the neurons receive inputs from the prior layer. When neurons receive the inputs, the same mathematical process described by equation 3-9 can be performed on each neuron, while the new neurons provide an output layer (Figure 3-7).
As depicted in Figure 3-7, all the neurons located in the same layer receive the same inputs with different allocated weights and bias terms. The calculated output by each neuron can be an input for the following layer.

Generically, according to the received inputs, neurons can be categorized into 3 major types: (a) Output layer; (b) Input layer; and (c) Hidden layers. All the neurons in the hidden and output layer take the outputs of the former layer as an input. Besides, from a statistical point of view, the input neurons are linked to independent variables while output neurons are connected to dependent variables.

In recent years, researchers have been developing new techniques to connect multiple hidden neurons to each other, which are also known as neural network architecture (NNA) [78]. The most important methods to connect neurons resulted in 3 major NNA categories, including feedforward network, recurrent network, and hamming network [79]. In the research presented here, the feedforward algorithm was used to build the network architecture. It should be noted that, a feedforward neural network must have at least three layers including input layer, output layer and at least one hidden layer. The architecture of a multilayer neural network is coded by $R - S^1 -$
$S^2 - \cdots - S^m$. Where $R$ is representing the number of neurons in the input layer and $S^m$ is standing for the number of neurons in the $m$-th layer. Figure 3-8 depicts a general representation of multilayer neural network to show the propagation of information.

As noted, despite the fact that the layers in a neural network are linked and collectively define the final output layer, they could each have different numbers of neurons. Thus, one important aspect of neural network design is the specification of the number of neurons in each hidden layer, also known as neural architecture optimization. The final step to design a neural network is selecting an appropriate transfer function. Trial and error, prior experience of the modeler and specifications of the desired output could be used to find the suitable transfer function [80].

For a designed network architecture, defining the initial weights and updating them would be the next step. This step, which is also known as the learning or training algorithm, is in essence the process of minimizing the network error, which will be discussed in more details in equation 3-11. The training procedure starts with calculating the error with the initial weights and it continues with adjusting the interconnecting weights until a maximum iteration level or an acceptable error level is achieved. Along with various techniques developed to build the neural network architecture, different methods have also evolved to train the designed architectures. *Supervised learning, unsupervised learning, and reinforcement learning* are among the common used methods to train neural networks [81]. Neural networks trained with supervised algorithms try to predict
outputs when desired outputs are available (i.e. when the desired output corresponding to each input vector is available). On the other hand, networks developed based on unsupervised training methods aim to cluster the inputs based on the discovered internal relationship between them. On the other hand, the distance to a desired value or cluster of the datasets is not concerned in the reinforcement training; instead, this training system focuses on the sequence of inputs (please see [82] for more details).

For a multilayer neural network the Equation (3-9) can be turned into the following form:

\[ X_j^{(n)} = f(\sum_i W_{ji}^{(n)}X_i^{(n-1)}) \]  

(3-10)

Where, \( X_j^{(n)} \) is the output of the \( j \)-th node in the \( n \)-th layer, and \( f \) is the transfer function. \( W_{ji}^{(n)} \) defines the weight of the interconnection between node \( i \) in the \((n - 1)\)-th layer and node \( j \) in the \( n \) th layer. \( X_i^{(n-1)} \) represents the output of node \( i \) in the \((n - 1)\)th layer.

All the above mentioned training algorithms aim to improve the network performance by means of reduction of errors. The network performance would be evaluated by Mean Squared Error (MSE) between the desired and the predicted values of the output:

\[ E = \frac{1}{2N} \sum_{i=1}^{N} [t_i - a_i]^2 \]  

(3-11)

Where \( N \) stands for the number of training sample points, \( t \) is the desired value and \( a \) is the predicted value for the output of the \( i \)-th sample point. As the network error is calculated, the weights and biases are updated through back propagation to reduce the error value. This process is repeated until the error becomes minimized. Generally, the gradient descent method [83], which is an iterative optimization technique to find the local minimum of functions, is used for this purpose. In each iteration, an adjusted weight is calculated based on:
\[ W'_{ji}^{(n)}(k) = W_{ji}^{(n)}(k - 1) - \alpha \left( \frac{\partial E}{\partial W'_{ji}} \right) \]  \hspace{1cm} (3-12)

Where, \( W_{ji}^{(n)}(k) \) is an updated weight of the \( n \)-th layer in the \( k \)-th iteration (a.k.a. epoch).

\( \frac{\partial E}{\partial W_{ji}^{(n)}} \) is the partial derivative of error. In this equation \( \alpha \) is the learning rate, which is less than 1.

Calculation of the derivative part of the equation 3-12 is normally achieved by the chain rule, as follows [83].

\[ W_{ji}^{(n)}(k) = W_{ji}^{(n)}(k - 1) - \alpha \left( \frac{\partial E}{\partial X_{ji}^{(n)}} \cdot \frac{\partial X_{ji}^{(n)}}{\partial W_{ji}^{(n)}} \right) \]  \hspace{1cm} (3-13)

In the above equation, the term \( \frac{\partial E}{\partial X_{ji}^{(n)}} \) shows the sensitivity of the \( j \)-th node in the \( n \)-th layer which is shown by \( s_{j}^{(n)} \), and is also calculated by the chain rule;

\[ S_{j}^{(n)} = \frac{\partial E}{\partial X_{ji}^{(n)}} = \frac{\partial f_{j}^{(n)}}{\partial X_{ji}^{(n)}} \cdot \Sigma_{k} W_{kj}^{(n+1)} S_{j}^{(n+1)} \]  \hspace{1cm} (3-14)

Updating the bias term is similar to the weight updating formula; it obeys the equation (3-13) and it just needs replacing \( \frac{\partial X_{ji}^{(n)}}{\partial W_{ji}^{(n)}} = 1 \). Therefore, the updated bias will be:

\[ b_{ji}^{(n)}(k) = b_{ji}^{(n)}(k - 1) - \alpha \left( S_{j}^{(n)} \right) \]  \hspace{1cm} (3-15)

In the back propagation algorithm, which has been used in this research, the sensitivity factor propagates from the last layer to the first layer step by step [83].

In practice, development of a well-trained neural network is highly dependent on the selection of network parameters and the experience of the modeler; a comprehensive review of the theoretical aspects of Neural Network design can be found in [83-84].
3.9 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is known as a powerful numerical method to optimize a function by finding the best solution in a space of all feasible solutions. This technique, which has been inspired by social behavior of animals, was first introduced by Eberhart and Kennedy [85]. A simple interpretation of PSO is the behavior of group of birds who are seeking for food. All the birds do not know where the single piece of food is located. But, they know their distance to the other birds. Therefore, the simplest and fastest way to achieve the food is following the closest bird to that food. Despite the fact that this optimization technique is based on a series of simple mathematical rules, it has been applied in numerous applications, including data science and engineering successfully [86-88].

In PSO, each candidate solution is called a “particle”, which is part of a community known as a “swarm”. PSO solves the optimization problem by moving the particles in a space of all feasible solutions, which is also known as the search space. Each particle has a memory to keep its best experience and the cooperation of particles help them to find the best global solution in the search space. The position of particle i, denoted by \( \bar{X}_i(t) \), and its velocity, denoted by \( \bar{V}_i(t) \), are the key properties to define a particle. The previous experience of each particle (\( \bar{X}_i(t) \)), its previous movement (\( \bar{V}_i(t) \)), and the best experience of the whole swarm (\( g(t) \)) force each particle move towards its next position by \( \bar{X}_i(t+1) \), which is probably a better experience. This process continues until the swarm meets its best experience (denoted by \( P_i \)). Figure 3-9, illustrates the described process schematically.
According to Figure 3-9, each particle obeys two simple mathematical rules to update its position and velocity vectors:

\[
\begin{align*}
\overrightarrow{X_i(t+1)} &= \overrightarrow{X_i(t)} + \overrightarrow{V_i(t+1)} \\
\overrightarrow{V_i(t+1)} &= w\overrightarrow{V_i(t)} + C_1(\overrightarrow{P_i(t)} - \overrightarrow{X_i(t)}) + C_2(\overrightarrow{g(t)} - \overrightarrow{X_i(t)})
\end{align*}
\] (3-16) (3-17)

Where, \(w\) is the inertia coefficient and \(C_1\) and \(C_2\) are acceleration coefficients.

The \(j\)–th component of new position and speed vectors can be calculated as follows:

\[
\begin{align*}
X_{ij}(t+1) &= X_{ij}(t) + V_{ij}(t+1) \\
V_{ij}(t+1) &= wV_{ij}(t) + r_1C_1\left(P_{ij}(t) - X_{ij}(t)\right) + r_2C_2\left(g_{ij}(t) - X_{ij}(t)\right)
\end{align*}
\] (3-18) (3-19)

Where, \(V_{ij}(t+1)\) is the \(j\)–th component of velocity of particle \(i\) at time step \((t+1)\). In the equation 3-19, the first component (\(wV_{ij}(t)\)) is known as inertia term. The second component is also called cognitive component and the third term is social component; \(r_1\) and \(r_2\) are the uniformly distributed numbers in the range of 0 and 1.
3.10 Summary of chapter

In this chapter the materials and characterization methods employed in this research were outlined. The artificial neural network technique, which will be used as a modelling tool to capture the complex relationship between FDM process parameters and the response variables, was described briefly. The particle swarm optimization method, through which the optimum values of the process parameters are to be assessed, was also outlined.
Chapter 4: Dynamic mechanical analysis

4.1 Overview

Chapter 2 reviewed some of the main studies in the field of additive manufacturing focusing on the process characterization and optimization aspects. Chapter 3 outlined the materials and methods by which the characterization to be performed in this research. This chapter employs the described methods in Chapter 3 to characterize the viscoelastic properties of the FDM fabricated ABS parts. Specifically, the existing lack in the literature as reviewed in Chapter 2 regarding the influence of the FDM process parameters on the dynamic mechanical behavior of 3D printed parts, is addressed in this chapter. The complex nonlinear relationship between the dependent and independent factors of the process is built via a neural network. Finally, the PSO optimization was performed to find the optimum values of process parameters at various working temperatures ranging from 40°C to 140°C.

4.2 Experimental

4.2.1 DMA test under dual cantilever bending

As outlined in Chapter 3, in order to characterize the viscoelastic properties of FDM fabricated ABS samples, the dynamic mechanical analysis can be used. Shown in Figure 4-1, a dual cantilever clamp was used to operate the DMA test. In thus test mode, the sample is fixed at both ends and a sinusoidal force is applied in the middle of specimen. The test procedure could evaluate the thermomechanical properties of thermoplastic/thermoset/composite specimens such as transition temperature, damping properties and creep coefficients. The main viscoelastic properties of the material are normally characterized in DMA by means of variation of the storage modulus (E’) and the loss modulus (E”) with respect to temperature, oscillation frequency or time.
4.2.2 Sample shape and geometry

Depicted in Figure 4-2 the DMA test samples were prepared in a rectangular shape with the dimensions of $57 \times 14 \times 1.25\text{mm}^3$ ($\text{length} \times \text{width} \times \text{thickness}$). The CAD models were modeled by Solidworks2015 and sliced and printed into thin 2D layers with Simplify 3D. In order to obtain accurate and reliable results, it was crucial to have the dimension of the specimens precisely measured and care was taken to mount the samples evenly (with balanced distributed loads on either sides).

Figure 4-2 The designed CAD model for DMA test coupons (dimensions are in mm)
Once the CAD model was transferred to the Makergear M2 3D printer, the FDM process with the assigned controlled and fixed factors (mentioned in sections 3-3 and 3-4) began. In order to keep the consistency of the tests between DMA (this chapter) and tensile tests (next chapter), all the required specimens (per each process condition as in Table 3-4) were printed entirely in one run. Figure 4-3 is showing a 3D printed ABS sample for DMA test.

4.2.3 Loading and operating conditions

To investigate the effect of process control factors, the DMA tests were carried out in a multi-frequency mode with temperature ramp. The oscillation frequency and displacement (loading) amplitude were kept constant on 1Hz and 15 μm, respectively. Specimens were heated from room temperature to 150°C at the rate of 2°C/min.
4.3 Results and discussions

Figure 4-4 and Figure 4-5, respectively, demonstrate the observed trends of storage modulus and loss modulus of the FDM fabricated samples. According to the distinct trends seen between processed (3D printed) and unprocessed samples (cutting coupons from the as-received filaments), it can be concluded that all the processed tested samples generally follow a similar trend. However, the comparison between processed and unprocessed ABS samples shows that the FDM has reduced the magnitude of both storage and loss moduli regardless of the combination of process parameters used.

As it is discussed in section 3.6, damping ability of a viscoelastic material is representing by tan δ. Based on the equation 3-7, the variation of tan δ as a function of temperature is obtained for the ABS samples and presented in Figure 4-6. This graph with its zoomed view, is also providing useful information on the transition of mechanical properties between glassy and rubbery material; namely through the glass transition temperature, denoted as $T_g$. Glass transition temperature serves as an important material property limiting thermal performance of thermoplastic parts in practice. It is common to identify/measure $T_g$ via the onset of dropping point of $Temperature - E'$ curve, the peak of $Temperature - E''$ curve, or the peak of tan δ curve. In this work, the latter option was used to measure the glass transition temperature. Thus, Table 4-1 is presenting the values of $T_g$ linked to each FDM process condition as in Table 3-4.
Figure 4-4 The variation of the storage modulus versus temperature for the test specimens
Figure 4-5 The variation of the loss modulus versus temperature for the test specimens
Figure 4-6 The variation of tan delta versus temperature for the test specimens, with the more detailed view of the variation in the range of 110°C to 130 °C
Table 4-1 Values of glass transition temperature measured by DMA technique

<table>
<thead>
<tr>
<th>Sample</th>
<th>$T_g$ (°C)</th>
<th>sample</th>
<th>$T_g$ (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>119.466</td>
<td>9</td>
<td>119.268</td>
</tr>
<tr>
<td>2</td>
<td>119.363</td>
<td>10</td>
<td>119.682</td>
</tr>
<tr>
<td>3</td>
<td>120.578</td>
<td>11</td>
<td>119.131</td>
</tr>
<tr>
<td>4</td>
<td>119.156</td>
<td>12</td>
<td>118.986</td>
</tr>
<tr>
<td>5</td>
<td>119.608</td>
<td>13</td>
<td>118.918</td>
</tr>
<tr>
<td>6</td>
<td>119.178</td>
<td>14</td>
<td>119.771</td>
</tr>
<tr>
<td>7</td>
<td>119.711</td>
<td>15</td>
<td>117.984</td>
</tr>
<tr>
<td>8</td>
<td>118.667</td>
<td>16</td>
<td>118.514</td>
</tr>
<tr>
<td>Unprocessed ABS filament</td>
<td></td>
<td></td>
<td>112.854</td>
</tr>
</tbody>
</table>

According to the values presented in Table 4-1, it can be concluded that the FDM increases the magnitude of glass transition temperature compared to the unprocessed ABS, regardless of the combination of process parameters used. More specifically, the FDM processed parts stay longer in the glassy region in comparison to unprocessed parts. For instance, according to Table 4-1, the glass transition temperature has jumped from 112.8°C for unprocessed ABS filament to 120.5 °C under sample 3 (i.e., a 6% increase). Consequently, it can be induced that the FDM process could increase the stability of fabricated parts in higher working temperatures.
Figure 4-7 provides a detailed view of the effect of each process parameter on the glass transition temperature of the FDM processed parts. Based on visual inspection of Figure 4-7, it would hard to precisely rank the parameters based on their effect on the response variable (in this case $T_g$). However, it could be roughly said that the raster orientation is the most influential factor to change the glass transition temperature. The 90° raster orientation has given the highest glass transition temperature, while increasing the raster orientation from 0° up to 45° enhances the $T_g$. Using a bi-directional raster orientation ($\pm 45^\circ$) could not improve the stability in higher working temperature. A higher value of the glass transition temperature was obtained when the layer height was at 130 microns. The maximum $T_g$ for the FDM processed part was achieved when the nozzle temperature was set at 290°C. By increasing the nozzle temperature above this point, the glass transition temperature decreased. Increasing the deposition speed is not varying the glass transition temperature in a linear manner. The deposition speed of 3000 mm/min maximizes the $T_g$, after which it is decreased.

In order to determine the effect of selected process parameter on the glass transition temperature more systematically, a ‘Lenth’s approach’ was employed. Lenth’s method, first developed by Russell V. Lenth, is a powerful tool to analyze costly experiments with a single replicate factorial design [89-90].
Figure 4.7 The variation of glass transition temperature of FDM processed ABS as a function of: (a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed

Assuming a factorial design, with \( m \) effects considering both factors and interactions, denoted by \( c_1, c_2, \ldots, c_m \), Lenth’s method performs the effect analyses by using a numerical value called the Pseudo Standard Error (PSE). It should be noted that for a \( 2^k \) factorial design, \( m \) is equal to \( 2^k - 1 \).

\[
PSE = 1.5 \times \text{median}(|c_j|; |c_j| < 2.5S_0)
\]  

(4-1)

Where

\[
S_0 = 1.5 \times \text{median}(|c_j|)
\]  

(4-2)
According to the Lenth’s method, when there is no sufficient information on repeats of a test, PSE could be a reasonable measure to estimate the Standard Error. Margin of Error (ME) is the final factor used by this method to compare factor effects:

\[ ME = \frac{t_{\alpha/2}}{d} PSE \]  (4-3)

Where \( t_{\alpha/2} \) is the t-distribution with the significance level of \( \alpha \) and the degree of freedom of \( d = \frac{m}{3} \). Finally, for a specific factor if the absolute value of an effect is greater than \( ME \), that factor is considered effective (statistically significant).

Table 4-2 Lenth’s method of factor analysis for glass transition temperature; the values for factor levels correspond to the average of response under each corresponding level according to 4-1; the physical values of factor levels are given in Table 3-3

<table>
<thead>
<tr>
<th>Level</th>
<th>Raster orientation</th>
<th>Layer height</th>
<th>Temperature</th>
<th>Deposition speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>118.8</td>
<td>119.3</td>
<td>119.1</td>
<td>119.5</td>
</tr>
<tr>
<td>2</td>
<td>119.6</td>
<td>119.5</td>
<td>119</td>
<td>119</td>
</tr>
<tr>
<td>3</td>
<td>119.3</td>
<td>119.4</td>
<td>119.6</td>
<td>119.6</td>
</tr>
<tr>
<td>4</td>
<td>119.3</td>
<td>118.8</td>
<td>119.4</td>
<td>118.9</td>
</tr>
<tr>
<td>Delta</td>
<td>0.8</td>
<td>0.7</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td>ME threshold</td>
<td>0.515</td>
<td>0.515</td>
<td>0.515</td>
<td>0.515</td>
</tr>
</tbody>
</table>

Table 4-2 represents the mean value of \( T_g \) for under each factor, based on Figure 4-7. The delta parameter that is added to this table as the difference between the maximum and minimum value of each column and is considered as the factor effect. The Lenth’s parameter
(ME threshold) has been calculated in this table by employing equations 4-1 to 4-3. Comparing the Delta values with each corresponding threshold, it can be concluded that the raster orientation is ranked above all other factors, followed by the feeding rate, layer height, and nozzle temperature to control glass transition temperature in FDM of ABS parts.

Concerning the trends of viscoelastic moduli versus temperature for the FDM processed and unprocessed ABS samples (i.e. Figures 4-4 and 4-5), distinct trends can be seen in both processed and unprocessed samples as function of temperature increase. This is happening due to the increase in the ability of polymer molecular chains to move freely as a result of heating up the samples, hence leading to a decrease in the modulus (known as second order transitions). However, after a drastic decrease in the values of storage modulus, a slight increase happens due to entanglement of molecules to each other. Then at glass transition temperature, the amorphous parts of the thermoplastic structure start melting, and more large-scale motions would occur, leading to a much more noticeable drop in the storage modulus occurs.

Moreover, the decrease in the value of storage modulus due to the FDM process is unavoidable. As an instance, according to Figure 4-4, an average reduction of 40% is observed on the storage modulus when pooling all processes samples. This reduction varies from 15% to 62% corresponding to the experiments (Samples) 2 and 9, respectively. However, at a specific working temperature e.g. 100°C, there is an average reduction of 25% in the storage modulus due to the FDM process.

Similarly, the same trends can be seen while measuring the loss modulus of 3D printed ABS samples. As it is shown in in Figure 4-5, regardless of the assigned values of the process parameters, the FDM process decreases the loss modulus of fabricated parts. For instance, at 40°C the loss modulus has a decrease of 11% - 56% as a result of all FDM process conditions at different working temperatures. The reduction at 40°C (as a nominal working temperature example) has an average value of 33.5%. Nevertheless, the reduction increases drastically and reaches to the average value of 60.7% at working temperature of 100°C. Regardless of the selected process parameters, on average, it is interesting to notice that the FDM fabricated
samples heated up to 100°C show a lower viscos behavior (represented by the loss modulus) compared to the samples tested at 40°C. Although the FDM process seems to unavoidably decrease the storage and loss moduli of the printed parts, by selecting a suitable set of process parameters, this reduction can be minimized.

Figures 4-8 and 4-9 depict the relationship between process parameters and the reductions in dynamic mechanical moduli at two specific working temperatures; including 40°C and 100°C. As seen, the relationship between response modulus and process parameters is nonlinear and highly depending on the working temperature. Owing to the complex nature of this additive manufacturing optimization, an artificial neural network (ANN) was next used as the modelling tool. As reviewed in Chapter 3, high capabilities of ANN in prediction, optimization, and data classification has lead the researchers to frequently employ this method as a robust modelling tool in different applications [91].
Figure 4-8 Percentage of reduction in storage modulus as a function of FDM process parameter: (a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed. The black line and grey line represent the average reduction in storage modulus at 40 °C and 100 °C respectively. The values for factor levels correspond to the average of response under each corresponding level according to Figure 4-4; the physical values of factor levels are given in Table 3-3.
Figure 4-9 Percentage of reduction in loss modulus as a function of FDM process parameter: (a) Raster orientation; (b) Layer height; (c) Nozzle temperature; (d) Deposition speed. The black line and grey line represent the average reduction in loss modulus at 40 °C and 100 °C respectively. The values for factor levels correspond to the average of response under each corresponding level according to Figure 4-5; the physical values of factor levels are given in Table 3-3.
Artificial neural network, as a knowledge-based modelling approach needs a comprehensive data set which is large enough to capture the relationship between inputs and outputs. In order to provide an adequate information to model the dynamic mechanical responses of FDM fabricated ABS parts, the moduli were collected at working temperature steps of 5°C under each process condition (i.e. discretization of response curves in Figures 4-4 and 4-5). For each of the storage and loss modulus responses, a separate neural network architecture was designed (Figure 4-10). The neural networks developed are multi-layer perceptron, including input layer, hidden layer and output layer as outlined in section 3.8.1.

Figure 4-10 The developed neural network architectures to predict the viscoelastic properties of FDM processed ABS plates under various thermal ambient (working) conditions: (a) 5-9-1 architecture to approximate storage modulus (b) 5-7-1 architecture to approximate loss modulus
As explained in section 3.8.1, finding an adequate number of neurons in input and output layers is not challenging. Generally, number of variables in input layer is equal to the number of independent variables which are the focus of a given study; and the output layer contains actual physical response variables. In this research, although the original experimental layout was designed through the Taguchi method by considering four independent variables (Shown in Table 3-3) the working temperature was also taken into account as an input variable in each of the neural network architectures as in Figure 4-10.

Generically, hidden neurons are the complex computing units of neural network architectures and all the weights and transfer functions are applied on the neurons in hidden layer(s). Thus, neural networks with higher number of hidden layers are normally more capable to capture more complex relationships between input and output points. However, increasing the number of hidden layer and number of neurons in each of them would drastically increase the computational cost of the developed model. In fact, a successful ANN model is the one which can describe all the relationship between data points with a minimum number of hidden layers and neurons. Moreover, there is no universal rule of thumb to configure the best number of hidden neurons; and the conventional approach to find the optimum value is mostly based on trial and error. Nevertheless, it has been reported [83] that usually networks with one to two hidden layers have been mostly successful in different applications.

In this research, after performing a series of training algorithms and testing various ANN architectures the optimum model was selected. The considered ANN structures were compromising various number of neurons (ranging from 1-15) under various number of hidden layers (ranging from 1-3). Finally, as shown in Figure 4-12, it was concluded that using one hidden layer in each neural network would be adequate for the given application. The network selected to predict the storage modulus had 9 hidden neurons. However, the network selected to approximate the loss modulus contained 7 hidden neurons. The procedure of selecting the best network to approximate the modulus, was an iterative process. Three main steps of training, validation and testing were chosen to evaluate each network performance and report the best network configuration.
As described in section 3.8, the training step is aimed to adjust the weights assigned to the connections in a given network by minimizing the prediction error. While, the validation and test steps are aimed to evaluate the quality of the fitted (trained) model. Typically, the goodness of fit is assessed by using the mean squared error value (a.k.a MSE). The validation step evaluates the prediction error in model selection while the testing step estimates the generalized error of the final fitted model [92]. In this research, all the data points, except one experimental run (number 9) were used to build the storage modulus and loss modulus networks. The latter experimental run was selected randomly not to be used in training, testing and validation steps. Instead, the data points corresponding to the test 9 were used to evaluate the robustness of the final developed model and predict the response of this experimental run.

The training algorithm was performed on 60% of randomly selected data points via Levenberg-Marquardt algorithm. The testing-validation for each network was performed using a 20% - 20% data portion.

The developed network to approximate the storage modulus showed an acceptable performance represented by the coefficient of correlation (R). The R-values corresponding to training, validation, and testing, respectively, equaled to 0.99317, 0.99256, and 0.99503. Figure 4-11 illustrates the network performance in detail. This designed network was then employed to predict the storage modulus under the run 9 configuration. Figure 4-12 depicts the actual values versus the simulated values of the material response under run 9.
Figure 4-11 The performance of the developed 5-9-1 neural network to approximate the storage modulus of 3D printed parts.
As shown by Figure 4-12, the developed network is highly usable to predict the storage modulus of the untested sample. Consequently, this network could be used to approximate the response of FDM processed ABS parts and eventually optimize the process parameters using e.g. a PSO method (results to be presented later in the same section).

Similarly, a 5-7-1 network architecture shown in Figure 4-10-b was selected to predict the loss modulus of FDM fabricated ABS samples. The network performance is illustrated in Figure 4-13. The same data points, which were used to train the 5-9-1 network, also trained this network via Levenberg-Marquardt algorithm. Similar to the network designed to study the storage modulus, this network used 60% of provided data points randomly for training purpose. 20% of the rest of the data points were used for validation and 20% for the testing.
The final verification of the network performance was completed by evaluating the capability of the developed network under untested condition 9 (Figure 4-14).

Figure 4-13- The performance of the developed 5-7-1 neural network to approximate the loss modulus in training, validation and testing.
Considering the acceptable performance of the developed networks to predict the viscoelastic material properties, further simulations of untested FDM point were run by changing the layer height from 50 μm to 300 μm, the nozzle temperature from 250°C to 310°C and the deposition speed from 1000 mm/minute to 4000 mm/minute at each level of raster orientation. The working temperature was varied between 40°C to 140°C. Figure 4-15 to Figure 4-17 represent the simulated storage modulus response surface as a function of process parameters at working temperature of 40°C.

According to Figure 4-15(a), during printing of samples with 0° raster orientation, increasing the nozzle temperature decreases the general trend of storage modulus response at 40°C. However, as shown in Figure 4-15(b) increasing the nozzle temperature, first decreases and then increases the storage modulus. Moreover, both mentioned figures show that at higher
values of the layer height, the storage modulus would be higher. This trend is also visible with printing at 45° raster orientation, as depicted by Figure 4-15(c). According to Figure 4-15(c), the effect of nozzle temperature on the general trend of storage modulus based on the layer height and deposition speed at raster orientation of 45° is totally nonlinear (response surfaces cross each other, indicating high interaction of process parameters). Finally, as illustrated in Figure 4-15(d), at the raster orientation of ±45°, regardless of the value assigned to the nozzle temperature, the higher the layer height, the higher the storage modulus.
Figure 4-15 - Simulated response of the storage modulus numeral network at working temperature of 40 °C and fixed nozzle temperature (shown by different colors); (a) at 0° raster orientation, (b) at 90° raster orientation, (c) at 45° raster orientation, (d) at ±45° raster orientation; the yellow surface represents the lowest level of the nozzle temperature and the pink surface represents the nozzle temperature highest level.
As it is illustrated in Figure 4-16, the effect of layer height on the relationship between nozzle temperature, deposition speed with the storage modulus response is very similar while printing at 0° and 90° raster orientations. For both cases, the lower value of nozzle temperature maximizes the storage modulus, regardless of the values assigned to layer height and deposition speed. However, when parts are being processed at 45° and ±45° raster orientations, the relationship between parameters changes. However, for both cases, similar to printing at 0° and 90° raster orientations, the lowest level of the layer height factor provides the lowest storage modulus. The effect of nozzle temperature on the storage modulus at raster orientation of 45° is completely different with that of ±45°. At 45°, increasing the nozzle temperature first decreases and then increases the modulus. But at ±45°, higher temperature values always tend to result in higher storage modulus. When parts are processed at 0° and 90° raster orientations, the faster (speed) deposition of melted thermoplastic provides higher storage modulus. But, when processing parts at 45° and ±45° of raster orientations, change in deposition speed does not drastically change the storage modulus.
Figure 4-16 Simulated response of the storage modulus network at fixed layer heights (varying from 50 μm to 300 μm and categorized by different colors): (a) at 0° raster orientation, (b) at 90° raster orientation, (c) at 45° raster orientation, (d) at ±45° raster orientation; the yellow surface represents the lowest level of the layer height and the pink surface represents the layer height highest level.
According to Figure 4-17 (a), for parts fabricated with 0° raster orientation, it is predicted that the storage modulus at 40°C decreases with increasing the nozzle temperature. Nevertheless, the increase in deposition speed will increase the modulus. The effect of deposition speed on the predicted trend between storage modulus, layer height and nozzle temperature for ABS samples fabricated at 90° raster orientation is similar to the one at 0° raster orientation. At all deposition speeds with 90° raster orientation, increasing the layer height first increase and then decrease the storage modulus at 40°C. Furthermore, increasing the nozzle temperature at both 0° and 90°, regardless of other parameters, decreases the storage modulus. The higher deposition speed at raster orientation of 45° would result in higher storage modulus at 40°C. The FDM process with raster orientation of ±45° is seen to yield a more complicated and nonlinear relationship between inputs and output of the process.
Figure 4-17 Simulated response of the storage modulus by neural network at working temperature of 40 °C and at fixed deposition speed (varying from $1000 \text{ mm/min}$ to $4000 \text{ mm/min}$ and categorized by different colors): (a) at $0^\circ$ raster orientation, (b) at $90^\circ$ raster orientation, (c) at $45^\circ$ raster orientation, (d) at $\pm45^\circ$ raster orientation; the yellow surface represents the lowest level of the nozzle temperature and the pink surface represents the nozzle temperature highest level.
Owing to the complicated relationship between the process parameter and the high degree of interactions between them, on one hand, and dependency of the properties on the working temperature, on the other hand, performing a nonlinear optimization of the process would be vital for FDM designers to ensure acceptable performance of the printed parts under a given working condition (application). Accordingly, the optimum set of process parameters would be the one at which the fabricated part shows the highest value of storage or loss modulus. Here, by employing the PSO method (as reviewed in section 3.9), the optimum set of process parameters at each working temperature condition was obtained. It should be noted that, prior to the optimization process, the data points were transformed to become between 0 and 1.

The PSO optimization algorithm was performed via MATLAB R2016b using 100 particles in each swarm. In order to end the iterating process, the maximum number of iterations was set to be 1000 and the function tolerance was set to be $1 \times 10^{-25}$. The minimum and maximum inertia weights were chosen to be 0.1 and 1.1, respectively.

The optimization algorithm was operated at each working temperature for both storage and loss moduli. The obtained optimum values of the process parameters along with the maximum achievable storage modulus are presented in Table 4-3. Table 4-4 also illustrates the optimization results for the loss modulus. A graphical representation of these values is also presented in Appendix A. This graphical representation could be used as a simple tool for manufacturer to select the process parameters straightforwardly.
Table 4-3 The obtained optimum values of the process parameters using PSO on E’ at each under each working temperature

<table>
<thead>
<tr>
<th>R*</th>
<th>LH*</th>
<th>NT*</th>
<th>DS*</th>
<th>WT*</th>
<th>E’*</th>
<th></th>
<th>R*</th>
<th>LH*</th>
<th>NT*</th>
<th>DS*</th>
<th>WT*</th>
<th>E’*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(μm)</td>
<td>(℃)</td>
<td>(mm/min)</td>
<td>(℃)</td>
<td>(MPa)</td>
<td></td>
<td>(μm)</td>
<td>(℃)</td>
<td>(mm/min)</td>
<td>(℃)</td>
<td>(MPa)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>310</td>
<td>1275</td>
<td>40</td>
<td>2292</td>
<td>2</td>
<td>270</td>
<td>250</td>
<td>3374</td>
<td>40</td>
<td>2227</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>310</td>
<td>1281</td>
<td>45</td>
<td>2282</td>
<td>2</td>
<td>279</td>
<td>250</td>
<td>3357</td>
<td>45</td>
<td>2285</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>310</td>
<td>1295</td>
<td>50</td>
<td>2277</td>
<td>2</td>
<td>286</td>
<td>250</td>
<td>3338</td>
<td>50</td>
<td>2199</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1464</td>
<td>55</td>
<td>2263</td>
<td>2</td>
<td>288</td>
<td>250</td>
<td>3320</td>
<td>55</td>
<td>2172</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1527</td>
<td>60</td>
<td>2234</td>
<td>2</td>
<td>292</td>
<td>250</td>
<td>3314</td>
<td>60</td>
<td>2136</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1567</td>
<td>65</td>
<td>2193</td>
<td>2</td>
<td>299</td>
<td>250</td>
<td>3318</td>
<td>65</td>
<td>2093</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1575</td>
<td>70</td>
<td>2141</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3332</td>
<td>70</td>
<td>2046</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1548</td>
<td>75</td>
<td>2099</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3344</td>
<td>75</td>
<td>2003</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1484</td>
<td>80</td>
<td>2058</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3341</td>
<td>80</td>
<td>1972</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>1378</td>
<td>85</td>
<td>2033</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3314</td>
<td>85</td>
<td>1973</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>76</td>
<td>310</td>
<td>1211</td>
<td>90</td>
<td>2039</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3268</td>
<td>90</td>
<td>2011</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>87</td>
<td>310</td>
<td>1000</td>
<td>95</td>
<td>2080</td>
<td>2</td>
<td>300</td>
<td>250</td>
<td>3229</td>
<td>95</td>
<td>2066</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>94</td>
<td>310</td>
<td>1000</td>
<td>100</td>
<td>2125</td>
<td>2</td>
<td>300</td>
<td>252</td>
<td>3263</td>
<td>100</td>
<td>2105</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>102</td>
<td>310</td>
<td>1000</td>
<td>105</td>
<td>2128</td>
<td>2</td>
<td>300</td>
<td>253</td>
<td>3081</td>
<td>105</td>
<td>2088</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>118</td>
<td>310</td>
<td>1000</td>
<td>110</td>
<td>1945</td>
<td>2</td>
<td>300</td>
<td>253</td>
<td>2841</td>
<td>110</td>
<td>1817</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>268</td>
<td>3956</td>
<td>115</td>
<td>922</td>
<td>2</td>
<td>300</td>
<td>251</td>
<td>2564</td>
<td>115</td>
<td>607</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>269</td>
<td>3941</td>
<td>120</td>
<td>71</td>
<td>2</td>
<td>300</td>
<td>252</td>
<td>2601</td>
<td>120</td>
<td>37</td>
<td></td>
</tr>
</tbody>
</table>
Table 4-3 Continued

<table>
<thead>
<tr>
<th>R*</th>
<th>LH* (µm)</th>
<th>NT* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E'* (MPa)</th>
<th>R*</th>
<th>LH* (µm)</th>
<th>NT* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E'* (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>175</td>
<td>310</td>
<td>1237</td>
<td>125</td>
<td>6</td>
<td>4</td>
<td>300</td>
<td>310</td>
<td>2023</td>
<td>40</td>
<td>1887</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>297</td>
<td>1000</td>
<td>130</td>
<td>2</td>
<td>4</td>
<td>177</td>
<td>296</td>
<td>1000</td>
<td>45</td>
<td>1692</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>296</td>
<td>1000</td>
<td>135</td>
<td>2</td>
<td>4</td>
<td>194</td>
<td>297</td>
<td>1000</td>
<td>50</td>
<td>1573</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>298</td>
<td>1048</td>
<td>140</td>
<td>2</td>
<td>4</td>
<td>207</td>
<td>297</td>
<td>1000</td>
<td>55</td>
<td>1443</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>310</td>
<td>4000</td>
<td>40</td>
<td>2111</td>
<td>4</td>
<td>220</td>
<td>298</td>
<td>1000</td>
<td>60</td>
<td>1312</td>
</tr>
<tr>
<td>3</td>
<td>235</td>
<td>250</td>
<td>4000</td>
<td>45</td>
<td>2092</td>
<td>4</td>
<td>239</td>
<td>297</td>
<td>1000</td>
<td>65</td>
<td>1196</td>
</tr>
<tr>
<td>3</td>
<td>242</td>
<td>250</td>
<td>4000</td>
<td>50</td>
<td>2056</td>
<td>4</td>
<td>300</td>
<td>292</td>
<td>1000</td>
<td>70</td>
<td>1131</td>
</tr>
<tr>
<td>3</td>
<td>251</td>
<td>250</td>
<td>4000</td>
<td>55</td>
<td>2004</td>
<td>4</td>
<td>300</td>
<td>292</td>
<td>1000</td>
<td>75</td>
<td>1130</td>
</tr>
<tr>
<td>3</td>
<td>265</td>
<td>250</td>
<td>4000</td>
<td>60</td>
<td>1944</td>
<td>4</td>
<td>300</td>
<td>293</td>
<td>1000</td>
<td>80</td>
<td>1222</td>
</tr>
<tr>
<td>3</td>
<td>287</td>
<td>250</td>
<td>4000</td>
<td>65</td>
<td>1886</td>
<td>4</td>
<td>300</td>
<td>294</td>
<td>1000</td>
<td>85</td>
<td>1423</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>70</td>
<td>1848</td>
<td>4</td>
<td>167</td>
<td>310</td>
<td>1000</td>
<td>90</td>
<td>1696</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>75</td>
<td>1817</td>
<td>4</td>
<td>167</td>
<td>310</td>
<td>1000</td>
<td>95</td>
<td>1931</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>80</td>
<td>1810</td>
<td>4</td>
<td>173</td>
<td>310</td>
<td>1000</td>
<td>100</td>
<td>2051</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>85</td>
<td>1842</td>
<td>4</td>
<td>190</td>
<td>310</td>
<td>1000</td>
<td>105</td>
<td>2060</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>90</td>
<td>1910</td>
<td>4</td>
<td>300</td>
<td>310</td>
<td>2023</td>
<td>40</td>
<td>1887</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3774</td>
<td>95</td>
<td>2008</td>
<td>4</td>
<td>177</td>
<td>296</td>
<td>1000</td>
<td>45</td>
<td>1692</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3639</td>
<td>100</td>
<td>2086</td>
<td>4</td>
<td>194</td>
<td>297</td>
<td>1000</td>
<td>50</td>
<td>1573</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3577</td>
<td>105</td>
<td>2056</td>
<td>4</td>
<td>207</td>
<td>297</td>
<td>1000</td>
<td>55</td>
<td>1443</td>
</tr>
</tbody>
</table>
Table 4.3 Continued

<table>
<thead>
<tr>
<th>R* (µm)</th>
<th>LH* (°C)</th>
<th>NT* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E** (MPa)</th>
<th>R* (µm)</th>
<th>LH* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E** (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3548</td>
<td>110</td>
<td>1620</td>
<td>4</td>
<td>229</td>
<td>310</td>
<td>1000</td>
<td>110</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>310</td>
<td>1000</td>
<td>115</td>
<td>414</td>
<td>4</td>
<td>223</td>
<td>310</td>
<td>1000</td>
<td>115</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>310</td>
<td>1000</td>
<td>120</td>
<td>22</td>
<td>4</td>
<td>300</td>
<td>310</td>
<td>1000</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3861</td>
<td>125</td>
<td>3</td>
<td>4</td>
<td>300</td>
<td>310</td>
<td>1000</td>
<td>125</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>130</td>
<td>2</td>
<td>4</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>130</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>135</td>
<td>2</td>
<td>4</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>135</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>4000</td>
<td>140</td>
<td>2</td>
<td>4</td>
<td>162</td>
<td>250</td>
<td>4000</td>
<td>140</td>
</tr>
</tbody>
</table>

*R, LH, NT, DS and WT stand for Raster orientation, Layer height, Nozzle temperature, Deposition speed and Working temperature, respectively.
Table 4-4 The obtained optimum values of the process parameters using PSO on E’’ at each working temperature

<table>
<thead>
<tr>
<th>R*</th>
<th>LH* (μm)</th>
<th>NT* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E’’* (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>4000</td>
<td>40</td>
<td>79.8</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>4000</td>
<td>45</td>
<td>78.3</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>4000</td>
<td>50</td>
<td>76.7</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>4000</td>
<td>55</td>
<td>75.3</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>310</td>
<td>4000</td>
<td>60</td>
<td>73.4</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>273</td>
<td>1000</td>
<td>65</td>
<td>80</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>70</td>
<td>99.3</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>75</td>
<td>146.7</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>80</td>
<td>188.8</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>85</td>
<td>208.7</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>90</td>
<td>204.5</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>95</td>
<td>189.6</td>
</tr>
<tr>
<td>1</td>
<td>50</td>
<td>250</td>
<td>3548</td>
<td>100</td>
<td>239.6</td>
</tr>
<tr>
<td>1</td>
<td>98</td>
<td>250</td>
<td>3967</td>
<td>105</td>
<td>334</td>
</tr>
<tr>
<td>1</td>
<td>110</td>
<td>250</td>
<td>4000</td>
<td>110</td>
<td>448.5</td>
</tr>
<tr>
<td>1</td>
<td>115</td>
<td>254</td>
<td>4000</td>
<td>115</td>
<td>442.2</td>
</tr>
<tr>
<td>1</td>
<td>284</td>
<td>278</td>
<td>4000</td>
<td>120</td>
<td>176.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>R*</th>
<th>LH* (μm)</th>
<th>NT* (°C)</th>
<th>DS* (mm/min)</th>
<th>WT* (°C)</th>
<th>E’’* (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>54</td>
<td>277</td>
<td>4000</td>
<td>40</td>
<td>74.1</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>276</td>
<td>4000</td>
<td>45</td>
<td>73.9</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>50</td>
<td>90.5</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>250</td>
<td>1000</td>
<td>55</td>
<td>91.2</td>
</tr>
<tr>
<td>2</td>
<td>278</td>
<td>250</td>
<td>1000</td>
<td>60</td>
<td>84.4</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>310</td>
<td>4000</td>
<td>65</td>
<td>80.2</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>310</td>
<td>4000</td>
<td>70</td>
<td>85.6</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>75</td>
<td>98.2</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>80</td>
<td>107.6</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>85</td>
<td>107.4</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>296</td>
<td>4000</td>
<td>90</td>
<td>129.6</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>297</td>
<td>4000</td>
<td>95</td>
<td>163.1</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>298</td>
<td>4000</td>
<td>100</td>
<td>213.8</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>298</td>
<td>4000</td>
<td>105</td>
<td>313.5</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>279</td>
<td>4000</td>
<td>110</td>
<td>448.9</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>282</td>
<td>4000</td>
<td>115</td>
<td>407.6</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>310</td>
<td>4000</td>
<td>120</td>
<td>89.4</td>
</tr>
<tr>
<td>R*</td>
<td>LH*</td>
<td>NT*</td>
<td>DS*</td>
<td>WT*</td>
<td>E***</td>
</tr>
<tr>
<td>----</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>-------</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>283</td>
<td>4000</td>
<td>125</td>
<td>34</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>285</td>
<td>4000</td>
<td>130</td>
<td>17.2</td>
</tr>
<tr>
<td>1</td>
<td>186</td>
<td>280</td>
<td>4000</td>
<td>135</td>
<td>14.7</td>
</tr>
<tr>
<td>1</td>
<td>148</td>
<td>281</td>
<td>4000</td>
<td>140</td>
<td>14.4</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>40</td>
<td>117.7</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>45</td>
<td>114.9</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>50</td>
<td>111</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>55</td>
<td>105.2</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>60</td>
<td>97</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>65</td>
<td>86.2</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>70</td>
<td>76</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>75</td>
<td>86.1</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>1000</td>
<td>80</td>
<td>92.4</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>1000</td>
<td>85</td>
<td>93.9</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>1000</td>
<td>90</td>
<td>96.9</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>250</td>
<td>3364</td>
<td>95</td>
<td>116.7</td>
</tr>
<tr>
<td>3</td>
<td>258</td>
<td>310</td>
<td>1000</td>
<td>95</td>
<td>116.7</td>
</tr>
<tr>
<td>3</td>
<td>255</td>
<td>310</td>
<td>1000</td>
<td>100</td>
<td>158.2</td>
</tr>
<tr>
<td>3</td>
<td>251</td>
<td>310</td>
<td>1000</td>
<td>105</td>
<td>251.9</td>
</tr>
<tr>
<td>R*</td>
<td>LH* (μm)</td>
<td>NT* (°C)</td>
<td>DS* (mm/min)</td>
<td>WT* (°C)</td>
<td>E*** (MPa)</td>
</tr>
<tr>
<td>-----</td>
<td>-----------</td>
<td>-----------</td>
<td>---------------</td>
<td>----------</td>
<td>------------</td>
</tr>
<tr>
<td>3</td>
<td>102</td>
<td>250</td>
<td>4000</td>
<td>110</td>
<td>412.5</td>
</tr>
<tr>
<td>3</td>
<td>67</td>
<td>250</td>
<td>4000</td>
<td>115</td>
<td>458.6</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>120</td>
<td>164.1</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>125</td>
<td>37.3</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>130</td>
<td>21.6</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>4000</td>
<td>135</td>
<td>18.2</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>250</td>
<td>3911</td>
<td>140</td>
<td>16.7</td>
</tr>
</tbody>
</table>

*R, LH, NT, DS and WT stand for Raster orientation, Layer height, Nozzle temperature, Deposition speed and Working temperature, respectively.
4.4 Summary of findings

In this chapter, the variation of viscoelastic response of 3D printed ABS samples at a large range of working temperatures as a function of four considered FDM process parameters was studied. The experimental layout was designed via Taguchi orthogonal array. Due to the involvement of large number of process parameters with complex interacting effects on the behavior of FDM processed part, conventional statistical analyses were substituted by empirical modeling techniques. Namely, the artificial neural network models were developed to capture the relationships between process parameters and the viscoelastic properties of the 3D-printed ABS under full range of working temperatures. Finally, optimum values corresponding to the process parameters were obtained via the PSO method. The optimum values were reported for various working temperatures, maximizing the storage modulus or loss modulus depending on a given application. Results clearly showed that there is no single optimum process condition that can optimize the printed part performance at all working temperature conditions.
Chapter 5: Characterization of the tensile properties

5.1 Overview

Chapter 4 outlined the effect of selected process parameters on the dynamic mechanical properties of the FDM fabricated ABS samples. The artificial neural network technique and particle swarm optimization method were coupled together to find the optimum process parameters to achieve the best dynamic mechanical performance of the printed parts under different working temperature conditions. This chapter will characterize the tensile characteristics of FDM processed parts. Specifically, the relationship between process parameters and the quasi-static mechanical behavior of 3D printed samples will be studied, while linking the observed macro-level measurements and simulations to the underlying mechanisms at meso/micro levels.

5.2 Experimental

Displacement at the rate of $1 \frac{mm}{minute}$ was applied on each 3D printed test coupon and the force response of the material was recorded. The loading was continued under breakage point of each sample. Accordingly, it was of interest to measure the nominal tensile strength, percent elongation at break, and modulus of elasticity of the FDM fabricated ABS samples.
5.2.1 Sample shape and geometry

Depicted in Figure 5-1, the dog bone tensile test samples were modeled based on ASTM D5937 using Solidworks2015 and sliced into tiny 2D layer with simplify 3D. Similar to chapter 4, the test coupons were fabricated with the modified 3D printer described in section 3.3.

![Figure 5-1 The CAD model corresponding to the tensile test specimens; (a) Dimensions (in mm) and geometric specifications (b) the final shape of the sample](image)

Once the CAD model was transferred to the makerge M2 3D printer, the FDM process with the assigned controlled and fixed factors (per sections 3-3 and 3-4) was started. In order to keep the repeatability under each processing condition, each tensile test was repeated three times and all the required specimens were printed entirely in one FDM run. Example of the final prepared tensile test coupons is illustrated in Figure 5-2.
5.3 Results and discussions

The general relationship between the force (stress) and displacement (strain) for all test coupons was anticipated to follow a similar trend. However, owing to the change in process parameters, specifically raster orientation (analogous to reinforcement direction in composite materials), the exact magnitude of tensile properties of the FDM fabricated parts was expected to vary notably. As an illustrative example, Figure 5-3 shows the material tensile response under the experimental condition #14 (per Table 3-4). The nominal tensile strength, Young’s modulus and percent elongation at the break from each tensile test can be calculated by[93].

Nominal tensile strength = \[ \frac{\text{Maximum bearing load}}{\text{Initial crosssectional area}} \]  

% Elongation at break = \[ \frac{\text{Extension at break}}{\text{Original gauge length}} \times 100 \]  

Modulus of elasticity = Slope of the curve in initial linear region
Given Figure 5-3, the material response is initially linear. By increasing the extension, the cracks start growing in each test specimen, which results in an inelastic response. The elastic behavior portion ends at the maximum stress value (referred to as tensile stress). Afterwards, the deformation continues without significant increase in stress until breakage point. This overall trend in each sample would occur as a result of de-bonding between adjacent deposited roads. Regardless of the exact values of the tensile strengths, all other FDM experimental runs, described in Table 3-4, indicated a similar material behavior. As represented in Figure 5-3, the behavior of each test coupon, specifically in the linear region and regarding the maximum tensile strain, was highly repeatable. Results of the tensile characterization for all samples are summarized in Table 5-1.

In order to illustrate the effect of each process parameter on the tensile properties of FDM fabricated parts, the main effect plots are provided further in Figure 5-4.
Table 5-1 – The experimental results of FDM-ABS parts under experimental layout described in Table 3-4

<table>
<thead>
<tr>
<th>Run</th>
<th>Nominal tensile strength</th>
<th>Percent of Elongation</th>
<th>Young's Modulus (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>rep1</td>
<td>rep2</td>
<td>rep3</td>
</tr>
<tr>
<td>1</td>
<td>30.87</td>
<td>33.2</td>
<td>31.8</td>
</tr>
<tr>
<td>2</td>
<td>33.01</td>
<td>32.3</td>
<td>32.7</td>
</tr>
<tr>
<td>3</td>
<td>31.08</td>
<td>31.5</td>
<td>31.3</td>
</tr>
<tr>
<td>4</td>
<td>28.8</td>
<td>28.8</td>
<td>28.8</td>
</tr>
<tr>
<td>5</td>
<td>30.6</td>
<td>29.9</td>
<td>29.9</td>
</tr>
<tr>
<td>6</td>
<td>27.9</td>
<td>30.9</td>
<td>26.9</td>
</tr>
<tr>
<td>7</td>
<td>25.0</td>
<td>26.1</td>
<td>25.7</td>
</tr>
<tr>
<td>8</td>
<td>21.18</td>
<td>19.6</td>
<td>19.01</td>
</tr>
<tr>
<td>9</td>
<td>28.31</td>
<td>27.1</td>
<td>28.6</td>
</tr>
<tr>
<td>10</td>
<td>24.32</td>
<td>22.2</td>
<td>24.12</td>
</tr>
<tr>
<td>11</td>
<td>27.23</td>
<td>23.0</td>
<td>27.29</td>
</tr>
<tr>
<td>12</td>
<td>23.36</td>
<td>23.7</td>
<td>21.8</td>
</tr>
<tr>
<td>13</td>
<td>28.53</td>
<td>29.2</td>
<td>29.3</td>
</tr>
<tr>
<td>14</td>
<td>27.92</td>
<td>25.3</td>
<td>26.1</td>
</tr>
<tr>
<td>15</td>
<td>28.10</td>
<td>28.3</td>
<td>27.9</td>
</tr>
<tr>
<td>16</td>
<td>27.25</td>
<td>27.2</td>
<td>27.2</td>
</tr>
</tbody>
</table>
Figure 5-4 The effect of process parameters on; (a) Nominal tensile strength, (b) Percent elongation at break, and (C) the Young’s modulus of FDM fabricated ABS parts; for physical levels of factors, see Table 3-3.
The values for each response property under each level in Figure 5-4 correspond to the mean values in Table 5-1; the physical values of factor levels were given in Table 3-3. As depicted in Figure 5-4, the relationship between the process parameters and the behavior of the FDM fabricated parts is nonlinear and fairly complex, similar to what was concluded from the DMA analysis of the samples in Chapter 4.

According to the main effect plots of experiments in Figure 5-4, it is noted that the raster orientation is the most effective factor to control the values of nominal tensile strength (shows the highest drop in Figure 5.4(a)). After that, the layer height, nozzle temperature and deposition speed may be ranked consecutively. Moreover, by calculating the difference between the maximum and the minimum values of the average response for each factor, the same ranking can be concluded.

However, the order of effect of the same process parameters on the %elongation response is found to be quite different: the layer height is ranked first, followed by the nozzle temperature, raster orientation and deposition speed. Nevertheless, the ranking of process parameters based on their impact on the Young’s modulus response was also seen to be different: the layer height, raster orientation, deposition speed and the nozzle temperature were ranked from the most to the least effective factor for this response variable.

Considering the nature of the FDM process, there can be several conflicting phenomena at the material level that may contribute to the complex state of prediction of tensile properties of 3D printed parts as noticed above. For instance, the polymeric filaments are extruded through a hot nozzle and therefore, the material molecular chains are aligned with the direction of deposition. Accordingly, the direction of roads can highly control the strength of the FDM processed parts. On the other hand, the FDM fabricated parts are made by deposition of adjacent roads and stacking of 2D layers. Therefore, the existence of porosity in the FDM structures (specially between the roads) is not preventable. Moreover, the heating and cooling rates and heat dissipation (due to viscoelastic behavior of the material) could change the strength of the FDM processed parts. Additionally, existence of thermal residual stress in the structure of fabricated parts may result in low tensile performance.
Generally, due to the involvement of a considerable number of FDM process parameters and their interactions to build the final parts, finding an explicit relationship between process parameters and the part mechanical properties is complicated. Thus, similar to DMA modeling in Chapter 4, a artificial neural network technique was employed herein to model the processing-properties relationship of the FDM processed parts.

The main purpose to design a tensile property neural network in the context of this chapter is to be able to approximate the material stress-strain curve for any given FDM process condition. As depicted in Figure 5-5, five input variables including the raster orientation, layer height, deposition speed, nozzle temperature and extension was used to form the input layer of this ANN. The stress was selected to be the output of the neural network architecture, while input also included the applied strain at an interval of 0.01 mm. Five interconnecting neurons formed the hidden layer of the ANN.

![Diagram of artificial neural network](image)

*Figure 5-5 - The artificial neural network designed to approximate mechanical properties of FDM fabricated ABS samples*
In order to train, validate and test the developed neural network, a large number of data points including the process parameters, tensile displacement (strain) and the measured force (stress) in elastic region was extracted (Appendix B). Beyond the elastic region, the material response was rather non-repeatable (specially the breaking point) and hence was not included in the ANN training. In the elastic ANN, the strain and stress were the average values obtained from test replications. In addition, likewise Chapter 4, data points corresponding to one specific FDM condition (run #9) were not used to develop the network. Instead, this unused data set was employed to validate the performance of the final network on simulating the tensile response of the material under untested FDM process conditions. The network was trained by 60% of the data points randomly. The testing and validation steps were performed by employing 20% of the remaining data points for each. Figure 5-6 illustrates the performance of the developed neural network in training, testing and validation steps.

![Diagram showing performance of neural network](image)

**Figure 5-6** The performance of the developed neural network to predict the tensile behavior of FDM fabricated ABD samples as a function of FDM process parameters in: (a) training, (b) testing, and (c) validation
The developed 5-5-1 neural network architecture showed an acceptable performance in training, validation and testing with the R values of 0.99315, 0.99395, and 0.99337 respectively. Consequently, this network was used to predict the response of the untested run condition #9 in its elastic region. The graphical comparison between the actual measured values of test sample 9 and the simulated values is provided in Figure 5-7.

According to Figure 5-7 the developed network is robust enough to predict the tensile behavior of FDM processed parts. Consequently, an imaginary full factorial design of experiment layout considering four mentioned factors and four corresponding levels was designed. Then, the developed neural network was employed to predict the tensile behavior of the FDM ABS samples under 256 building configurations. Subsequently, for each FDM process condition, the stress response was estimated. It must be noted that to assess the strain values, the extension values are applied to samples with a fixed initial length of 39 mm. The simulation results are provided in Figures 5-8 to 5-10.

Figure 5-8 represents the variation of mechanical strength of the parts as a function of nozzle temperature and deposition speed for various levels of layer height and raster orientation. As it is depicted in Figure 5-8, the maximum strength is achieved at the highest level of deposition speed.
and nozzle temperature. The main reason of this phenomenon would go back to the heating and cooling rates that each deposited road is experiencing during FDM. Generally, an extruded thermoplastic filament dissipates its heat and solidifies rapidly during FDM. Some part of this thermal energy is absorbed by previously (adjacent) deposited filaments, which would cause local re-melting in them. As a result, the re-melted polymers of adjacent new and old roads solidify together and form a strong bonding. Thus, the higher the nozzle temperature, the bigger the melted interface area, and therefore the higher the final part strength (due to better chance of chemical bonding with no defects/voids in the interface). Additionally, it has been reported that for ABS the natural cooling process (under free convection condition) takes approximately 1750 ms to reach from 270 °C to 70°C [94]. Moreover, with the deposition speed of 1,000mm/min it takes approximately 6,600 ms to deposit a single road with the length of 110 mm. However, this deposition time reduces to 1650 ms for the deposition speed of 4,000 mm/min. Therefore, by increasing the deposition speed, the already deposited thermoplastic roads may not have enough time to completely cool down before the next road is deposited. Thus, by absorbing the same amount of thermal energy, the deposited material at higher deposition speeds could get warmer and consequently the re-melted area would be wider. Thus, increasing the deposition speed along with nozzle temperature would result in higher mechanical strength of FDM fabricated parts.

By changing the raster orientation from 0° to 90°, the length of the depositing roads decreases drastically. In fact, in deposition of samples with 90°, the adjacent roads are laying in the direction of sample width (by the size of 5mm and 10mm as in Figure 5-1). Therefore, the nozzle will start deposition of new raster before complete solidification of the deposited one. This uneven temperature gradient could also result in accumulation of thermal residual stresses and be responsible for making distortions along the direction of the deposition of the roads which is perpendicular to the loading direction. Thus, the mechanical strength of the parts fabricated with 90° raster orientation are expected to be dropped notably (Figure 5.4). The other reason for this drop under 90° raster orientation may be having more number of beads to fill a given area. Namely, by increasing the number of required roads to print a sample of given dimensions, the total inter-bead bonding area, which would be highly prone to porosity, increases and hence the overall strength of the processed part decreases.
Figure 5-8 The simulated response of FDM fabricated parts under tensile loading with: (a) R = 0° and Lh = 50 μm, (b) R = 0° and Lh = 130 μm, (c) R = 0° and Lh = 210 μm, (d) R = 0° and Lh = 300 μm, (e) R = 90° and Lh = 50 μm, (f) R = 90° and Lh = 130 μm, (g) R = 90° and Lh = 210 μm, (h) R = 90° and Lh = 300 μm, (i) R = 45° and Lh = 50 μm, (j) R = 45° and Lh = 130 μm, (k) R = 45° and Lh = 210 μm, (l) R = 45° and Lh = 300 μm, (m) R = ±45° and Lh = 50 μm, (n) R = ±45° and Lh = 130 μm, (o) R = ±45° and Lh = 210 μm, (p) R = ±45° and Lh = 300 μm.
Figure 5-8 Continued.
Figure 5-8 Continued.
The relationship between the tensile strength of FDM fabricated parts, nozzle temperature, and layer height is pictured in Figure 5-9. Generally, by increasing the raster orientation from 0° to 45° and consequently 90°, the overall tensile performance of the FDM fabricated parts decreases. The observed trend of the effect of layer height on the tensile strength of 3D printed parts is complex. On one hand, decreasing the layer height would result in increased number of deposited layer and consequently, higher value of integrity [95]. On the other hand, deposition of thinner layers in the process of 3D printing would result in requiring more number of layers to build a specific height of sample, and accordingly chance of more porous internal boundary regions.

Seen in Figure 5-9, for parts fabricated with 0° raster orientation, at lower values of deposition speed, the lower values of nozzle temperature would result in a higher strength. However, with lowering the deposition speed, the maximum nozzle temperature will provide the maximum strength. The relationship between the FDM process parameters and the tensile performance of printed parts changes drastically at raster orientation of 90°. Based on the simulated results in Figure 5-9 one can conclude that during FDM process with raster orientation of 90°, regardless of the values assigned to layer height, increasing the nozzle temperature would enhance the tensile strength. Moreover, with the raster orientation of 45° and ±45°, the strength of the FDM fabricated parts is somewhere between that of 0° and 90° cases.
Figure 5-9  The simulated response of FDM fabricated parts under tensile loading with: (a) R = 0° and speed = 1000 mm/min, (b) R = 0° and speed = 2000 mm/min, (c) R = 0° and speed = 3000 mm/min, (d) R = 0° and speed = 4000 mm/min, (e) R = 90° and speed = 1000 mm/min, (f) R = 90° and speed = 2000 mm/min, (g) R = 90° and speed = 3000 mm/min, (h) R = 90° and speed = 4000 mm/min, (i) R = 45° and speed = 1000 mm/min, (j) R = 45° and speed = 2000 mm/min, (k) R = 45° and speed = 3000 mm/min, (l) R = 45° and speed = 4000 mm/min, (m) R = ±45° and speed = 1000 mm/min, (n) R = ±45° and speed = 2000 mm/min, (o) R = ±45° and speed = 3000 mm/min, (p) R = ±45° and speed = 4000 mm/min.
Figure 5-9 Continued
Figure 5-9 Continued
Figure 5-10 presents the relationship between the tensile strength of FDM fabricated parts, deposition speed, and layer height, while the nozzle temperature is kept constant. Similar to Figure 5-10 and Figure 5-10, the 3D printed samples with 90° raster orientation are showing the minimum tensile strength. At raster orientation of 0°, when the nozzle temperature is at its lower level, the layer height and deposition speed do not effectively control the tensile strength. However, at nozzle temperature of 290°, combination of the slowest deposition speed and the thinnest layer height would result in the lowest tensile strength. Similarly, when ABS parts are manufactured at raster orientation of 90°, the relationship between the process parameters and tensile behavior is seen to be totally different compared to other raster orientations. Although, deposited parts with the raster orientation of 90° show a weak tensile behavior, the deposition with the fastest speed would achieve relatively a better strength. Typically, by decreasing the deposition speed the tensile strength drops drastically.
Figure 5-10 The simulated response of FDM fabricated parts under tensile loading with: (a) $R= 0^\circ$ and $T=250^\circ C$, (b) $R= 0^\circ$ and $T=270^\circ C$, (c) $R= 0^\circ$ and $T=290^\circ C$, (d) $R= 0^\circ$ and $T=310^\circ C$, (e) $R= 90^\circ$ and $T=250^\circ C$, (f) $R= 90^\circ$ and $T=270^\circ C$, (g) $R= 90^\circ$ and $T=290^\circ C$, (h) $R= 90^\circ$ and $T=310^\circ C$, (i) $R= 45^\circ$ and $T=250^\circ C$, (j) $R= 45^\circ$ and $T=270^\circ C$, (k) $R= 45^\circ$ and $T=290^\circ C$, (l) $R= 45^\circ$ and $T=310^\circ C$, (m) $R= \pm 45^\circ$ and $T=250^\circ C$, (n) $R= \pm 45^\circ$ and $T=270^\circ C$, (o) $R= \pm 45^\circ$ and $T=290^\circ C$, (p) $R= \pm 45^\circ$ and $T=310^\circ C$
Figure 5-10 Continued
Figure 5-10 Continued
According to the above results, it is apparent that developing explicit relationships between the FDM process parameters and the tensile response of the 3d printed ABS is highly complicated. The complex process of FDM involves several conflicting factors to form the final part, highlighting the necessity of using a powerful mathematical modeling tool such the neural network. Using the ANN, the simulated tensile behavior of FDM processed ABS samples were also analyzed statistically in this work via the Lenth’s method -- similar to section 4.3 on DMA. The results are presented in Table 5-2.

Table 5-2 The Lenth's method effect analyses of the simulated stress to expansion ratio for FDM printed samples with 39mm gauge length; the values for factor levels correspond to the average of response under each corresponding level according to neural network response per Figure 5-8 to Figure 5-10 the physical values of factor levels are given in Table 3-3.3-3

<table>
<thead>
<tr>
<th>Level</th>
<th>Raster orientation</th>
<th>Layer height</th>
<th>Nozzle Temperature</th>
<th>Deposition speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28.6</td>
<td>25.8</td>
<td>22.3</td>
<td>21.5</td>
</tr>
<tr>
<td>2</td>
<td>19.3</td>
<td>25</td>
<td>25.6</td>
<td>24.5</td>
</tr>
<tr>
<td>3</td>
<td>25.9</td>
<td>24.8</td>
<td>26.2</td>
<td>25.9</td>
</tr>
<tr>
<td>4</td>
<td>26.2</td>
<td>24.3</td>
<td>25.7</td>
<td>28</td>
</tr>
<tr>
<td>Delta</td>
<td>9.3</td>
<td>2.3</td>
<td>3.9</td>
<td>6.5</td>
</tr>
<tr>
<td>ME threshold</td>
<td>3.810527</td>
<td>3.810527</td>
<td>3.810527</td>
<td>3.810527</td>
</tr>
</tbody>
</table>

96
According to the Lenth’s analysis, the raster orientation is the most effective process parameter controlling the tensile behavior of FDM processed parts, which is aligned with earlier reports [34,53] on FDM of ABS. The deposition speed and nozzle temperature are found to be the second and third effective process parameters, respectively. Moreover, it can be concluded that the layer height is not an effective factor (at significance level of 5%) to impact the tensile behavior of the 3D printed parts in this case study. It is important to note that, in spite of the fact that the Lenth’s approach provided a reliable ranking of individual FDM process parameters, it cannot provide adequate information about the effect of interactions. Therefore, ANOVA method was next used to elaborately determine the percent of contribution of process parameters and their interactions on the tensile performance of ABS fabricated parts. Assume $y_i$ denotes the response value for each of the $n$ number of tests, considering factors $A$, $B$, $C$, $D$ with $a$, $b$, $c$, $d$ levels; $y_{xi}$ is then calculated as the average response of $i$ – th level of factor $x$. The ANOVA parameters can then be established as follows to estimate the % contribution of factors and their interaction (please see [96-97] for more details).

\[
\bar{y}_T = \frac{1}{n} \sum_{i=1}^{n} y_i \text{ (Total Average)} \quad (5-4)
\]

\[
SS_T = \sum_{i=1}^{n} (y_i - \bar{y}_L)^2 \text{ (Total sum of squares)} \quad (5-5)
\]

\[
SS_x = m \sum_{i=1}^{m} (y_{xi} - \bar{y}_L)^2 \text{ (Sum of squares corresponding to Factor } x) \quad (5-6)
\]

\[
SS_{Error} = SS_{Total} - SS_R - SS_{LH} - SS_S - SS_{NT} \text{ (Pooled error)} \quad (5-7)
\]

\[
MS_{Error} = \frac{SS_{Error}}{DOF_{Error}} \text{ (Mean squared error)} \quad (5-8)
\]

\[
SS'_x = SS_x - SS_{Error} \text{ (Pure sum of square for factor } x) \quad (5-9)
\]

\[
\% \text{ Contribution } x = \frac{SS'_x}{SS_{Total}} \text{ (Percentage of contribution for factor } x) \quad (5-10)
\]
Table 5-3 presents the ANOVA statistics corresponding to the main factors, two-way and three-way interactions, based on the predicted results obtained from the developed neural network (given in Figure 5-5). It is noteworthy that, with 256 number of tests for four independent factors with four corresponding levels for each, the critical F-value at 95% of confidence level was calculated to be 2.6. In Table 5-3, R, LH, NT and S are, respectively, the Raster orientation, layer height, nozzle temperature and deposition speed. It must be noted that the validity of ANOVA analysis directly depends on the distribution of residuals. Therefore, a residual distribution diagram (Figure 5-1) was plotted to check the normality assumption of residuals with a zero mean (having p-value greater than 0.05).
Table 5-3 ANOVA results for the simulated tensile behavior of FDM processed ABS parts (assuming a confidence level of 95%)

<table>
<thead>
<tr>
<th>Source of variation*</th>
<th>DOF</th>
<th>SS'</th>
<th>MS'</th>
<th>F-value</th>
<th>P-value</th>
<th>%Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>3</td>
<td>3063.5</td>
<td>1021.17</td>
<td>96.42</td>
<td>0.000</td>
<td>28.47</td>
</tr>
<tr>
<td>LH</td>
<td>3</td>
<td>81.1</td>
<td>27.04</td>
<td>2.55</td>
<td>0.061</td>
<td>0.75</td>
</tr>
<tr>
<td>NT</td>
<td>3</td>
<td>610.7</td>
<td>203.57</td>
<td>19.22</td>
<td>0.000</td>
<td>5.68</td>
</tr>
<tr>
<td>DS</td>
<td>3</td>
<td>1405.3</td>
<td>468.42</td>
<td>44.23</td>
<td>0.000</td>
<td>13.06</td>
</tr>
<tr>
<td>R&amp;LH</td>
<td>9</td>
<td>53.8</td>
<td>5.98</td>
<td>0.56</td>
<td>0.8222</td>
<td>0.50</td>
</tr>
<tr>
<td>R&amp;NT</td>
<td>9</td>
<td>931.5</td>
<td>103.50</td>
<td>9.77</td>
<td>0.000</td>
<td>8.66</td>
</tr>
<tr>
<td>R&amp;DS</td>
<td>9</td>
<td>838.4</td>
<td>93.15</td>
<td>8.8</td>
<td>0.000</td>
<td>7.79</td>
</tr>
<tr>
<td>LH&amp;NT</td>
<td>9</td>
<td>135.7</td>
<td>15.08</td>
<td>1.42</td>
<td>0.192</td>
<td>1.26</td>
</tr>
<tr>
<td>LH&amp;DS</td>
<td>9</td>
<td>47.2</td>
<td>5.24</td>
<td>0.5</td>
<td>0.874</td>
<td>0.44</td>
</tr>
<tr>
<td>NT&amp;DS</td>
<td>9</td>
<td>316.8</td>
<td>32.20</td>
<td>3.32</td>
<td>0.002</td>
<td>2.94</td>
</tr>
<tr>
<td>R&amp;LH&amp;NT</td>
<td>27</td>
<td>129.8</td>
<td>4.81</td>
<td>0.45</td>
<td>0.989</td>
<td>1.21</td>
</tr>
<tr>
<td>R&amp;LH&amp;DS</td>
<td>27</td>
<td>213.4</td>
<td>7.90</td>
<td>0.75</td>
<td>0.803</td>
<td>1.98</td>
</tr>
<tr>
<td>R&amp;NT&amp;DS</td>
<td>27</td>
<td>1775.7</td>
<td>65.77</td>
<td>6.21</td>
<td>0.000</td>
<td>16.50</td>
</tr>
<tr>
<td>LH&amp;NT&amp;DS</td>
<td>27</td>
<td>299.3</td>
<td>11.09</td>
<td>1.05</td>
<td>0.422</td>
<td>2.78</td>
</tr>
<tr>
<td>Error</td>
<td>81</td>
<td>857.8</td>
<td>10.59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>255</td>
<td>10760.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*R, LH, NT, and DS stand for Raster orientation, Layer height, Nozzle temperature and Deposition speed, respectively.
As noticed from the P-values in Table 5-3, the raster orientation (R) has had the largest percent of contribution on the tensile behavior of FDM processed ABS parts, followed with deposition speed (DS) and nozzle temperature (NT), which is in full agreement with the Lenth’s analysis, while the layer height was not significant individually. Additionally, ANOVA reveals extremely high interaction effects including R&NT, R&S, and R&NT&S which if ignored in practice, the optimization of the FDM process can be inefficient.

5.4 Microscopic Inspections and Raman Spectroscopy

Finally, in order to obtain a better point of view regarding the effect of process parameters on the 3D printed parts, the macroscopic results obtained from tensile test analyses were combined together with visual inspections via a Celestron Microscope, as well as a Raman spectroscopy analysis.
Figure 5-12 The microscopic inspections of the cut cross section of ABS parts fabricated by FDM under process conditions 1 to 16 per Table 3-4. Δ$T_g$ is showing the proportional change in the value of glass transition temperature due to the FDM process and Δ$E$ is representing the proportional change in the value of Young’s modulus due to the FDM process.
According to Figure 5-12 one can conclude that fabricated samples with higher dispersion of porosity (shown as an example in Figure 5-11 (b)) would result in lower tensile strengths. For example, samples 7 and 8 (Figure 5-11 (g) and (h)) show more randomly scattered porosity compared to other samples, and accordingly to Table 5-1 they have had overall, a lower Young’s modulus (for some cases more than 55% reduction in Young’s modulus was observed). These values will be later discussed in Figure 6-1. Interestingly for the samples with larger drop in the Young’s modulus, the increase in glass transition temperature was generally higher.
In order to see how the FDM process could change the dispersion of acrylonitrile, butadiene and styrene components in the processed ABS samples, Raman spectroscopy was employed. As it was shown previously in Figure 3-5, each component could cause a distinguished peak due to inelastic scattering of photons radiated into the sample. In this study, sample 1, which exhibited the maximum Young’s modulus among all test conditions, was selected for the Raman analysis.

Few spots located on the sample to be studied by the Raman spectrum with a 633 nm laser. The sample was exposed for 60 seconds with 10% of the laser power. As shown in Figure 5-12, the selected spots were located in one direction containing two adjacent FDM roads and at their boundary (interface) region. It must be noted that, the assessed signals were all centered and normalized to provide a better comparability [98].

![Figure 5-13 The graphical illustration of the points characterized via Raman spectroscopy; R1 and R2 represent two adjacent roads separated by the interface boundary region](image-url)
Figure 5.14 The Raman spectrum obtained for five different points of 3D printed sample 1; (a) to (e) are respectively representing the spectrum obtained for points 1 to 5 illustrated in Figure 5.12.
As shown in Figure 5-14 spectra corresponding to points 1 and 5 in Figure 5-13 are showing the peaks related to Acrylonitrile, Butadiene and Styrene (also see Figure 3-5). Points 1 and 5 show a similar trend (similar peaks) with a slight difference in their values. This similarity is directly pointing to the fact that these two points are taken from areas with the same position within each respective road. Moreover, the slight difference between those two points suggests that even on theoretically two identical deposited roads, chemical structure and distribution of monomers could be different due to the FDM process. However, by moving towards the interface (boundary) region (i.e. points 3 and 4), the peaks regarding the Butadiene becomes dominant, which means lowering mechanical properties [73]. Therefore, due to the low stiffness of Butadiene, the boundary regions locating between two adjacent roads with a high concentration of Butadiene would behave similar to a (chemical) defect in the part. Finally, point 2 which is close to a geometrical defect (crack) within one of the roads (R1), also implies a similar low modulus region. This analysis highly confirms the earlier discussions in the effect of inter layer bonding between adjacent 3D printed roads studied by [99] regarding the critical effect of rods inter-bead quality on the effective mechanical performance of 3D printed parts.

5.5 Summary of findings

This chapter investigated the effect of selected process parameters on the tensile behavior of FDM printed ABS samples. The investigation was undertaken through employment of a Taguchi experimental approach along with the neural network modelling. The neural network was used as an empirical modelling tool to find the complex relationship between process parameters and the tensile properties of the samples. In addition, the effects from individual and interacting process factors were explored using the Lenth’s method as well as ANOVA. Finally, visual inspections on the cross section of 3D printed samples were used to better describe the effect of FDM process at the meso/micro level. Moreover, due to the expected impact of bead boundary (interface) regions on the behavior of fabricated parts, the Raman spectroscopy was utilized. Raman spectroscopy confirmed that the beads boundary regions can be closely responsible for lowering strength of
FDM processed parts, in addition to the dispersed porosities seen under different processing conditions. Besides, it was noted that the dispersion of monomers (Acrylonitrile, Butadiene and Styrene) changes at the boundary regions, with a high concentration of Butadiene which has a low stiffness.
Chapter 6: Conclusions and Future Work Recommendations

6.1 Summary

The potential of additive manufacturing (AM) methods to build parts with 3D complex geometries along with lowering the time, cost and material waste are the main reasons encouraging industries to invest more and more on the development of AM techniques. Amongst various kinds of AM, Fused Deposition Modelling (a.k.a FDM) has commonly received much attention. Simplicity and economic efficiency are two main features of the FDM technique, making it more attractive to the manufacturers compared to AM methods such SLS and SLA. Nevertheless, during the FDM, a large number of process parameters need to be interacting to form the final 3D part. In turn, the complexity of relationships between these process parameters can make the performance of additive manufacturing-processed parts hard to control. Consequently, investigations on the most effective process parameters along with their optimization are deemed critical to ensure quality of the final part with a given shape and made of a particular filament type.

The research presented in this thesis was aimed to study the effect of select FDM process parameters (raster orientation, layer height, nozzle temperature, and deposition speed) to control the quality of 3D printed plates made of ABS. Due to the existing gap in the literature on fully understanding the relationships between the process parameters and the viscoelastic behavior of FDM processed parts, in the first step of this research, a DMA experimental layout was designed based on the Taguchi L-16 orthogonal array. Dependency of the viscoelastic properties of the FDM processed ABS parts on the process control factors was closely shown via the performed statistical analysis in Chapter 4. Consequently, the optimum parameter values corresponding to each working condition were obtained using an artificial neural network integrated with the particle swarm optimization. Similarly, in Chapter 5, the impact of process parameters on the tensile behavior of FDM fabricated parts at room temperature was proven using the same Taguchi experimental design for learning a novel neural network. The performed ANOVA using the latter network, clearly confirmed the existence of very high interaction between process parameters during FDM.
Lastly, the main macro-level observation from Chapters 4 and 5 were compared against microscopic images to find a more in-depth correlation between process parameters and the quality of the 3D printed parts. The summary of specific conclusions drawn from these phases is as follows.

Investigation on the effect of process parameters on the viscoelastic behavior of FDM processed ABS:

- It was shown that, the FDM process condition could directly affect the maximum allowable working temperature (represented by glass transition temperature) for 3D printed thermoplastic. However, due to the complexity of the process, the presence of high interactions between the parameters necessitates using advanced modeling (machine learning) techniques to predict the material behaviour under FDM.

- Based on the Lenth’s statistical analysis, among the various considered process parameters, the raster orientation was the most effective factor to increase the glass transition temperature of the 3D printed part. Subsequently, the deposition speed was ranked second, following the layer height and nozzle temperature.

- The variation of storage modulus and loss modulus as a function of working temperature was measured and represented the viscoelastic behavior of the FDM fabricated ABS parts. Distinct trends between the viscoelastic responses of the unprocessed and processed ABS filaments under various process conditions pointed to the fact that, the FDM process condition significantly (on average 40%) lowers the magnitude of viscoelastic moduli regardless of the specific combination of process parameters used, which is also in agreement with earlier studies [27]. This effect is deemed critical for designers to consider for reliable application of 3D printed parts, especially at high temperatures.
Although it was shown that there are distinct trends between the behavior of processed and unprocessed ABS samples, the exact change in the moduli was highly dependent on the working temperature at which the part viscoelastic properties were measured. For instance, at working temperature of 100°C there was an average reduction of 25% in the storage modulus when compared to the unprocessed sample. On the other hand, this reduction at 40°C working temperature was about %33.5. The reduction increases drastically and reaches to as high as 60.7% at high working temperatures >100°C.

It was shown that the developed neural network architectures are capable of predicting the entire DMA curve of 3D printed parts, even for untested samples (i.e. those that were not included during the network training). Using such networks, the optimum values of the process parameters can be obtained e.g. via a Particle swarm optimization (PSO). In this work, the optimum FDM process parameters for ABS were identified and tabulated (Table 4-3and Table 4-4) at each working temperature ranging from 40°C to 140°C.

Investigation on the effect of process parameters on the tensile behavior of FDM processed ABS:

- Nominal tensile strength, percent elongation at break, and the Young’s modulus at room temperature of the FDM fabricated parts under various process conditions were assessed. Based on the statistical analysis results, the process parameters were ranked as: the raster orientation → the deposition speed → the nozzle temperature. However, in this case study, the layer height showed no significant effect to control the tensile performance of the printed parts.

- It was shown that due to the highly complex interactions between the process parameters, an artificial neural network technique would be suitable to capture the processing-properties relationship between regarding the tensile response of the FDM printed parts.
It was concluded that the FDM process unavoidably decreases the tensile properties of the printed parts, up to 56% which is surprisingly very close to the maximum loss of 60.7% of storage modulus based on the DMA results. On the other hand, the FMD process for all printed sample increased the glass transition temperature. The trade-off between these two performance measures has been summarized in Figure 6-1, which suggests that the designer should highly concern about the loss (and accordingly optimization) of elastic properties of 3D printed thermoplastic parts, especially at high working temperatures, when compared to the minimal increase seen in the parts glass transition temperature.

Figure 6-1 Graphical comparison between the effect of process parameters on changing glass transition temperature and Young’s modulus
6.2 Contributions to knowledge

- The effect of FDM process parameters on both static (tensile) and dynamic (viscoelastic) properties of 3D printed ABS samples were characterized and optimized concurrently (i.e. under a unified study).

- Using the developed neural networks and global optimization approach (namely Particle Swarm Optimization) was adapted for the first time to estimate the optimum levels of the process parameters, maximizing the storage and loss moduli of the prints under various working temperatures.

- The integration of the neural network modeling with statistical analysis, microscopy and Raman spectroscopy provided an enhanced understanding of the interaction effects between the FDM process parameters along with their ensuing meso/micro level defects.

6.3 Future Work

The following recommendations may be proposed as possible future research directions:

- Similar characterization approaches can be conducted for other types of pure thermoplastic filament materials used for 3D printing, such as PLA, PEI, and PEEK. The same approach could also be adapted to characterize and predict the performance of FDM processed composites.

- A larger number of process parameters could be considered in the further investigations.

- Other material properties such as thermal conductivity and density can be added to explore a wider range of effect of process parameters on quality of FDM processed parts.

- Other sophisticated machine learning tools (e.g. random forests) could be employed and compared to model the response of the FDM processed parts.
Bibliography


[12] W. K. Swainson, Method, Medium and Apparatus for Producing Three-Dimensional Figure Product, 1977.


[20] ()


[63] (). *ABS Filament*.


Appendices

Appendix A

This appendix graphically summarizes the simulation results presented in Tables 4-3 and 4-4.

Figure S-1 The graphical demonstration of optimum values of process parameters to maximize $E'$ (also provided in Table in 4-3) for various levels of raster orientation shown by different colors; (a) showing the

![Graphical demonstration of optimum values of process parameters](image-url)
optimum deposition speed, (b) representing optimum layer height and (c) showing optimum nozzle temperature.

Figure S-1 Continued
Figure S-2 The graphical demonstration of optimum values of process parameters to maximize E’’ (also provided in Table in 4-3) for various levels of raster orientation shown by different colors; (a) showing the optimum deposition speed, (b) showing the optimum layer height.

125
optimum deposition speed, (b) representing optimum layer height and (c) showing optimum nozzle temperature.

Figure S-2 Continued
Appendix B

This appendix includes all the stress-strain graphs obtained via performed tensile tests. Figure A-1(a) to (p) represent the tensile behavior of FDM processed parts under test conditions #1 to #16 (see also Table 3-4).

Figure S-3 The strain-stress curves of FDM processed parts under test conditions #1 to #16 (also see Table 3-4)
Figure S-3 Continued
Figure S-3 Continued