THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

On Characterization and Optimization of Engineering Surfaces

VIJETH VENKATARAM REDDY

Department of Industrial and Materials Science
Chalmers University of Technology
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Abstract

Swedish manufacturing industry in collaboration with academia is exploring innovative ways to manufacture eco-efficient and resource efficient products. Consequently, improving *manufacturing efficiency* and *quality* has become the priority for the manufacturing sector to remain competitive in a sustainable way. To achieve this, control and optimization of manufacturing process and product's performance are necessary. This has led to increase in demand for functional surfaces, which are engineering surfaces tailored to different applications. With new advancements in manufacturing and surface metrology, investigations are steadily progressing towards re-defining quality and meeting dynamic customer demands. In this thesis, surfaces produced by different manufacturing systems are investigated, and methods are proposed to improve specification and optimization.

The definition and interpretation of surface roughness vary across the manufacturing industry and academia. It is well known that surface characterization helps to understand the manufacturing process and its influence on surface functional properties such as wear, friction, adhesivity, wettability, fluid retention and aesthetic properties such as gloss. Manufactured surfaces consist of features that are relevant and features that are not of interest. To be able to produce the intended function, it is important to identify and quantify the features of relevance. Use of surface texture parameters helps in quantifying these surface features with respect to type, region, spacing and distribution. Currently, surface parameters Ra or Sa that represent average roughness are widely used in the industry, but they may not provide adequate information on the surface. In this thesis, a general methodology, based on the standard surface parameters and statistical approach, is proposed to improve the specification for surface roughness and identify the combination of significant surface texture parameters that best describe the surface and extract valuable surface information.

Surface topography generated by additive, subtractive and formative processes is investigated with the developed research approach. The roughness profile parameters and areal surface parameters defined in ISO, along with power spectral density and scale sensitive fractal analysis, are used for surface characterization and analysis. In this thesis, the application of regression statistics to identify the set of significant surface parameters that improve the specification for surface roughness is shown. These surface parameters are used to discriminate between the surfaces produced by multiple process variables at multiple levels. By analyzing the influence of process variables on the surface topography, the research methodology helps to understand the underlying physical phenomenon and enhance the domain-specific knowledge with respect to surface topography. Subsequently, it helps to interpret processing conditions for process and surface function optimization.

The research methods employed in this study are valid and applicable for different manufacturing processes. This thesis can support the guidelines for manufacturing industry focusing on process and functional optimization through surface analysis. With increase in use of machine learning and artificial intelligence in automation, methodologies such as the one proposed in this thesis are vital in exploring and extracting new possibilities in functional surfaces.

Keywords: Functional surfaces, Characterization, Stylus Profilometer, Coherence Scanning Interferometer, Regression, Manufacturing, Areal surface parameters, Surface profile parameters, Optimization.

Dedicated to my father,
Byanna Venkatarama Reddy

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VIJETH VENKATARAM REDDY

Halmstad, May 2023

List of appended papers

The results presented in this thesis are based on the work in the following appended papers:

Paper I: **Vijeth V Reddy**, Amogh Vedantha Krishna, Fredrik Schultheiss and BG Rosén, *Surface Topography Characterization of Brass Alloys: Lead Brass (Cuzn39pb3) and Lead-free Brass (Cuzn21si3p),* Surf. Topogr.: Metrol. Prop. 5 025001, 2017.

Contribution: Vijeth and Amogh conceptualized the paper, performed surface measurements and data analysis. Vijeth developed the method for surface analysis and wrote the paper. Fredrik and Prof. BG Rosén were involved in planning and reviewed the paper.

Paper II: **Vijeth V Reddy**, Olena Flys, Amogh Vedantha Krishna, B-G Rosen, 2017, *Topography characterization of Fused Deposition Modeling surfaces*, Special Interest Group Meeting: Additive Manufacturing, Leuven, Belgium.

Contribution: Vijeth and Olena initiated the study and conceptualized the paper. Olena performed surface measurements. Vijeth and Olena performed data analysis and wrote the paper. Amogh and Prof. BG Rosén took part in discussions and contributed as reviewers.

Paper III: **Vijeth Reddy**, Olena Flys, Anish Chaparala, Chihab E Berrimi, Amogh V, BG Rosen, *Study on surface texture of Fused Deposition Modeling*, Procedia Manufacturing, Volume 25, Pages 389-396, ISSN 2351-9789, 2018.

Contribution: Vijeth initiated the study and planned the experiments. Vijeth and Amogh performed data analysis and conceptualized the paper. Anish and Chihab produced the samples and took surface measurements. Olena, Amogh and Prof. BG Rosén took part in discussions and contributed as reviewers.

Paper IV: Amogh V. Krishna, M. Faulcon, B. Timmers, **Vijeth V. Reddy**, H. Barth, G. Nilsson and B.-G. Rosén. (2020) *Influence of different post-processing methods on surface topography of fused deposition modelling samples*. Journal of Surface Topography: Metrology and Properties, Volume 8, 014001.

Contribution: Amogh initiated the study, conceptualized and wrote the paper. Vijeth and Amogh planned the experiments and performed data analysis. Faulcon and Timmers produced samples and performed surface measurements. Henrik Barth and Prof. BG Rosén participated in planning and contributed as reviewers.

Paper V: **Vijeth V Reddy**, Amogh V Krishna, Anders Sjögren, & B.-G Rosén, (2023). *Surface characterization and analysis of textured injection molded PC-ABS automotive interior components*. Surface Topography: Metrology and Properties, 11(1), 014003.

Contribution: Vijeth conceptualized the paper, performed surface measurements, data analysis and wrote the paper. Amogh and BG Rosén were involved in planning/discussions. Prof. BG Rosén and Anders reviewed the paper.

Paper VI: **Vijeth V Reddy**, Amogh Vedantha Krishna, A Sjögren and B-G Rosén, *Controlling the surface texture of injection moulded automotive interior components*. Poster at Met & Props 2022. Scotland. Submitted to The International Journal of Advanced Manufacturing Technology, Springer 2023.

Contribution: Vijeth conceptualized the paper, performed surface measurements, data analysis and wrote the paper. Amogh and BG Rosén were involved in planning/discussions. Prof. BG Rosén and Anders reviewed the paper.

Additional Publications

Paper VII: Amogh V Krishna, O. Flys, **Vijeth V Reddy**, J. Berglund, and B. G. Rosen, *Areal surface topography representation of as-built and post-processed samples produced by powder bed fusion using laser beam melting*, Surf. Topogr. Metrol. Prop., vol. 8, no. 2, p. 024012, Jun. 2020, doi: 10.1088/2051-672X/ab9b73.

Paper VIII: Amogh V Krishna, O Flys, **Vijeth V Reddy**, A. Leicht, L. Hammar, and B. G. Rosen, *Potential approach towards effective topography characterization of 316L stainless steel components produced by selective laser melting process,* Eur. Soc. Precis. Eng. Nanotechnology, Conf. Proc. - 18th Int. Conf. Exhib. EUSPEN 2018, no. June, pp. 259–260, 2018.

Paper IX: **Vijeth V Reddy**, P. L. Tam, Amogh V. Krishna, and B. G. Rosén, *Characterization of subsurface deformation of turned brasses: lead brass (CuZn39Pb3) and lead-free brass (CuZn21Si3P)*, J. Phys. Conf. Ser., vol. 1183, no. 1, p. 012006, Mar. 2019, doi: 10.1088/1742-6596/1183/1/012006.

Paper X: Amogh V Krishna, O. Flys, **Vijeth V Reddy**, and B. G. Rosén, *Surface topography characterization using 3D stereoscopic reconstruction of SEM images*, Surf. Topogr. Metrol. Prop., vol. 6, no. 2, 2018, doi: 10.1088/2051-672X/aabde1.

Paper XI: Amogh V Krishna, **Vijeth V Reddy**, Dyall W Dexter, Dan-Åke Wälivaara, Peter Abrahamsson, B-G Rosen and Jonas Anderud, *Quality assurance of Stereolithography based biocompatible materials for dental applications*, Surf. Topogr. Metrol. Prop., 2023

List of symbols and acronyms

ABS	Acrylonitrile Butadiene Styrene
AM	Additive Manufacturing
ANOVA	Analysis of Variance
BJT	Binder Jetting
BBD	Box-Behnken Design
β	Regression coefficient
CAD	Computer Aided Drawing
CCD	Central Composite Design
CSI	Coherence scanning interferometry
df	Degrees of freedom
DoE	Design of Experiment
DED	Directed Energy Deposition
DRM	Design Research Methodology
DS	Descriptive Study
FDM	Fused Deposition Modeling
FFT	Fast Fourier transform
F-operator	Form operator
F_0	Test statistic
GPS	Geometrical product specifications
i	Number of measurements
ISO	International Organization of Standardization
k	Number of process variables
L-filter	Large-scale filter
LOM	Laminated Object Manufacturing
UAM	Ultraviolet Additive Manufacturing
LVDT	Linear Variable Differential Transducer
MRA	Multiple Regression Analysis
MEX	Material Extrusion
MJT	Material Jetting
MSE	Mean square residual
MSR	Mean square regression
n	Number of surfaces
PBF	Powder Bed Fusion
PC-ABS	Polycarbonate-Acrylonitrile Butadiene Styrene
PDF	Probability density functions
PP	Polypropylene
PS	Prescriptive Study
PSD	Power Spectral Density
R	Correlation coefficient
R^2	Coefficient of determination
Ra	Arithmetic mean deviation of the roughness profile.
RC	Research Clarification

Rc	Mean height of the roughness profile elements.
Rdc	Roughness profile Section Height difference
Rdq	Root-mean-square slope of the roughness profile.
Rku	Kurtosis of the roughness profile.
Rmr	Relative Material Ratio of the roughness profile.
Rmr (Rz/4)	Automatic relative material ratio of the roughness profile.
Rp	Maximum peak height of the roughness profile.
Rp1max	Maximum local profile peak height
RPc	Peak count on the roughness profile.
Rq	Root-mean-square (RMS) deviation of the roughness profile.
Rsk	Skewness of the roughness profile.
RSm	Mean width of the roughness profile elements.
Rt	Total height of roughness profile.
Rv	Maximum valley depth of the roughness profile.
Rv1max	Maximum local profile valley depth
Rz	Maximum Height of roughness profile.
Rz1max	Maximum local height of the profile
S/N	Signal-to-noise ratio
S10z	Ten-point height
S5p	Five-point peak height
S5v	Five-point pit height
Sa	Arithmetic mean height
Sal	Autocorrelation length
Sda	Mean dale area
SDG	Sustainable Development Goals
Sdq	Root-mean-square gradient
Sdr	Developed interfacial area ratio
Sdv	Mean dale volume
SE	Standard error
SEM	Scanning electron microscopy
SEM	Scanning Electron Microscope
S-F	Surface after applying F-operator
S-filter	Small scale filter
Sha	Mean hill area
SHL	Sheet Lamination
Shv	Mean hill volume
SI	International System of Units
Sk	Core roughness depth
Sku	Kurtosis
S-L	Surface obtained after applying L-filter
Smc	Inverse areal material ratio
Smq	Material ratio at plateau-to-valley transition
Smr	Areal material ratio
Smr1	Upper bearing area

Smr2	Lower bearing area
SN_i	Signal-to-noise
Sp	Maximum peak height
Spc	Arithmetic mean peak curvature
Spd	Density of peaks
Spk	Reduced summit height
Spq	Plateau root-mean-square roughness
Sq	Root-mean-square height
SSE	Sum of squares of residuals
SSFA	Scale-sensitive fractal analysis
Ssk	Skewness
SSR	Regression sum of squares
SST	Total sum of squares
Std	Texture direction
STL	Stereolithography
Str	Texture-aspect ratio
Sv	Maximum pit height
Svk	Reduced valley depth
Svq	Valley root-mean-square roughness
Sx	Surface parameter
Sx_m	Mean of surface parameter
Sxp	Extreme peak height
Sy	Modelled surface parameter
Sz	Maximum height
$\widehat{Sx}$	Modelled equation of surface parameter
t	t-distribution
Vm	Material volume
Vmc	Core material volume
Vmp	Peak material volume
Vv	Void volume
Vvc	Core void volume
Vvv	Dale void volume

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1 INTRODUCTION

The growing demands for sustainable materials and manufacturing processes along with geo-political challenges has increased competitiveness in the manufacturing industry. This has led to advances in efficient techniques and methods to produce products or features that meet customer requirements and are free from defects and deficiencies. For robust manufacturing of quality goods, it is important to understand and control material's behavior during manufacturing. With appropriate measurement, filtering, characterization and evaluation, manufacturing accuracy and performance of parts can be improved.

This chapter opens with the background to the research area, current practices, and challenges in manufacturing industry. Followed by research focus together with the aim of the thesis, research questions, approach, delimitations, and thesis disposition.

1.1 Background

Manufacturing processes produce surface deviations or irregularities on the product from the nominal form. Each process has its unique signature features imparted on the part primarily due to their exclusive tool-workpiece interaction [1]. Surface metrology deals with measurement and evaluation of deviations or features on the surface known as surface topography or surface texture. This topographical deviation on the manufactured component is known to substantially affect its functionality, bulk properties and consequently the cost of product [2, 3]. The methods for evaluating surfaces can be challenging due to its sensitivity to data measurement techniques and is often disputable when applied to different engineering surfaces.

Surface topography is captured in the form of 2-dimensional or 3-dimensional data using high-resolution tactile or optical techniques. The captured data are statistically quantified using surface parameters based on their amplitudes, spacing, volume, area, slope, and curvature. These are indexed by profile parameters in ISO 21920-2 [4], and areal surface parameters in ISO 25178-2 [5]. There exist hundreds of surface parameters but not all surface parameters are useful and proliferation of surface parameters referred to as *'parameter rash'* [6] is the dispute around which the research outlines are framed.

Surface parameters help in quantitatively characterizing the surface topographical features and empowers designers to describe the requirements with precision [7]. However, it is not imperative and is often redundant and time-consuming to use all surface parameters to specify the requirements or to describe the surface [8]. This becomes even more inefficient and perplexing while comparing multiple surfaces. Furthermore, the relevance of surface parameters varies with respect to different processes, process variables and functional performance. Surface parameters, Ra (average roughness) in profile and Sa (arithmetic mean height) in areal parameters are widely used in industry [9]. But the use of a single surface parameter can be insufficient for a comprehensive characterization and limits the possibilities of exploring and extracting maximum surface information compared to a set of parameters [10, 11]. Hence, a systematic approach is needed for identifying significant surface parameters that could discriminate between multiple surfaces and evaluate the influence of material, manufacturing tool and process variables.

Previously, research has been conducted to identify the appropriate surface parameters with regards to different applications [7, 12-15] using statistical methods. Likewise, a mathematical and statistical approach is proposed in this thesis to identify the significant surface parameters representing the deterministic distribution of features applicable to different manufacturing process. The surfaces produced from subtractive manufacturing by turning operation, additive manufacturing by fused deposition modelling and formative by injection molding process are captured and characterized using profile and areal surface parameters. Furthermore, multi-scale characterization techniques are employed to support the characterization and evaluation of scale-limited surfaces.

1.2 Research Aim and objectives

The overall aim of this thesis is *'to develop a comprehensive framework for systematic characterization and analysis of surface topography applicable to different manufacturing process'*.

The research objectives are focused on:

- Characterization and analysis with focus on identifying significant surface parameters with application of suitable statistical tools and to improve specification of surface roughness produced by multiple process variables.
- Discrimination of study surfaces and identification of the effects of process variables on significant surface parameters in scale-limited multiple surface analysis.
- Use of multi-scale methods to support surface characterization and analysis.
- Surface interpretations for process and functional optimization.

The underlying objective is to contribute towards increasing the domain-knowledge base and develop a robust decision support tool for selection of appropriate processing conditions to achieve the desired surface function.

1.3 Research questions

Based on the research objectives, the following research questions are formulated:

Research Question 1. How to improve specification for surface roughness applicable to different manufacturing systems?

This question addresses the characterization of manufactured surfaces using standard surface parameters. The question precedes the challenges of comparing the surfaces produced with multiple levels of process variables in an experimental research study and focuses on identifying the significant surface parameters.

Research Question 2. How can the significant surface parameters improve scale-limited multiple surface analysis?

This question focuses on the statistical methods to identify the effect of manufacturing process variables on significant surface parameters. This question concerns scale-limited surface measurements on samples produced by multiple process variables and the surface parameters that discriminate between the sample surfaces.

Research Question 3. How can multi-scale surface characterization techniques support scale-limited surface analysis?

This question addresses the use of multi-scale characterization techniques including Power Spectral Density (PSD) and Scale Sensitive Fractal Analysis (SSFA) in facilitating characterization and analysis of surfaces.

Research Question 4. How could statistical methods be applied for modelling and prediction of surface parameters?

This question probes the use of regression statistics to model and predict the significant surface parameters. It also covers surface and functional interpretations.

1.4 Approach

The research approach follows the surface control loop presented by Stout and Davis, shown in figure 1, where surface characterization is used as the basis for manufacturing process and functional optimization. Surfaces from additive, subtractive and formative processes are captured using optical and tactile methods. Standard surface parameters are used to characterize and quantify the captured surface topography. Scale sensitive fractal analysis (SSFA) and Power Spectral Density (PSD) are used to support the characterization by identifying the scales of interest. Statistical methods are used to identify the significant surface parameters and critical process variables that affect the surface functional behavior and efficiency of the process.

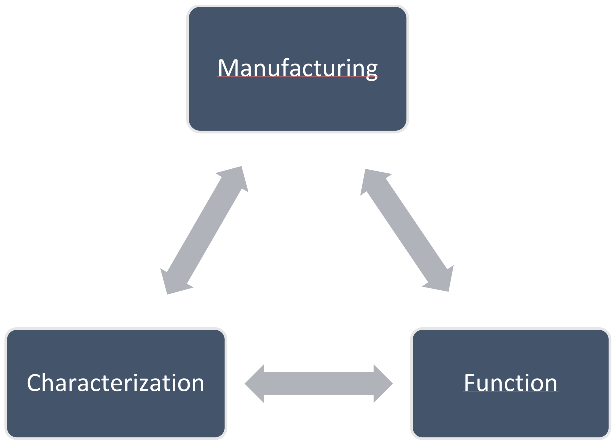


Figure 1: Surface control loop proposed by Stout and Davis [16]

1.5 Delimitations

The following are certain limitations within the research approach:

- Material bulk properties and sub-surface also contribute to the variation in surface function, but this topic is not covered in this thesis. In this study, a homogenous material property is assumed within each sample.
- Surface defects caused by external noise including mechanical vibrations, environmental conditions, and temperature fluctuations, which have detrimental effect on surface properties, are not discussed in this thesis.
- Discussion and comparison between the surfaces produced from different manufacturing processes namely additive, subtractive, and formative are not included.
- This thesis primarily focuses on studying the variation in surface topography by scale-limited approach.
- Linear statistical approach is adapted to identify the significant surface parameters and interpret surfaces for process and functional optimization.
- Multi-scale analysis using wavelets is not included in this thesis.

1.6 Thesis structure

The thesis focuses on analyzing the surface data, produced at different levels of process variables, using both visual and statistical approaches. Surface parameters proposed by the International Organization for Standardization are used for quantitative characterization. The graphical representation of the thesis structure is shown in Figure 2. In this thesis, different manufacturing systems; additive, subtractive and injection molding processes, investigated in the appended papers are discussed with regard to critical process variables and a brief literature review on the resulting engineering surfaces is presented. Definition and description of sustainable manufacturing along with the contribution of research studies towards achieving sustainable development goals are discussed. The chapter on surface metrology includes surface measuring instruments and their principle, surface data filtering techniques, characterization methods and related standards. Design Research Methodology (DRM) framework is utilized in this thesis to describe the research plan and approach systematically. The application of statistical methods to identify and analyze the deterministic surface information is described. The synthesis of research results from the appended papers contributing to the research objectives are discussed.

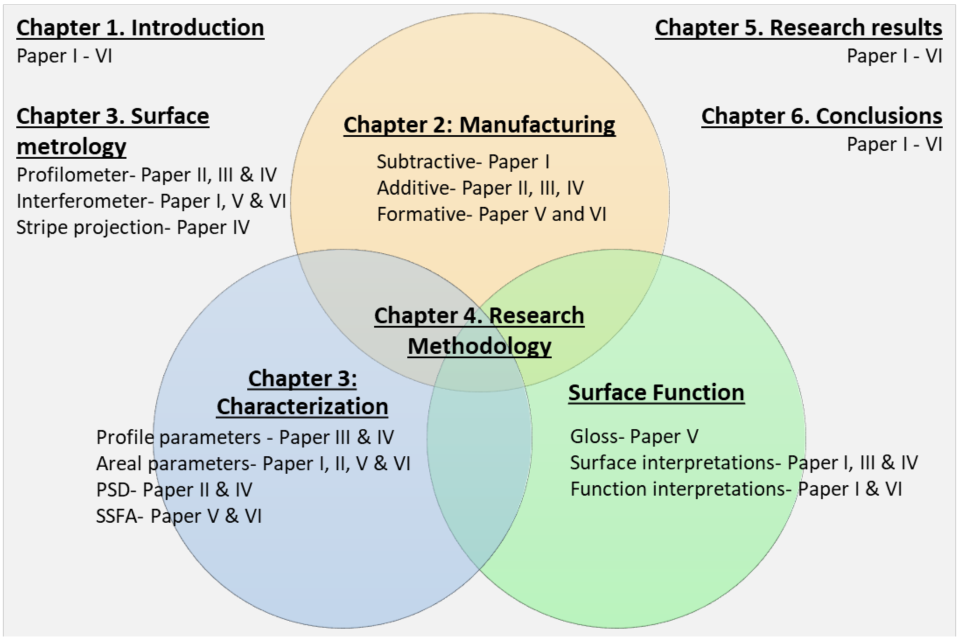


Figure 2: Thesis structure

Chapter 1 states the aim of the thesis with research approach and delimitations.
Chapter 2 describes the different manufacturing process and its variables affecting surface topography.
Chapter 3 is an overview of surface metrology instruments, their working principles and overview of surface characterization methods.
Chapter 4 describes the research methodology and its industrial implications
Chapter 5 discusses the results from the appended papers
Chapter 6 summarizes the conclusions and future work

2 MANUFACTURING

Manufacturing is the creation of goods by processing raw materials with the use of tools, human labor, and processing. This chapter provides an overview of the different manufacturing systems and the manufactured surfaces. Literature on the critical process variables and their influence on the surface is reviewed. Furthermore, sustainable manufacturing and its importance is discussed in this chapter.

Manufacturing systems

Manufacturing includes all stages right from design to delivery of finished products and in this chapter the manufacturing processes investigated in this thesis along with its variables and resulting surfaces are discussed. Manufacturing processes can be classified into three categories; subtractive, additive and formative processes based on the principle of operation [17]. Subtractive and formative are more conventional processes compared to additive manufacturing. Manufacturing attributes include cost, time, quality and flexibility [18]. The primary objective of a manufacturing system is to minimize the cost and time with acceptable quality. Quality can be defined as the products fitness for purpose with the aim of meeting customer requirements and being defect free [19]. Being contradictory concepts, to optimize costs and quality, it is important to improve our understanding and control over materials behavior during manufacturing. Achieving the desired surface quality through manufacturing is crucial to maintain the intended surface function and product's performance.

2.1 Subtractive manufacturing

Subtractive manufacturing basically involves removal of material from blocks or cylinders using suitable tools with cutting medium. Subtractive processes include traditional and non-traditional operations depending on the cutting tools and medium. Traditional operations are turning, milling, drilling, boring while non-traditional operations include electric discharge machining, abrasive water jet machining, electrochemical machining. Traditional operations produce surfaces that are unique and shaped by the cutting tool edge and fracture of material under shear stress. In this section, the turning operation and the surfaces that it generates are discussed.

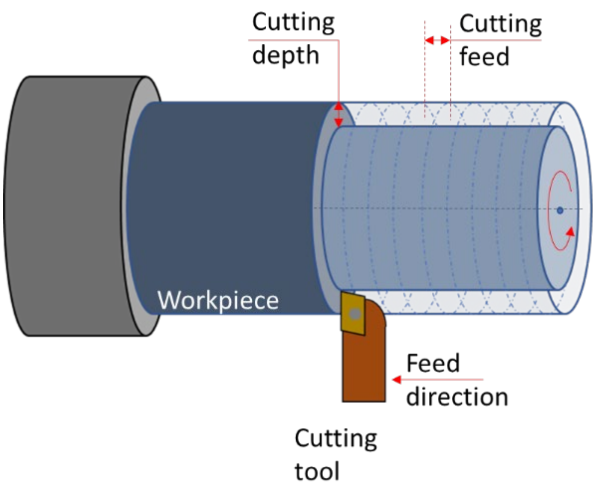


Figure 3: Illustration of Turning operation

The turning operation is widely used for metal cutting near-net finish to finished products. In a turning operation, the cutting tool removes material in the form of chips from the rotating workpiece held by the chuck of a lathe. The cutting tool is fed linearly to the rotating workpiece, as illustrated in figure 3, and has three important process variables, viz: cutting speed, cutting feed and depth of cut [20]. Face turning involves removing of material with movement of cutting tool perpendicular to the rotational axis of the workpiece. Cutting speed is the rate at which rotating workpiece passes through the cutting tool edge, cutting feed is the distance moved by the tool axially to the workpiece per rotation and the depth of cut is the thickness of material removed measured radially [20]. During the turning operation, high cutting forces and temperature are generated which affect the cutting tool edge and the cutting tool life. Manufacturing cost, time and surface roughness is influenced by all these factors along with material's machinability. Other factors affecting the surface roughness are cutting tool geometry, quality and type, lubricant used, vibrations between the workpiece, cutting tool and machine tool.

The surface topography produced by turning operation consists of form, waviness, micro- and macroscopic roughness attributed to different controllable and uncontrollable variables. The form and waviness are attributed to the machine tool error, workpiece geometry, setup errors, vibration or the workpiece material itself [21]. Whereas the manufacturing process signature or the surface effects are the dominant lay produced by the cutting tool edge along the work piece in the feed direction, as shown in figure 4. In general, for turning, surface roughness decreases at higher cutting speed, whereas higher cutting feed and depth of cut increases surface roughness [22].

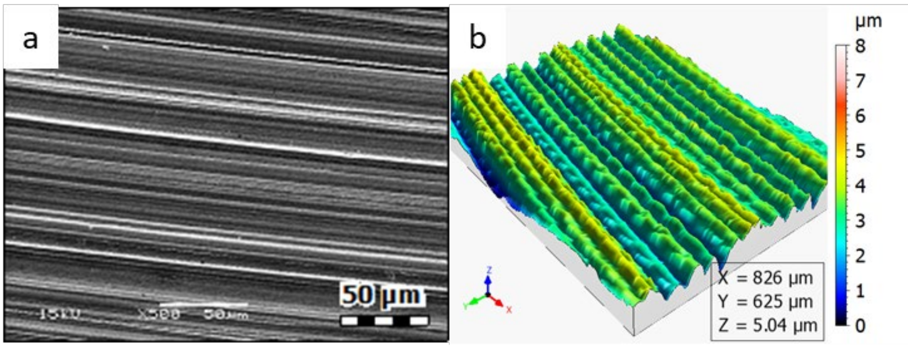


Figure 4: Turned surface topography a. SEM image b. Optical interferometer

Turned surfaces: Several studies have been conducted to analyze and optimize the surface roughness characterized by standard surface parameters and some of these research investigations are summarized in this section. Natarajan et al. [23] employed Artificial Neural Networks (ANN) to predict the surface roughness of turned brass C26000. Taguchi's orthogonal array Design of Experiment (DoE) assigned to cutting speed, feed and depth of cut is performed to model and predict surface parameter, arithmetic mean height (Ra). The predicted values of Ra were in proximity to experimental values. Toulfatzis et al. [24] investigated machinability of different lead-free brass alloys in comparison with leaded brass evaluating cutting force and surface roughness. Taguchi's orthogonal array DoE with ANOVA and signal-to-noise (SN) ratios were employed to identify the critical process variables for turning the brass alloys. The turned brass surface is characterized using Ra and it was observed that the feed rates are the most influential process variable. Importantly, lead free alloy CW511L has lower Ra values compared to its other lead-free and leaded counterparts. Zhang et al. [25] have implemented Gaussian process regression (GPR) to model and predict the turned surface of brass samples characterized by Ra. It is stated that the influence of the process variables on the surface roughness is complicated and synergistic. However, it is observed that the GPR models helps in identifying the individual and interaction effects of cutting speed, feed, and depth of cut. Javidikia et al. [26] analyzed and optimized the surface roughness of turned aluminum alloy AA6061-T6 using central composite design of experiment (DoE) with response surface methodology (RSM) and analysis of variance (ANOVA). Surface profile parameters, Ra and Rt (maximum height of profile) are used to characterize the surfaces generated at different cutting speed, feed rate and depth of cut at different environmental conditions. With feed rates as the most effective variable, the values of Ra and Rt were observed to be lower at lower feed rates and DRY mode. Das and Bajpai [27] analyzed the machinability of lead-free brass in high-speed micro turning using Taguchi's DoE and ANOVA. The resulting surface roughness are characterized using areal surface parameters, arithmetic mean height, Sa and maximum height, Sz. The effect of cutting speed, feed and depth of cut is evaluated using SN ratio and the results suggest cutting speed to have the highest effect among the process variables. Advanced statistical and machine learning methods have been employed for optimization of turned surfaces. However, most of the investigations have utilized single or few surface texture parameters that are chosen mostly for their widespread use in manufacturing industry.

2.2 Additive manufacturing

Additive manufacturing (AM) is a process of joining materials layer-by-layer to produce parts from three dimensional CAD models [28]. AM can produce parts with complex geometries in reasonable time and offers design freedom to engineers and designers. Additionally, it offers mass customization and is enabler for low volume production. Currently, a majority of the AM processes are used for *rapid prototyping,* but they have the capability for *rapid manufacturing* so as to complement the existing systems to significantly reduce production time and costs. To achieve this, it is important to produce accurate and repeatable output quality. The quality of the AM part is dependent on material, geometry and a large number of process parameters [28]. Additive manufacturing involves a series of steps starting from a CAD model converted to stereolithography (.STL) file format. This file is later processed by the slicing software based on the build parameters such as layer thickness, build temperature, speed. The sliced format is fed to the AM machine that is equipped with appropriate material and machine settings. The part is built layer-by-layer and is removed from the build platform after the process is completed. More often than not depending on the part produced, parts built with AM processes require post-processing. This might lead to increase in production time and costs. Surface topography investigations can be utilized to identify the output quality and the requirements for post-processing. AM is classified into seven categories based on the processing material and working principle [28].

Binder Jetting (BJT): involves gluing of powder material using suitable binders that are selectively deposited as per the CAD model. The glued part is consolidated by curing in the printer for polymer materials and by sintering for metallic materials.

Directed Energy Deposition (DED): involves melting of materials using thermal energy and deposited layer-by-layer. A laser beam or electron beam is used as the source of energy to melt the material.

Material Extrusion (MEX): Here, the material melted in a nozzle is selectively deposited on the build platform by the application of pressure.

Material Jetting (MJT): involves deposition of photo-sensitive resins in the form of droplets cured by an ultraviolet source.

Powder Bed Fusion (PBF): is a process that selectively fuses powder particles in a powder bed. It requires a laser beam or electron beam as the thermal source.

Sheet Lamination (SHL): includes two variants; Laminated Object Manufacturing (LOM) and Ultraviolet Additive Manufacturing (UAM). LOM involves deposition and fusion of material

sheets that are cut according to the cross-section of the part design. UAM uses ultraviolet vibrations to fuse sheets and the net shape of the part is achieved by removing the material.
Vat photopolymerization (VPP): involves selectively solidifying the photo sensitive polymer resins using UV or visible light, layer-by-layer to build the part.

2.2.1 Fused Deposition Modeling (FDM)

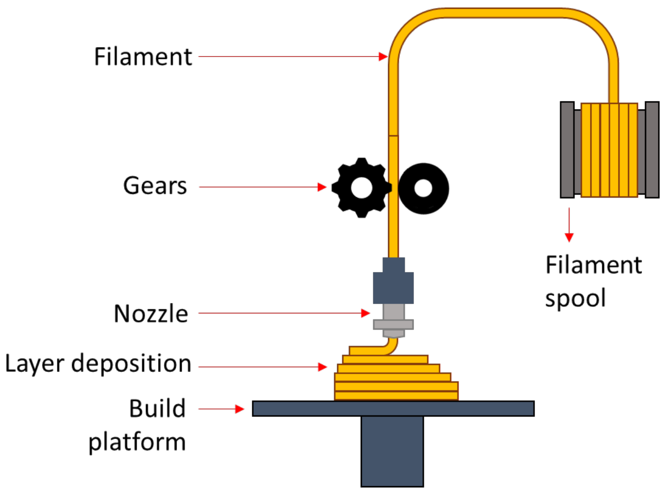


Figure 5: Illustration of Fused Deposition Modeling

FDM is a material extrusion AM process in which the material in the form of filament or pellets is melted in the nozzle and selectively deposited on to the build platform, as illustrated in figure 5, according to the settings of sliced CAD model. FDM is a widely used AM process for prototyping and to produce end parts, as it is inexpensive and easy to operate compared to other AM processes [28, 29]. Both polymer and metal parts can be produced with this technique. However, metal parts produced by FDM will need additional processing steps such as sintering to form the final part. FDM has a large number of process settings that influence the part quality and some of the critical process settings include build inclination, layer thickness, print speed, print temperature, print infill, raster width, number of perimeters and others [29]. Build inclination is the orientation of the part on the build platform. Layer thickness is the thickness of each layer of material deposited and print speed is the speed of material deposition. Print infill relates to the density of the part built and raster settings relate to the material deposited in raster pattern.

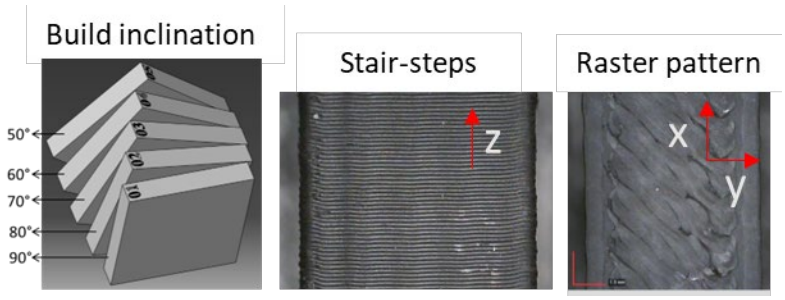


Figure 6: Illustration of build inclination, stair steps and raster pattern

The surface topography of FDM parts consists of unavoidable stair-steps and raster pattern as shown in figure 6. Stair-steps are the result of layer-by-layer deposition and raster pattern is the movement of the print head required to deposit the material in each layer. The raster pattern can vary in deposition angle, direction, width, and air gap settings. In the pre-processing step, the tessellated CAD model is generally sliced in constant layer thickness and fed into the FDM machine. In the adaptive slicing, variable layer thickness is adapted to slice the CAD model and maintain a constant cusp height, shown in figure 7, along the inclined and curved surfaces [30]. Lower layer thickness might help reduce the effect of stair-steps and produce surface quality closer to the tolerance but increases the build time.

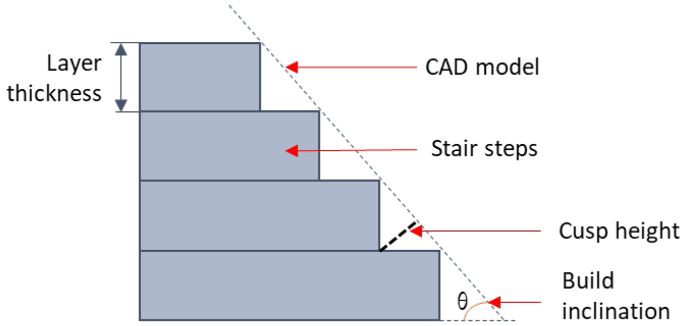


Figure 7: Illustration of stair-step effect and cusp height

FDM Surfaces: Several models are proposed [31-33] to assess the quality of surfaces, mostly represented by Ra, build at different inclinations, layer thickness and other process parameters. Anitha et al. [34] investigated the effect of FDM process variables on surface roughness represented by Ra. Taguchi's DoE and ANOVA is implemented to evaluate the FDM surfaces produced at different layer thickness, road width and speed deposition (printing speed). With SN ratio, layer thickness is found to be the most effective variable followed by speed and width. Boschetto et al. [32] investigated the influence of process parameters on a wide range of surface profile parameters including amplitude and spacing parameters. Nuñez et al. [35] studied the dimensional accuracy and surface texture of ABS material produced by the FDM process. The effects of layer thickness and density on areal surface parameters, Sa and Sq were evaluated. Buj-Corral et al. [36] investigated the FDM surfaces built at different build inclinations and evaluated the surfaces using surface profile parameters, Ra and maximum height of profile, Rz, kurtosis, Rku, skewness, Rsk, and mean width of the profile elements, Rsm. It is observed that these surface parameters tend to vary distinctly providing valuable surface information.

2.2.2 Post-processing FDM surfaces

Surfaces produced by the FDM process have stair-steps and raster patterns which vary along the part geometry and are unconventional compared to surfaces produced by subtractive and formative processes. Though FDM offers good flexibility and shorter lead time, FDM build parts have poor surface quality which hinders adoption for industrial applications. To achieve the intended surface finish, several methods are proposed including machining [37, 38], chemical processing [39-41] or laser finishing [42, 43]. Some of these methods are briefly summarized in this section.

Machining: The outer layer of the build part is removed either by machining or subjected to abrasive particles to provide a smooth surface finish. Kulkarni and Dutta [44] investigated an FDM process integrated with a milling operation and Pandey et al. [38] employed hot cutter milling to attain a smoother surface finish. These post-process operations were restricted by the part geometry and dimensions. Boschetto and Botini [45] investigated barrel finishing in which the build part is rotated in a barrel with abrasive particles. This type of finishing is less affected by the part shape and significantly reduced the surface roughness characterized by surface parameter Ra.

Chemical processing: Materials that are sensitive to certain chemicals are immersed or exposed for a specific amount of time until the outermost layer of the build part erodes. Galantucci et al. [40] investigated chemical finishing of acrylonitrile butadiene styrene (ABS) using acetone immersion. The results suggested improved surface roughness with significant reduction in surface parameter Ra. Similar results are observed by Garg et al. [46] investigating the effect of acetone on an FDM produced ABS part but instead of immersion, the FDM parts were exposed to acetone vapours in an airtight container. The authors used surface roughness parameter Ra to characterize and compare as-built surfaces with chemically treated surfaces.

Laser finishing: This post-process involves vaporization of material at high temperature using a laser beam. Taufik and Jain [42] post-processed the FDM surfaces with laser assisted finishing and employed three roughness parameters, Ra, Rku (kurtosis) and Rsk (skewness) to characterize the surface roughness. The effects of laser power, resolution and build inclination were investigated with a central composite design of experiment (CCD) and ANOVA. The results suggest an improvement in the surface finish resulting in isotropic surfaces. Similar studies have been conducted by Chai et al. [43] on FDM built ABS and PLA (polylactic acid) samples and they used arithmetic mean height, Sa to compare the surfaces before and after post-processing.

In most of the post-processing investigations, very few surface parameters were considered to characterize and compare the surfaces. As mentioned in [30], it is important to identify appropriate surface parameters that help to achieve a better understanding of the distinct features of FDM surfaces.

2.3 Injection molding

Injection molding, as illustrated in figure 8, is a manufacturing process in which the material subjected to thermal softening with aid of heat is injected into the mold cavity which is a replica of the intended part geometry. Injection molding offers large scale industrial production, higher production rates, less material wastage, and flexibility in design of products in polymers, glass, and metals. To achieve this, it is important to maintain the quality of manufactured goods and avoid or reduce rejection of parts. Injection molding consists of four stages: filling, holding, cooling, and demolding phases. In the filling phase, the molten plastic is injected into the cavity under pressure until it is filled up to 95-99%. In the packing-holding phase, the pressure is adjusted, and additional material is injected to be able to attain the intended geometry and replicate the surface details of the mold cavity. The density of the part increases and the plastic part begins to form in the holding phase. In the cooling phase, the temperature of the plastic is reduced by transferring the heat though the cooling systems in the mold. Cooling time accounts for majority of the time in injection molding phases. Demolding is the release of the mold and removal of plastic part contemplating the adhesion force, friction force and shrinkage.

The quality of replication can be evaluated using the difference between the mold geometry and the final workpiece geometry [47]. As explained by Theilade and Hansen [48], the replication of micro-surface structures is affected by driving force, material deformability and microstructure geometry. The driving force is controlled by the cavity pressure and the holding pressure. Material deformability is controlled by the material's viscosity and elasticity. Frozen layer is another contributor to material's deformability and is formed when the molten material is in contact with the mold wall. Microstructure geometry or the surface topographical features, especially those with high aspect ratio affects the replication.

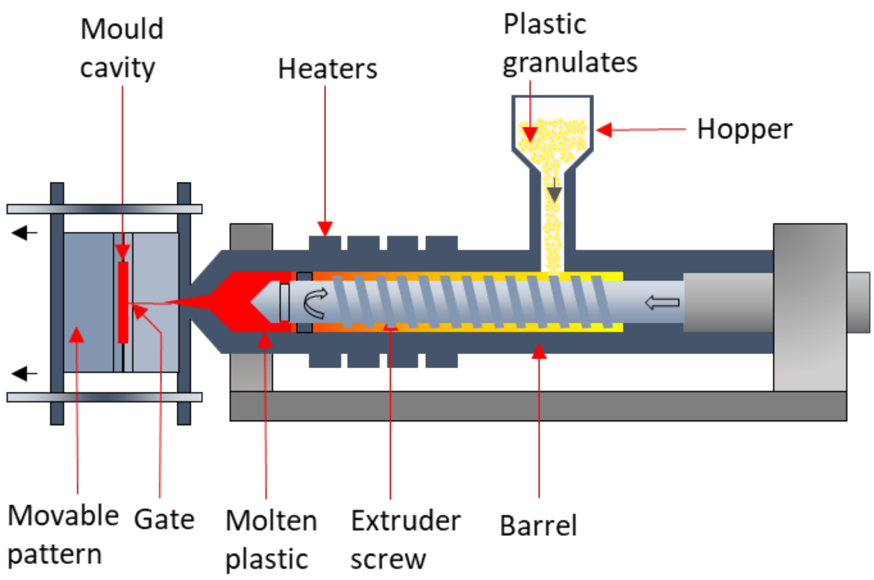


Figure 8: Illustration of injection molding process

Some of the manufacturing process variables that affect these factors and their effects on surface replication are summarized below:

Melt temperature is the actual temperature of the molten plastic as it enters the mold. It affects the viscosity thereby influencing the plastic flow. In general, melt temperature has a large effect on the replication of the molded part. High melt temperature reduces the viscosity of the material resulting in improved filling of the mold cavity and reduces the formation of the frozen layer [49-51]. But higher melt temperature increases the cooling time thereby affecting the cycle time.

Mold temperature is the temperature of the mold cavity surface during molding. It contributes towards decreasing the polymer viscosity, thereby aiding the polymer filling the surface microstructures [48, 49, 52, 53]. Mold temperature helps to maintain the melt temperature and reduce the formation of the frozen layer [51]. However, higher mold temperature also leads to longer cooling times and poor processing economy. The interaction of melt and mold temperature is critical in replicating surfaces with high aspect ratio [51].

Injection speed is the rate at which the molten polymer is injected into the mold. Higher injection speed helps to maintain the temperature of the polymer when it reaches the cavity surface, reducing the cooling rates during the filling phase [51]. Higher injection speed also results in higher shear stress at the cavity surface and molten material interface resulting in the reduction in material's viscosity [52, 53]. Further, higher injection speed will aid in homogenous filling of the mold tool cavity and better output quality. Lucchetta et al. [54] investigated the replication of high aspect ratio micro-structured surfaces and observed that uniformity in replication is better at low injection speed and high holding pressure.

Holding pressure is the pressure held against the cooling material until the gate freezes. Holding pressure has also a large effect on the replication of the surface microstructures counteracting for the shrinkage and trapped air pressure [51, 53]. Contrarily, from the investigations conducted by Masato et al. [55], on the replication of micro structured surfaces consisting of micro pillars, no significant main effect was observed from holding pressure but the effect of holding pressure can be maximized at higher mold temperature and features close to the injection gate [54]. Further, higher holding pressure can lead to ejection issues and flash at component edges.

Surface texture: The surface texture has, naturally, a large effect on the replication of the grain pattern. Small structures with high aspect ratios are generally more difficult to replicate than large structures with low aspect ratios [48]. To achieve a low gloss, which often is desirable for interior automotive components, a micro roughness is provided in the mold cavity by an after-etching of the grain pattern. This micro roughness is, however, often difficult to replicate, especially if the tool temperature and/or holding pressure are low. It can also be difficult to achieve a good replication of the micro roughness at ribs and bosses, due to material shrinkage and thereby lower contact pressure, which results in clearly visible variations in gloss.
Molecular weight: The molecular weight, and molecular weight distribution of the plastic material affects the melt viscosity and thereby both filling of the mold cavity and replication of the grain pattern. Low molecular weight implies low melt viscosity and results in good replication. But low molecular weight means also less entanglement of the molecular chains and thereby lower impact and wear resistance of the plastic material.
Degree of crystallinity: The degree of crystallinity has a rather large effect on the replication of the grain pattern. Amorphous plastic materials, i.e. plastic materials that do not crystallize, have generally less good flow properties than semi-crystalline plastic materials, and it is therefore normally more difficult to obtain a good replication of the grain pattern with amorphous plastic materials than with semi-crystalline plastic materials [56].
Fillers: Fillers in the plastic material affect the melt viscosity and thereby the replication of the grain pattern. A high amount of filler leads to a high melt viscosity and thereby more complicated replication of the grain pattern. Fillers can also affect the cooling of the plastic melt and thereby the development of a frozen layer next to the mold wall. Furthermore, a high amount of filler can also lead to filler particles at the surface, which reflects the light and reduce the gloss [57].
Several investigations [48, 49, 56, 58, 59] have been conducted to evaluate the influence of process variables on the replication of surface features from the mold tool. These studies suggest that by controlling the process variables, it is possible to maintain control over replication of features and resulting surface function such as gloss and scratch resistance.

2.4 Sustainable manufacturing

Sustainable manufacturing as defined by the Environmental Protection Agency [60] "*is the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources*". Sustainability in manufacturing helps to increase operational and resource efficiency reducing waste, increasing brand value, competitiveness and compliance with the standards [61]. Realizing the importance of sustainability, the manufacturing sector is striving to adapt and embrace new manufacturing technologies such as AM and strategies such as manufacturing optimization and simulation that support the transition. Among the 17 sustainable development goals (SDGs), shown in figure 9, adapted by the United Nations (UN) for a sustainable society, the 9th SDG focuses on building resilient infrastructure, promoting sustainable industrialization and fostering innovation and the 12th goal focuses on ensuring sustainable consumption and production patterns [62]. Sustainable manufacturing has common objectives with these SDGs which aims for efficient management and use of resources in addition to reducing waste and promoting recycling and reuse [63].

Surface topography characterization and analysis lead to an improved knowledge and understanding of the physical mechanisms in manufacturing. This knowledge can be applied to optimize product and processes which helps in reducing defective parts and improving part function. In this thesis, the investigations conducted are part of the sustainable manufacturing initiatives. In paper I, the surface investigations on turned lead- and lead-free brass is part of the project which aims at replacing lead in brass with silicon. The results suggest that it is possible to replicate the surface features and function of lead brass surfaces. Paper II, III and IV focused on characterization, optimization, and post processing of surfaces produced by Fused Deposition Modeling (FDM). FDM requires less material, less energy, less material wastage compared to its traditional counterparts and supports mass customization and decentralization which makes it a sustainable technique. Despite these advantages, FDM has challenges pertaining to high-volume production, dimensional error, and surface quality. The investigations performed help to identify the critical parameters and control the output surface quality. Similarly, in paper V and VI, the investigations on injection molded surfaces are focused on identifying the critical process variables and significant surface features that can be input to improve process and product efficiency. These studies were part of the project which aimed at producing sustainable plastics for automotive interiors.

Figure 9: Sustainable Development Goals [62]

3 SURFACE METROLOGY

Surface metrology is a branch of metrology that involves measurement and evaluation of surface topography or texture. In this chapter, the components of surfaces, measurement techniques, measuring instruments and standard protocols for measurement are discussed. Surface characterization with standard surface parameters and multi-scale approaches are discussed in this chapter.

3.1 Surface texture

A surface can be defined as the boundary between the workpiece and the surrounding medium [64]. Surface texture refers to the geometrical irregularities that are present on the top layer of the manufactured surface [2]. It is important to measure and quantify these surface irregularities as they influence the surface behavior and consequently the functionality of the part/product. Surface texture can be decomposed into roughness and waviness, as shown in figure 10, and does not include form or shape of the surface [5]. Roughness describes the high spatial frequency features that include the footprints of the manufacturing process. Waviness describes the unintended mid-frequency features caused by disturbances such as vibrations and temperature variations. The waviness and roughness are separated from the primary profile using a suitable filter explained later in this chapter.

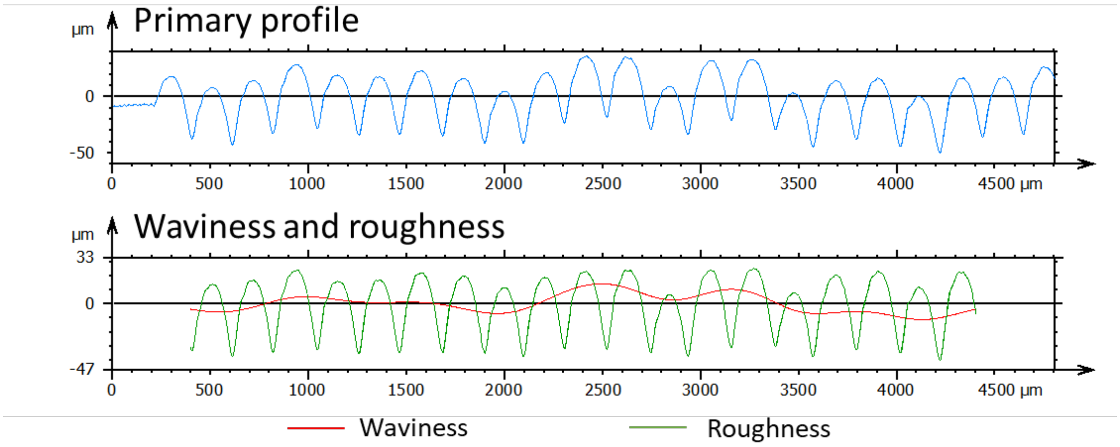


Figure 10: Roughness and Waviness components of surface profile

3.2 Surface texture measurement

Surface texture is measured using line-profiling, areal topography and area-integrating methods [65]. The *line-profiling methods* produce two-dimensional, or profile measurement of the surface irregularities represented as a height function z (x). Instruments such as the contact type profilometer [66] and the optical differential profiler [67] are some of the profile measurement instruments. The *areal-topography method* provides a topographical image of the surface represented as a height function z (x, y). Coherence scanning interferometer [68], focus variation microscopy [69], confocal microscopy [70], structured light projection [71], and atomic force microscopy [72] are some of the areal-topography methods. Areal measurements have more surface information and statistical significance compared to profile methods [64, 73]. Areal surface measurements can also be produced using a series of profiles with contact stylus instrument, although it is time consuming. *Area-integrating methods* produce measurements that rely on the area-integrated properties of the surface and do not produce surface profile or areal topography data [65]. Some of the area-integrating methods include total integrated light scatter [74], angle-resolved scatter [75], pneumatic flow measurement [76].

Stedman diagrams [77, 78] provide a graphic summary of the performance with respect to amplitude and wavelength coverage of different surface topographical measuring techniques. Different instruments provide different resolution with a wide range of wavelength-amplitude, capturing capability and different rate of data acquisition. This is well demonstrated in [79] for stylus and interferometer instruments using augmented Stedman diagram shown in figure 11. Stylus instruments have larger wavelength coverage whereas interferometers have a higher rate of data acquisition with better resolution of short wavelengths.

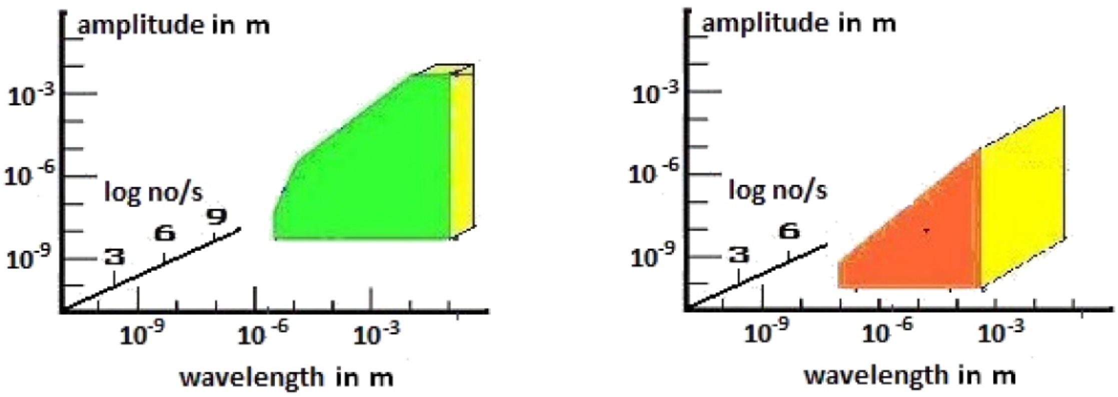


Figure 11: Augmented Stedman diagram for generic stylus (left) and interferometer (right) [reused from [79] with permission from IOP Publishing]

Surface texture measuring techniques using stylus profilometer, optical interferometer, structured light microscope, and Scanning Electron Microscope (SEM) are discussed in this section.

3.2.1 Stylus profilometer

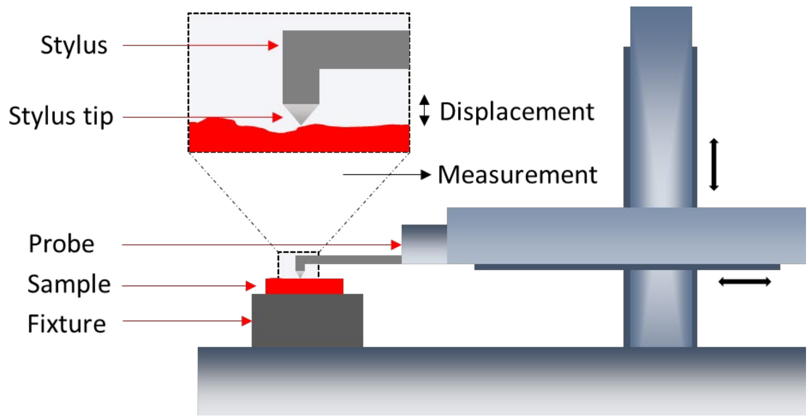


Figure 12: Stylus Profilometer

The stylus profilometer, illustrated in figure 12, is a contact type measuring instrument which uses a probe to detect and capture the surface height. The mechanical stylus is traversed against the surface texture over a predefined length and the vertical displacement is detected by a transducer such as LVDT (linear variable differential transducer) [1]. The stylus usually has a diamond tip with radius ranging from 0.5 to 50µm. The vertical displacements of the stylus due to surface irregularities are transformed into height data. The stylus tip shape and radius determine the vertical resolution of the instrument along with the maximum slope that can be captured. Stylus profilers are widely used and accepted surface measuring instruments primarily for traceability, with well-established standards and are less expensive. Both two-dimensional and areal surfaces can be recorded using this instrument. Some of the drawbacks include the concern over surface contact with stylus tip which may introduce ploughing marks depending on the material under investigation and slow measurement speed.

3.2.2 Coherence scanning interferometer

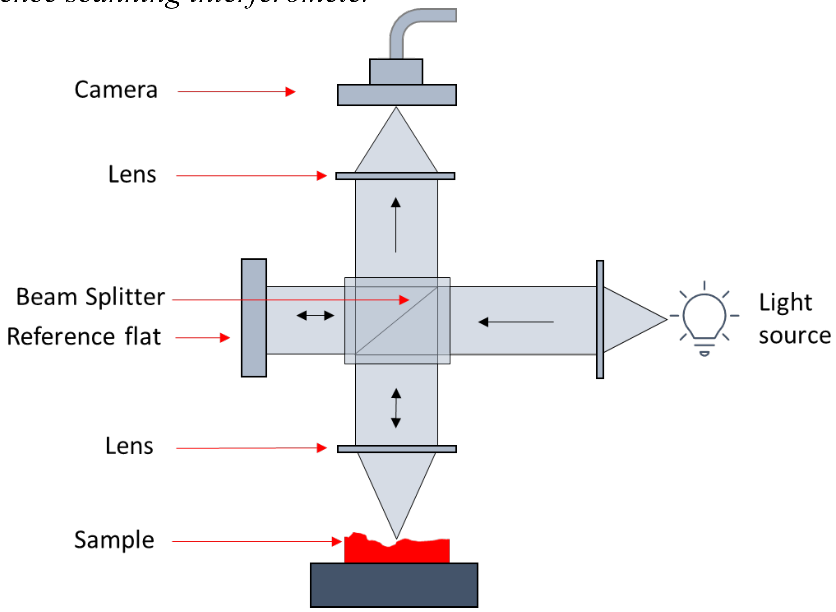


Figure 13: Illustration of Coherence Scanning Interferometer

Coherence scanning interferometer (CSI) is a non-contact and reflection mode interference microscope in which a three-dimensional image is acquired by stacking two-dimensional images scanned along the optical axis [80]. In this technique, the illumination from the light source is divided by a beam splitter into two paths as illustrated in figure 13. One path leads to the precision reference surface and the other travels to the sample surface. The reflected light from these two paths interferes and a pattern of light and dark intensities is created. These interference fringes, which represent the topography of the surface, vary as the objective lens is scanned vertically along the optical axis. CSI is also a well-established technique for areal surface measurement capable of measuring in sub-nanometer range and fast measurements. Drawbacks include limitation with respect to slope, non-reflective surfaces.

3.2.3 Structured Light Projection

In structured light projection, a predefined pattern of light or fringe is projected on the sample surface and the reflected light pattern is distorted due to the surface irregularities. This distortion is captured and with knowledge of incident light, the height information is calculated using a triangulation principle [65, 81]. The triangulation principle is illustrated with a single line in figure 14 and is calculated as in equation 1.

$$y = x \frac{sin\theta}{\sin{(\theta + \propto)}} \tag{1}$$

Where, y is the distance of the measured point on sample surface from the camera, x is the distance known between the projector and camera, θ and α are respectively the known angles of the light projector and camera with the sample surface. This technique is fast and capable of measuring large areas but limited in measuring highly reflective and high-resolution features.

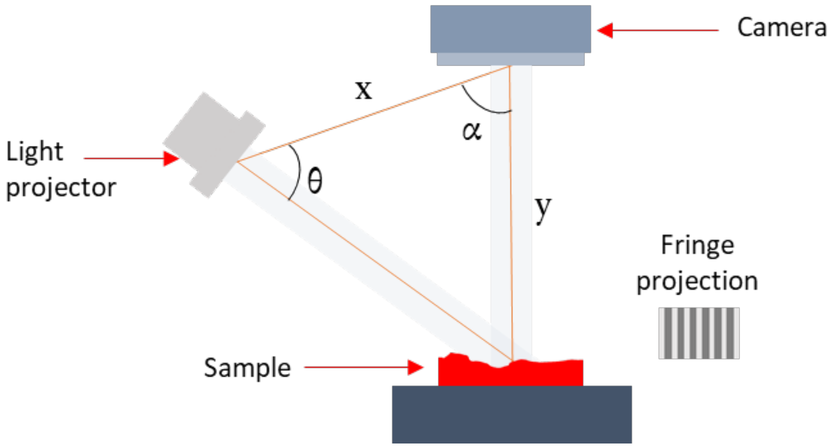


Figure 14: Illustration of triangulation principle

3.2.4 Scanning Electron Microscope

Scanning Electron Microscope (SEM) uses a focused beam of electrons that interacts with the sample surface and generates signals to form the image. SEM consists of a vacuum system with electron gun typically made of tungsten filament that generates the electron beam, condenser lens, objective lens, electron detector system for detecting secondary and backscattered electrons, deflector coils and sample mounting [82]. SEM is usually used to capture surface information in two-dimension but using photogrammetry, it is possible to generate a three-dimensional image which involves reconstruction of two or more 2D images captured at predefined angles [83, 84]. SEM can capture features at high-resolution, provides a broad magnification range and large depth of field.

3.3 Measurement strategies

Manufactured surfaces include footprints that are created by the manufacturing process-unintended form error, surface feature periodicity, surface defects, other surface irregularities caused due to tool wear, vibrations, or other uncontrolled factors. These entities influence in determining the evaluation length, area, number of measurements and the approach for surface characterization and analysis. Some of the critical steps in surface measurements are discussed in this section.

3.3.1 Filtration techniques

Surface filtering is necessary for surface characterization as it separates the raw surface measurements into different scales or wavelengths that help trace the manufacturing footprints and surface functionality [85]. Some of the metrological filters include Gaussian filter, spline filters, morphological filters, wavelet transforms. The terminologies and the fundamental framework for metrological filters are specified in ISO 16610 [86]. Nesting indices are the set of numbers that control the filters separating different scales or wavelengths. Scale limited profile, as defined in ISO 21920-2: 2021 [4], is the profile structure extracted after applying a profile filter with a specified nesting index. Raw profile measurements are filtered with S-filter nesting index (N_{is}) to remove the small wavelength features to obtain primary surface profile. Primary profile is derived from the primary surface profile after removing the form by applying F-operator nesting index (N_{if}). Roughness and waviness profile are derived by applying L-filter (N_{ic}).

Scale limited surfaces are the surfaces that are measured and analyzed at a particular scale of interest. As defined by ISO 25178-2:2021 [5], scale limited surfaces are S-F which refers to primary surface after removing surface form using F-operator and S-L surfaces which refers to the separation of waviness and roughness using L-filter. The primary surface is filtered of small-scale features usually caused by vibrations using S-filter before the application of F- and L-filter. Multi-scale surfaces are obtained by applying various nesting indices to characterize and analyze surface topographical features at different scale of observation. This thesis focuses on the scale-limited surface profile and surface analysis.

Surface measurements might include outliers and non-measured points due to the slope-sensitiveness of surface instruments. These are post-processed using suitable operators with interpolation using the neighboring pixels.

3.3.2 Evaluation length and area

For surface profile, the evaluation length is the length along the profile used for identifying the geometrical structures characterizing the scale-limited profile and by default, evaluation length is five times the section length [4]. Section length is the length of the profile used to calculate the section length parameters based on which the evaluation length is determined. The default settings for different nesting indices, section length, evaluation length are defined in ISO 21920-3:2021 [87].

Evaluation area is the area of measurement that covers the surface topography characterizing the scale-limited surface. Evaluation area, for measurements with square sides with length same as the L-filter nesting index should be typically five times the scale of the coarsest structure [88]. Another method to identify the minimum evaluation area is by using scale sensitive fractal analysis (SSFA), discussed in section 5.4.2. In general, it is ensured that the surface measurements are representative of the features of interest.

3.3.3 Number of measurements

Surface topography variations on a manufactured surface is statistically assessed with multiple measurements which are presumed to be probabilistically independent. The number of measurements or the sampling size is determined based on the intra-surface variation of surface parameters and the acceptable confidence interval. Higher variation requires higher number of measurements and in case of large variations, wavelengths of interest can be extracted by the application of suitable filters.

3.3.4 Surface Relocation

Surface relocation is the measuring strategy in which surface measurements are relocated to the same geometrical location [89] before and after a manufacturing or experimental procedure. Surface relocation helps to accurately trace and compare variation in surface topography generated from a manufacturing process or surface function such as wear [90]. There are several methods that are tested, some of which include sample stage relocation [89], relocation by indentation marks near region of interest [91], cross-correlation [92] and co-localization [93].

3.4 Surface characterization

Characterization of surface topography includes quantifying the irregularities or features on the surface with defined parameters or multi-scale analysis. Realizing the importance of stable and reliable surface parameters, the technical committee of International Organization of Standardization (ISO) revised the surface standard specification in 1996 and categorized the surface parameters into seven groups. The surface parameters represent the various type, size, and distribution of the topographical features present on the surface.

3.4.1 Profile parameters

Primary profile consists of waviness and roughness components. The primary profile is characterized using profile parameters abbreviated with P followed by suffix representing the region, type, or distribution of features in the surface profile. Similarly, waviness parameters start with W and roughness parameters start with R. Some of the roughness parameters used in the appended papers are listed in table 1. There are several changes and additions made to the profile parameters and its description in the new standard ISO 21920-2:2021 [4].

Table 1: Roughness parameters, ISO 4287:1997 [94]

Family	Abbreviation	Surface profile parameter	Unit
Amplitude parameters	Rp	Maximum peak height of the roughness profile.	µm
	Rv	Maximum valley depth of the roughness profile.	µm
	Rz	Maximum Height of roughness profile.	µm
	Rc	Mean height of the roughness profile elements.	µm
	Rt	Total height of roughness profile.	µm
	Ra	Arithmetic mean deviation of the roughness profile.	µm
	Rq	Root-mean-square (RMS) deviation of the roughness profile.	µm
	Rsk	Skewness of the roughness profile.	
	Rku	Kurtosis of the roughness profile.	
	Rp1max	Maximum local profile peak height	µm
	Rv1max	Maximum local profile valley depth	µm
	Rz1max	Maximum local height of the profile	µm
Spacing parameters	RSm	Mean width of the roughness profile elements.	mm
	Rdq	Root-mean-square slope of the roughness profile.	°
Material ratio parameters	Rmr	Relative Material Ratio of the roughness profile.	%
	Rdc	Roughness profile Section Height difference	µm
	Rmr (Rz/4)	Automatic relative material ratio of the roughness profile.	%
Peak parameters	RPc	Peak count on the roughness profile.	1/cm

3.4.2 Areal surface parameters

Areal surface parameters provide numerical characterization of three-dimensional surface. Areal surface parameters were initially developed in a EU funded project called *Birmingham 14* in 1993 [95]. The functional usefulness of these parameters was evaluated in the project SURFSTAND and published in [64]. This led to the development of ISO 25178-2 defining the areal surface parameters in 2012 [96]. The areal surface parameters utilized in the investigations presented in the appended papers are shown in table 2. Few changes and additions are made to the areal surface parameters in the standard ISO 25178-2:2021 [5].

Table 2: Areal surface parameters [96]

Family	Abbreviation	Surface profile parameter	Unit
Height Parameters	Sq	µm	Root-mean-square height
	Ssk		Skewness
	Sku		Kurtosis
	Sp	µm	Maximum peak height
	Sv	µm	Maximum pit height
	Sz	µm	Maximum height
	Sa	µm	Arithmetic mean height

Spatial Parameters		Sal	µm	Autocorrelation length
		Str		Texture-aspect ratio
		Std	°	Texture direction
Hybrid Parameters		Sdq		Root-mean-square gradient
		Sdr	%	Developed interfacial area ratio
Material ratio related parameters	**Material ratio parameters**	Smr	%	Areal material ratio
		Smc	µm	Inverse areal material ratio
		Sxp	µm	Extreme peak height
	Volume parameters	Vm	$\mu m^3/\mu m^2$	Material volume
		Vv	$\mu m^3/\mu m^2$	Void volume
		Vmp	$\mu m^3/\mu m^2$	Peak material volume
		Vmc	$\mu m^3/\mu m^2$	Core material volume
		Vvc	$\mu m^3/\mu m^2$	Core void volume
		Vvv	$\mu m^3/\mu m^2$	Dale void volume
	Areal parameters for stratified surfaces	Sk	µm	Core roughness depth
		Spk	µm	Reduced summit height
		Svk	µm	Reduced valley depth
		Smr1	%	Upper bearing area
		Smr2	%	Lower bearing area
		Spq		Plateau root-mean-square roughness
		Svq		Valley root-mean-square roughness
		Smq		Material ratio at plateau-to-valley transition
Feature Parameters		Spd	$1/\mu m^2$	Density of peaks
		Spc	1/µm	Arithmetic mean peak curvature
		S10z	µm	Ten-point height
		S5p	µm	Five-point peak height
		S5v	µm	Five-point pit height
		Sda	μm^2	Mean dale area
		Sha	μm^2	Mean hill area
		Sdv	μm^3	Mean dale volume
		Shv	μm^3	Mean hill volume

Height parameters characterize the surface topographical features normal to the surface and provide information on the surface amplitudes including root mean square height (Sq), arithmetic mean height (Sa), skewness (Ssk), Kurtosis (Sku), maximum peak height (Sp), Maximum valley height (Sv) and maximum height of surface (Sz) which is the sum of Sp and Sv.

- Root mean square height, Sq provides square root of the mean square of the ordinate values and Arithmetic mean height, Sa is the mean of the absolute of ordinate values [5]. Sq and Sq are often associated with average surface roughness and surface asperities.

$$S_q = \sqrt{\frac{1}{A}\iint_A z^2(x,y)dxdy}$$

$$S_a = \frac{1}{A}\iint_A |z(x,y)|dxdy$$

Where, A is the evaluation area, z is the surface height in x and y positions.

- Skewness, Ssk is the ratio of mean cube value of ordinate values and the cube of Sq and Kurtosis, Sku is the ratio of the mean quartile of ordinate values and fourth power of Sq [5]. Ssk and Sku characterize the aspect of surface texture height distribution. Skewness is positive for surfaces with bulk material above mean plane, negative if the bulk material is below mean plane. Kurtosis provides information on the spikiness of the surfaces [97].

$$S_{sk} = \frac{1}{A{S_q}^3} \iint_A z^3(x, y)dxdy$$

$$S_{ku} = \frac{1}{A{S_q}^4} \iint_A z^4(x, y)dxdy$$

Spatial parameters include Autocorrelation length (Sal), Texture aspect ratio (Str) and Texture direction (Std). Autocorrelation length is the horizontal distance of the autocorrelation function which has the fastest decay to a specified value *s*, with $0 \leq s \leq 1$ [5]. Surfaces dominated with low spatial frequency components have large Sal and vice versa. Str is the ratio of horizontal distance of the autocorrelation function which has fastest decay (r_{min}) to the slowest decay (r_{max}), shown in figure 15. Dominant spatial wavelength, Ssw, is new addition to the spatial parameters that gives information on the wavelength corresponding to the absolute values of Fourier transformation of ordinate values.

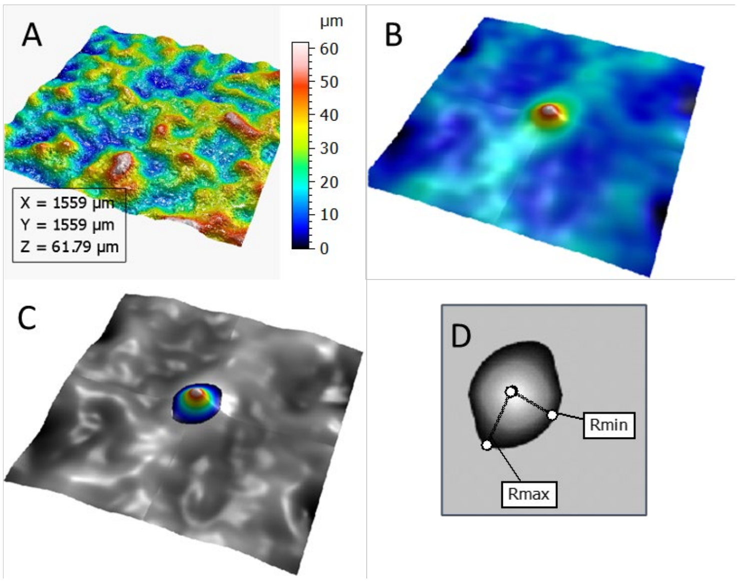


Figure 15: A. Areal surface image, B. Autocorrelation function, C. Autocorrelation peak with applied threshold of 0.2 (*s*), D. Minimum (r_{min}) and Maximum (r_{max}) radii measured on the central lobe of the autocorrelation peak

Hybrid parameters include root mean square gradient (Sdq) and developed interfacial area ratio (Sdr). Root mean square gradient, Sdq is the square root of the mean square of surface gradient and Developed interfacial area ratio, *Sdr* is the ratio of the increment of interfacial area over evaluation area [5]. Sdq and Sdr provide information on the slopes and complexity of the surface features and helps in assessing surfaces related to adhesivity, sealing and aesthetic properties [97].

Material ratio related parameters include material ratio parameters, volume parameters and areal parameters for stratified surfaces. These surface parameters are widely used in applications related to friction and lubrication. Peak parameters assess running-in issues, core parameters assess steady-state and valley parameters responsible for retention of fluid [98].

- *Material ratio parameters* include surface parameters areal material ratio (Smr), Inverse areal material ratio (Smc) and Section height difference or Material ratio height difference (Sdc). As shown in figure 16, Smr(c) is the material ratio 'p' of the area of the material at the specified height 'c' to the evaluation area. Smc (p) is the height 'c' at areal material ratio 'p'. Sdc is the material ratio height difference between p and q material ratio.

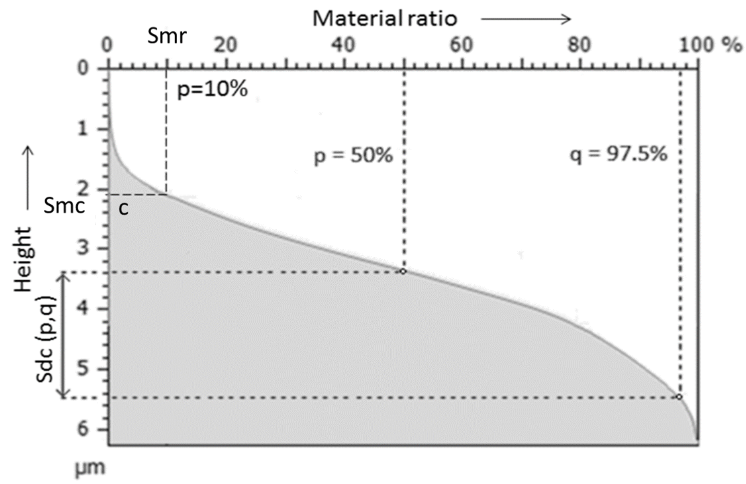


Figure 16: Illustration of surface parameters Smr (c), Smc(p) and Sdc(p,q) in material ratio curve

- *Volume parameters* include void volume and material volume parameters at different height distribution. Void volume, Vv is the volume of the voids per unit area at a specific material ratio calculated from the areal material ratio curve shown in figure 17. Dale void volume, Vvv is the dale volume at 'q' material ratio and provides information on the deepest valleys. Core void volume, Vvc is the difference in void volume between material ratio 'p' and 'q'. Material volume, Vm is the volume of material per unit area at a specific material ratio calculated from the areal material ratio curve.

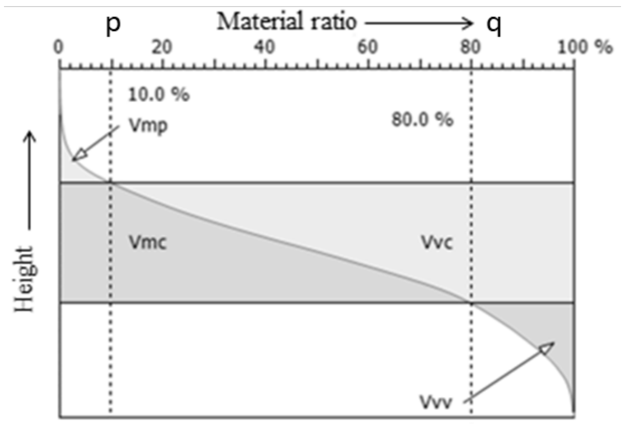


Figure 17: Illustration of volume parameters in a bearing areal ratio curve

- *Areal parameters for stratified surfaces,* illustrated in figure 18, include Core height (Sk), Reduced peak height (Spk), Reduced pit depth (Svk), Upper bearing area (Smr1), Lower bearing area (Smr2). These parameters are areal equivalent to the parameters Rk, Rpk, Rvk, Mr1 and Mr2 previously defined in ISO 13565-2 [97].

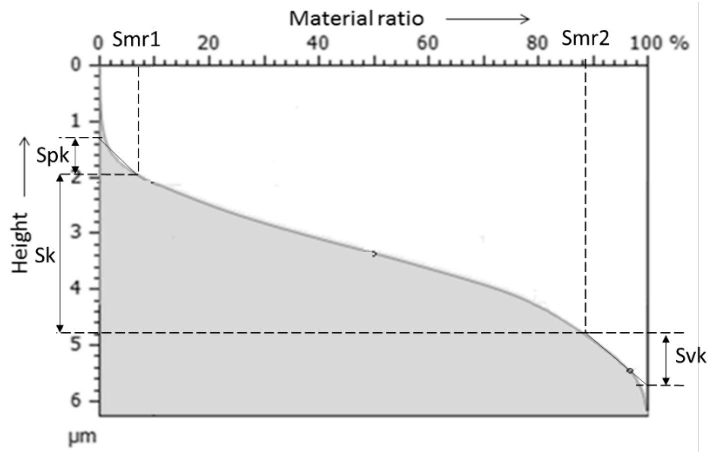


Figure 18: Illustration of areal parameters for stratified surfaces

3.4.3 Power Spectral Density

Power Spectral Density (PSD) provides a representation of the surface amplitudes as a function of spatial frequency or inverse of wavelength of surface features [11]. PSD is calculated as the Fourier transform of the autocorrelation function containing the power across a range of spatial wavelengths and is largely unbiased by the scan size and the pixel resolution [99]. Based on ISO 25178-2:2021 [5], Areal Power Spectral Density (APSD) is defined as the magnitude square of the Fourier transform of the measured surface normalized by the pixel size. The PSD and its use in capturing the manufacturing footprint is illustrated by Whitehouse [11]. The calculations and application of PSD are shown in [100, 101]. In the appended paper II, Power Spectral Density (PSD) is utilized to identify the dominant spatial frequencies of surfaces produced by FDM process at different build inclinations. The mathematical equation of 2-dimensional PSD calculation of surface topography data *z (x, y)* expressed as [75, 102]:

$$PSD\left(f_x, f_y\right) = \frac{1}{L^2}\left|\int_{-\frac{L}{2}}^{\frac{L}{2}}\int_{-\frac{L}{2}}^{\frac{L}{2}} z(x,y)e^{-2\pi i(f_x x + f_y y)}dxdy\right|^2 \tag{2}$$

Where, f_x and f_y are the rectangular components of the surface frequencies, L is the length of the pixel or the lateral resolution of measured surface.

Power Spectral Density (PSD) plots of FDM surfaces built at different surface inclination are shown in figure 19. PSD function describes primarily two aspects of surface; spread of the height from a mean plane and the lateral distance over which the height variation occurs [103]. Challenges with respect to different PSD calculation methods, application and strategies to mitigate are provided in [99].

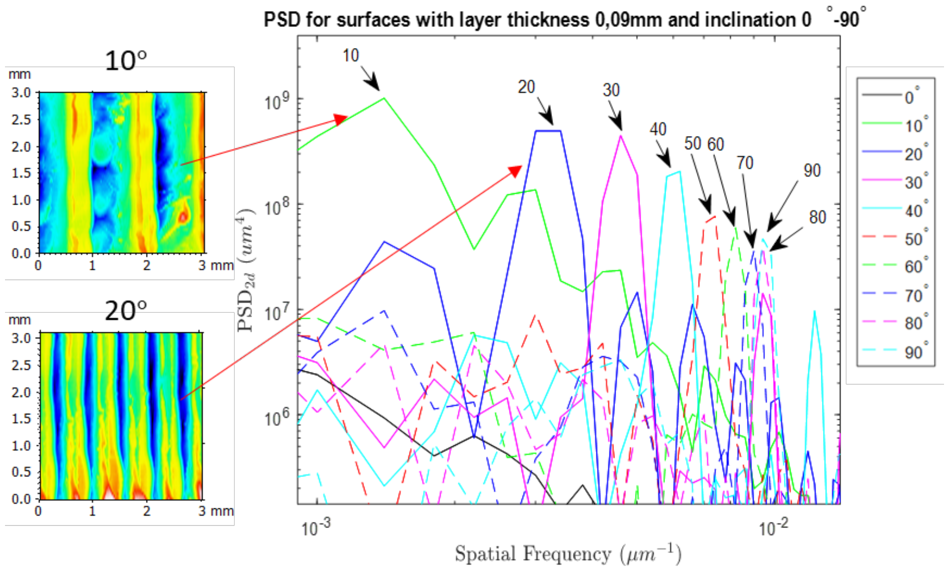


Figure 19: Power Spectral Density (PSD) plots of FDM surfaces

3.4.4 Scale-Sensitive Fractal Analysis

Scale-sensitive fractal analysis (SSFA) helps to decompose the surface features with respect to different scales of observation. It consists of two methods: length scale analysis and area scale analysis. Length scale analysis focuses on the profile features and area scale analyses focus on areal features. The area-scale analysis which involves virtual tiling algorithm generating a mesh of triangular tiles over the surface topography with each triangle having the same area, representing the areal scale of calculation [104]. At each scale, the relative area is, defined in ISO 25178-2:2021 [5], calculated by dividing the calculated area over nominal area and the calculated area is the product of number of triangular tiles covering the surface and area of each triangle at a specific scale. The nominal area is calculated with the area of the tiles projected onto the datum and varies with inclination. Relative area is plotted as function of scale which helps to visualize the surface topography at different scale of observation. Complexity plots are obtained with slope of relative area multiplied by order of magnitude [104]. The application of SSFA to identify the correlations between surface topography and process or functional performance is presented in [105]. In this thesis, complexity plots are utilized to identify the scales between which the surface topographies can be discriminated effectively. In another investigation, the complexity plots are used to identify the spatial wavelength of interest and calculate the evaluation area [106].

4 RESEARCH METHODOLOGY

Research is a process of systematic investigations on information gathered to understand a phenomenon and interpretation of that information using suitable research approaches to establish new facts [107]. Established research approaches helps to develop better understanding, universal acceptance, and reproducible results. In this chapter, an overview on the research methodologies and the research approach employed to answer the research questions is described and discussed. Further the employed research methodology to achieve the research objectives is presented.

4.1 Background

Design research helps to develop understanding and support for improving the design of product and process [108]. Here, support can be strategies, methodologies, or guidelines to improve one or more aspects of design. Design can be defined as the process of identifying and developing solutions to fulfil the need. Research methodology provides a framework for planning, implementation, and analysis of a study. Design research methodologies help to improve design research quality, identify research objectives, and produce scientifically valid research results.

Several methods are proposed to improve the quality of the research. Habka and Eder [109] developed design methods to analyze technical systems representing products and processes. They decomposed design science into theory of technical systems, design object knowledge, theory of design process and design process knowledge. Finger and Dixon [110], based on their literature studies classified mechanical design research into six areas including descriptive models; prescriptive models; computer based models; languages, representations, and environments for design; analysis to support design decisions; design for manufacturing and life cycle. Duffy and Andreasen [111] and O'Donnell and Duffy's [112] proposed framework for conducting design research which intends to build models based on *reality* (existing situation) and these models are continuously evolved to build tools to support design. Blessing and Chakrabarti [108] proposed Design Research Methodology (DRM) a more rigorous approach for design research to be more effective and efficient in developing tools to improve and achieve the desired goals. Several researchers have implemented and tested the DRM framework in their PhD projects [108].

In this thesis, Design Research Methodology (DRM) proposed by Blessing and Chakrabarti [108] is followed which provide framework to structure and implement systematic research approach. DRM includes four stages; research clarification, descriptive study 1, prescriptive study and descriptive study 2 and each stage has basic means and specific outcomes linked as shown in figure 20.

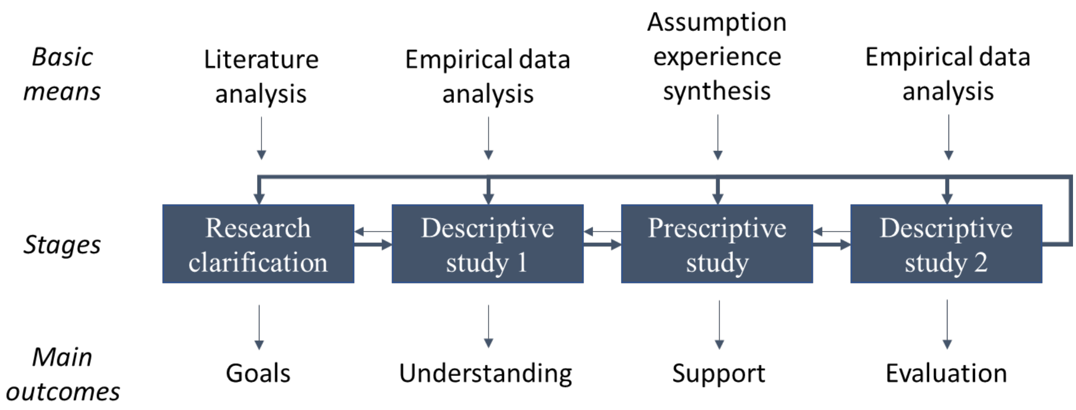


Figure 20: Design Research methodology adapted from [108]

The sequence of stages can be looped depending on the research project or purpose and includes [108]:
Research Clarification: Here, the desired goals and aim of the research are framed based on the literature review of existing situation. Preliminary definition of success criteria and measurable success criteria which form the research objectives are framed against which the methods developed are evaluated. The objective of this stage is fulfilled by literature review.
Descriptive Study 1: Here, the understanding and preliminary description of existing situation is further improved. The critical factors that improve the desired goals are determined. The objectives of this stage can be achieved by empirical investigations such as experiments, interviews, or observations. Deeper understanding and better definition of success and measurable success criteria are framed in this stage.
In *Prescriptive Study*, the support is developed to improve the existing situation and achieve the desired goals. Support can be in the form of tools, methods, or guidelines. Investigations are performed focusing on the problem and the possible means to resolve it.
In *Descriptive Study 2*, the developed methods in the prescriptive stage are evaluated for its effectiveness against the desired goals and objectives. Empirical studies are conducted to evaluate the effect of support in the change from existing to the desired goal outlined as measurable success criteria. Necessary improvements in the support are identified and DRM stages are iterated for further improvement.
In this thesis, the research topic is related to surface characterization and analysis. This research intends to improve specifications for surface roughness; and avoid over specification by identifying the significant surface parameters that not only discriminate between the study samples but also provide information on the effect of manufacturing process and its variables on surface topography. The knowledge and methods developed from the research results provide necessary information that helps to optimize the process and mitigate the variation.

4.2 Research framework based on DRM

The stages of DRM are utilized in this section to present the research process and research results. The research activities conducted resulted in appended papers and its connection with research questions are described in this section. The application of DRM connecting the research questions and appended papers are shown in figure 21. Each stage in DRM is marked with review, comprehensive or initial study. Review based study refers to the literature review of the problem, comprehensive study is conducted due to the lack of evidence for the problem and initial study conducted to show the prospect of the support from the comprehensive study.

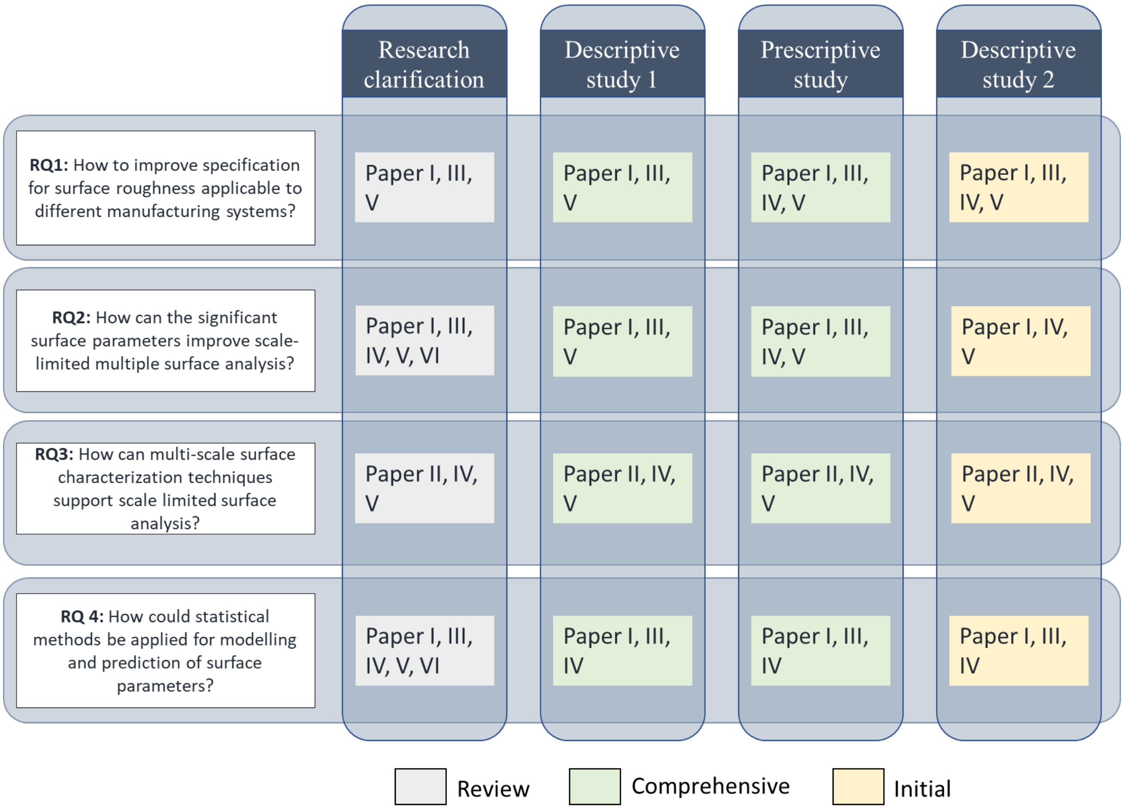


Figure 21: Applied Design Research Methodology

Research Clarification (RC): Surface topographical features are affected by different material and manufacturing technique and the variation in process variables. The desired situation of the research is to improve characterization and analysis of these surface topography features. Research questions are framed to elucidate how the desired situation can be achieved from existing situation of surface characterization and analysis. The research focus of Paper I, III and V is to characterize the surface topography produced by different systems and aims to answer RQ1 on improving the specification of surface roughness. Literature review [7, 8, 12-15] suggests that characterizing the variation in surfaces using standard surface parameters can help in understanding the manufacturing process *signature* or *footprints*. The investigations in Paper I, III, IV, V, VI and an industrial survey in [9] addresses RQ2 focusing on the existing situation and the importance of studying the variation with significant surface parameters. The complexity of surface features at various scales of observation discussed in research papers II, IV, V helps us to understand the relevance of multi-scale analysis for surface characterization and analysis. The scope of Paper I, III, IV, V helps to address RQ4 on optimization of process and function catering to different applications using significant surface parameters.

Descriptive Study 1 (DS 1): The next step is to improve the understanding of the existing situation by further analyzing the literature and conducting empirical studies. Based on the literature review and experimental investigations, surface parameters vary along with topographical features for different manufacturing process and processing conditions. Literature review in this concerned objective indicates that the problem identified is complex and has a large number of factors affecting the surface topography, mentioned in RC, along with dependencies such as measuring technique, measurement scale, size, resolution, and other instrumental constraints. Considering all these factors, the research aims at developing effective method to discriminate surfaces using a set of significant surface parameters and capture the effect of process variables. Discrimination of surfaces from different material and manufacturing conditions through *Design of Experiments* (DoE) is discussed in Paper I, III, V addresses RQ1. Identifying critical process variables using significant surface parameters representing the variation in the surface topographical features discussed in Paper I, III, V addresses RQ2 improving the scale-limited surface analysis. The use of multi-scale analysis discussed in Paper II, IV, V addresses RQ3. Statistical and machine learning methods discussed in Paper I, III and IV addresses RQ4 focusing on optimization of process. Based on these outlines, the success criteria can be defined as optimized engineering surfaces. The desired situation is to improve surface characterization and analysis of multiple surfaces produced by multiple levels of manufacturing process conditions to generate efficient and effective surfaces. Due to time constraints and scope of study, the iterative process to generate the optimal surfaces is not covered in this thesis. Hence the measurable success criteria can be defined as improved surface roughness specification which aims towards the desired goal discussed above.

Prescriptive Study (PS): In this stage, comprehensive investigations are conducted in developing methods to achieve the desired situation mentioned in DS1. Literature review in surface characterization using standard surface parameters suggests challenges related to *under specification* and *over specification*. Under specification is, for example, the application of average roughness parameters, Ra or Sa, to define the surface roughness without considering other pertinent surface parameters. Whereas over specification is the availability of too many standard surface parameters to define the surface roughness. Therefore, the focus is to identify the important surface features represented by significant surface parameters. Empirical investigations using statistical methods and the use of regression statistics shown in Paper I, III, IV, V answers RQ1 and RQ2. The application of power spectral density (PSD) and scale-sensitive fractal analysis (SSFA), explained in chapter 3, helps to identify the important scales for discrimination supporting the scale-limited surface study shown in Paper II, IV, V and addresses RQ3. The use of regression coefficients for predicting surface parameters in Paper I, III, IV answers RQ4.

Descriptive Study 2 (DS 2): In this stage, initial study is conducted to evaluate the usefulness of the methods proposed in PS1 and screened against the measurable success criteria defined in DS 1. Based on the outcomes in Paper I, III, IV, V, the methods employed successfully discriminate the surfaces manufactured at different process conditions. The significant surface parameters identified from the proposed methodology help to identify the varying topographical features and their magnitude with respect to material and process conditions. These outcomes answer RQ1 and RQ2. Multi-scale analysis helps to identify the important scales for investigations and is evaluated in qualitative analysis answering RQ3. The predicted significant surface parameters are compared and evaluated with the experimental results in Paper I, III, IV and answers RQ4.

The time and the scope of the research limit the investigations for additional iterations to validate and optimize the surfaces for engineering applications. The research methods employed to develop the support to achieve the research goals are discussed in the following section.

4.3 Research methods

Empirical studies are conducted, and a research methodology is synthesized that addresses the research questions and the desired outcome discussed in DS1. Different approaches for empirical studies include experimental, case study, systematic review, survey, and post-mortem analysis [113]. Experimental research design relates to collection of empirical data from experiments in a controlled simulation wherein one or more independent variables are manipulated using process controllers to confirm or refute the hypothesis. Experimental research design types include true experimental design, quasi experimental design, and pre-experimental design [114]. The research investigations discussed in this thesis are true experimental design conducted in a controlled condition to study, understand and interpret the phenomenon of surface topography formation from different manufacturing systems and understand the relationship between the process variables and surface parameters. True experimental design involves manipulating at least one independent or controllable variable and analyzing the response variable. Figure 22 provides an overview of the research workflow which is based on the surface control loop and consists of experiments, data generation and data analysis. Manufacturing and its process variables are covered in chapter 2. Characterization, surface measuring instrument and image processing are covered in chapter 3. In this section, the application of DoE and the data analysis methods employed to identify the significant surface parameters are discussed.

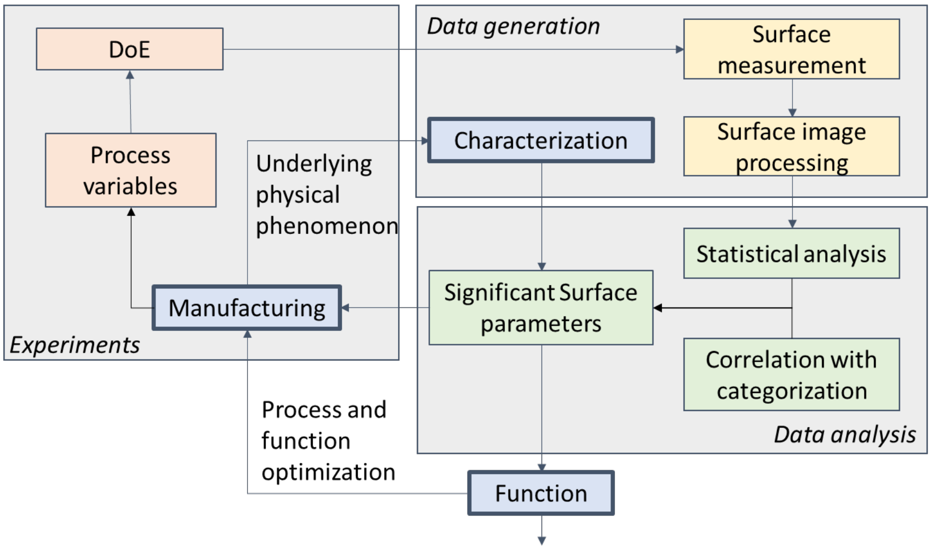


Figure 22: Research workflow

4.3.1 *Design of Experiment (DoE)*

Sir Ronald Fisher in 1920s used the DoE to increase agricultural yield which was later extensively used in applications of science and technology [115]. DoE's are primarily used to develop and optimize products and processes [116]. DoE includes a set of statistical tools used to classify and evaluate the relationship between controllable variables to the dependent or response variables. There are many types of DoE and selection of a particular DoE is based on the research objectives, whether it is a screening, characterization, or optimization problem. The selection and application of DoE is well summarized in the literature [115-117].

A block diagram of robust process design is illustrated in figure 23. The primary step in DoE is to state the objectives and select the process variables or controllable factors and its levels. Levels are the magnitude or scale upon which the response variables vary. In this case, the response variables are the standard surface parameters explained in Chapter 3. For controllable factors in this thesis, three different manufacturing systems: additive, subtractive and formative systems, with multiple process variables and multiple levels are addressed. The generation of surfaces is influenced by material and a wide range of process conditions depending on the type of manufacturing systems. Selection of controllable variables and their level are based on the literature review, pre-studies, and material supplier's recommendation. For additive manufacturing systems, build inclination and layer thickness were some of the process variables selected for investigations. For subtractive manufacturing by a turning operation, material, cutting tool coating and cutting feed are the factors considered in the investigation. For formative processes, tool temperature, injection speed, melt temperature and holding pressure are the process variables investigated. The influence of uncontrollable factors is assumed to be negligible. To ensure the reliability and accuracy of the experimental runs, randomization, replication, and blocking is adapted accordingly. In this thesis, characterization was the primary objective with full and fractional factorial DoE selected depending on the investigation.

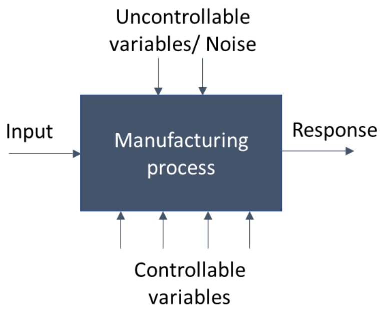


Figure 23: Block diagram of robust process design [118]

In a full factorial experiment design, all possible combinations and interactions of controllable variables are considered for the investigation [115, 117]. Here, a comprehensive understanding of the system behavior is accomplished. The number of experiments increases with number of variables and their levels. Fractional factorial experimental design using Taguchi's orthogonal array is an experimental setup in which the number of experiments is methodically reduced ensuring balanced inclusions of variables and levels [117]. For screening problems, there are Definitive Screening design (DSD) and Placket Burman design (PBD). For optimization problems, there are response surface methodology (RSM) which includes two experimental designs, Box-Behnken design (BBD) and Central-Composite design (CCD). These experimental designs are well summarized on their application in the literature [115-117]. For most of the investigations discussed in this thesis, three controllable factors with two to three levels are considered. Taguchi's orthogonal array and full factorial experimental designs are found to be sufficient and effective in extracting the information on system behavior.

4.3.2 Data analysis

Surface data generated from the manufactured surfaces using surface measuring instruments, discussed in Chapter 3, is subjected to image processing techniques to remove form, outliers and fill non-measured points. The processed image is characterized using the standard surface parameters, surface profile parameters for surface profiles and areal surface parameters for areal surfaces. These surface parameters characterize the surfaces based on their type, region, and distribution. This results in too many parameters to define surface topography and to decompose its features into several varied sizes and distribution [5, 97]. As discussed in Chapter 1 and 2, manufactured surfaces consist of signature features that are more relevant than others. There are several statistical methods that can be employed to identify these significant surface parameters. The selection of method depends on the investigation and this section provides a summary of the statistical methods for analyzing the surface data.

Correlation coefficient, R: Pearson's correlation coefficient, R, is the most widely used statistical method for analyzing the linear relationship between two variables [119]. Both magnitude and direction, positive or negative, of the relationship can be determined. The correlation coefficient can be used for analyzing the surfaces produced by varying one process variable with multiple levels. The surface parameters that have higher R, can be used to analyze the effect of that process variable. Negative R corresponds to an inverse relationship between the process variable and the surface parameter.

Average and Standard Deviation: For discriminating two types of surfaces, average and standard deviation method can be employed. Here, the variation of surface parameter is analyzed using standard deviation and confidence intervals [120]. Significance, F, is calculated by normalizing with the average values and used for discriminating between surfaces. Surface parameters with highest significance have the highest discrimination ability [120]. As shown in figure 24, the overlap or gap in the gaussian bell curve determines the ability to discriminate between the manufactured surfaces.

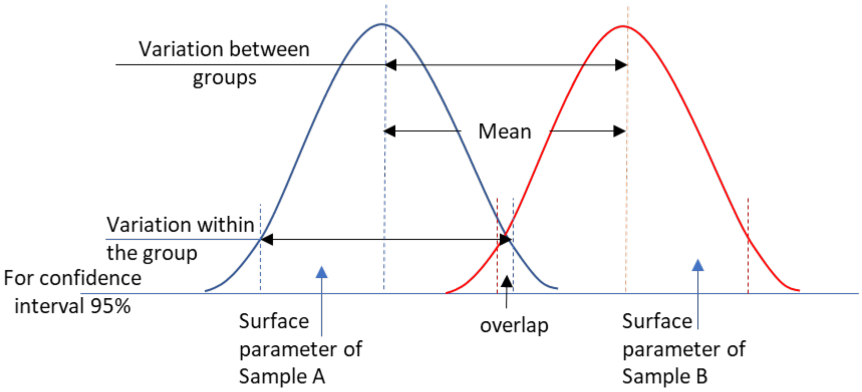


Figure 24: Average and standard deviation method

Analysis of Variance: Along with DoE, Sir Ronald Fisher developed ANOVA or Analysis of Variance, a statistical technique for testing the variances [121]. ANOVA is widely used in medical and engineering applications. ANOVA helps to analyze the variation in response variable, determine the differences between groups and to investigate whether the relationship is random or due to a particular effect [117, 122]. In the surface investigations described in this thesis, ANOVA is employed within regression analysis to identify the variation in the surface parameters and to identify the significance of process variables effect on the surface parameters.

Multiple Regression Analysis (MRA): Regression is a statistical technique used to estimate the relationship of one variable (dependent) with respect to other (one or more) independent variables [123]. Regression can be applied for data description, parameter estimation, prediction and estimation, and control [123]. To investigate surface data from multiple surfaces produced by multiple levels of process variables, Multiple Regression Analysis (MRA) is employed in the research methodology as shown in figure 25 and its application in surface analysis and modelling is discussed.

Manufactured surfaces consist of unique process signature primarily due to its working principle, the interaction of tool-workpiece and effect of process variables. Based on the initial data analysis and literature review, the critical process variables are identified, and experiments are conducted. Statistical tools such as multiple regression analysis are selected which provides information on the variation of the data in relation to the independent variables. Independent variables can be quantitative or numerical and non-quantitative or categorical. Categorical variables can be coded using dummy variables [124]. Dependent variables include surface measurements characterized by the standard surface parameters. The research methodology including regression output and its interpretations with respect to surface analysis is discussed in this section.

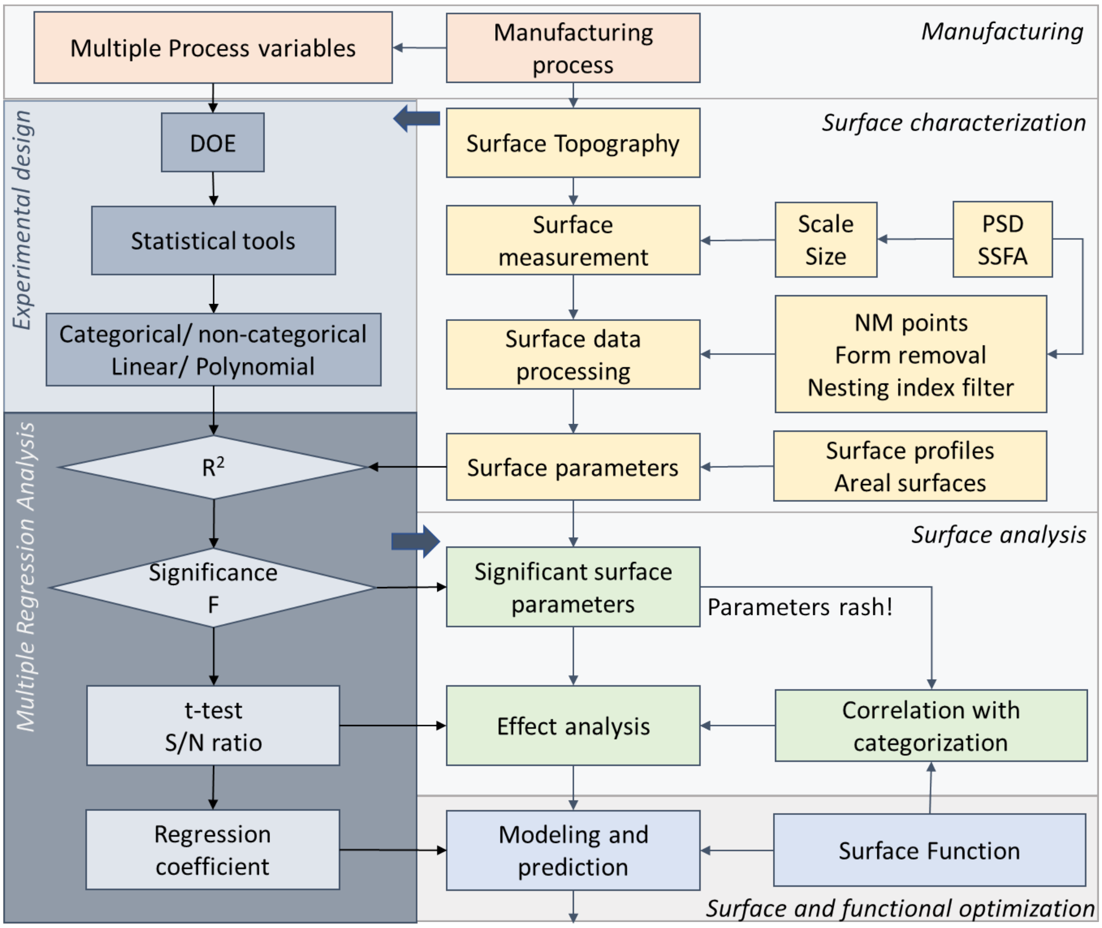


Figure 25: Research methodology

For surface parameters S_1, S_2, S_3…., S_x, consider the combination, tabulated in table 3, as the measurements at different combination of manufacturing process variables (A, B, C…, n):

Table 3: Data for multiple regression analysis

		Surface parameters, **S**				
		S_1	S_2	S_3	…	S_x
Combination of Process variables	A	S_{1A}	S_{2A}	S_{3A}	…	S_{xA}
	B	S_{1B}	S_{2B}	S_{3B}	…	S_{xB}
	C	S_{1C}	S_{2C}	S_{3C}	…	S_{xC}
	…	…	…	…	…	
	n	S_{1n}	S_{2n}	S_{3n}	…	S_{xn}

Significant surface parameters represent the topographical features that can be used to discriminate the surfaces produced at various levels of process variables. Statistically in MRA, significant surface parameters are identified by thresholding the coefficient of determination, R^2, and significance F.

Coefficient of Determination, R^2, provides information on the proportion of variation in dependent or response variables with respect to independent or input variables. The higher the R^2, the higher is the variability of the data explained with respect to independent variables. In surface analysis, R^2 provides information on the variability of the surface parameters due to the influence of process variables. Surface parameters with higher R^2 help to discriminate between the surfaces produced with different process variables with multiple levels. A threshold is set

depending on the investigation and the number of surface parameters qualified within the set range.
Consider Sx_m is the mean of the surface measurements from table 3, Sx_A, Sx_B, Sx_C, ... Sx_n,

$$\text{then, } Sx_m = \frac{1}{n}\sum_{i=A}^{n} Sx_i$$

Total sum of squares, $SST = \sum_i (Sx_i - Sx_m)^2$

Regression sum of squares, $SSR = \sum_i (Sy_i - Sx_m)^2$

Where, $Sy_A \ldots Sy_n$ is the modelled value for surface parameter S_1.

Sum of squares of residuals, $SSE = \sum_i (Sx_i - Sy_i)^2$

Coefficient of determination, $R^2 = 1 - \frac{SSE}{SST} = \frac{SSR}{SST}$

The addition of interaction terms might inflate the R^2. In such cases, the adjusted R^2 is calculated which considers the number of input variables in the model. The adjusted R^2 increases only if the addition of new term improves the model.

$$Adjusted\ R^2 = 1 - \frac{SSE/(n-k-1)}{SST/(n-1)}$$

$$Adjusted\ R^2 = 1 - (1 - R^2) * \frac{(n-1)}{(n-k-1)}$$

Where, n is the sample size and k is the number of process variables.

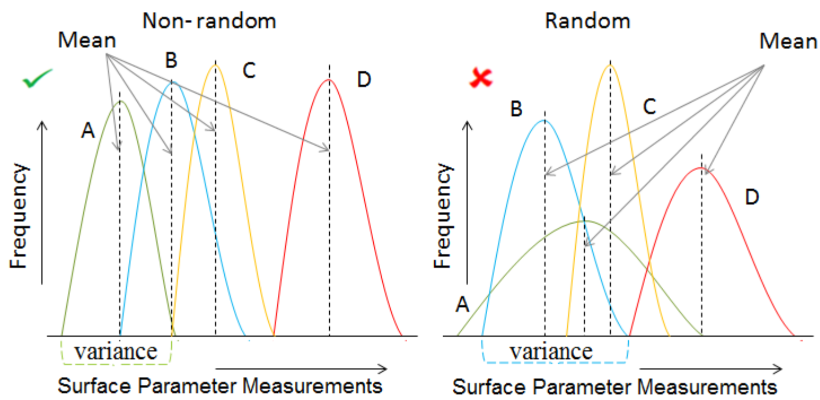


Figure 26: Illustration of Probability density plots of non-random and random surface measurements A, B, C, D of a single surface parameter [125]

Significance F or p-value from ANOVA provides information on randomness of the data. Probability of the surface parameters with respect to the process variables are not random if p-value associated with the F-test is less than 0.05 for $\alpha = 0.05$. In the probability density plots shown in figure 26, the surface parameters with lower variance and higher frequency of occurrence are selected as significant surface parameters.

$Test\ statistic,\ F_0 = \frac{MSR}{MSE}$

Mean Square Regression, $MSR = \frac{SSR}{df_{SSR}}$

Mean Square Residual, $MSE = \frac{SSE}{df_{SSE}}$

Degrees of freedom, df,

$df_{SST} = Total\ number\ of observations - 1$

$df_{SSR} = number\ of\ variables - 1$

$df_{SSE} = df_{SST} - df_{SSR}$

For significance level α=0.05,

Significance F = F_0 distribution with respect to df_{SSR} and df_{SSE} in the F distribution table.

Height parameters	Spatial parameters	Hybrid parameters	Feature parameters	Material ratio related parameters		
					Stratified	Volume
Sq	Sal	Sdq	Spd	Smr(c)	Sk	Vv(p)
Ssk	Str	Sdr	Svd	Smc(p)	Spk	Vvv
Sku	Std		Spc	Sdc	Svk	Vvc
Sp	Ssw		Svc		Smrk1	Vm(p)
Sv			S5p		Smrk2	Vmp
Sz			S5v		Svq	Vmc
Sa			S10z		Spq	
					Smq	

Figure 27: Areal surface parameters categorized [5]

Correlation with categorization: After the application of R^2, in cases of too many surface parameters qualified as significant, correlation within categories helps to further address the issue of *over-specification*. Here, highly correlated (R) surface parameters within the same category, as shown in figure 27, are substituted with surface parameters that has higher R^2 and considered for effect analysis [126]. Surface parameters that have higher R^2 but lower R with other surface parameters are not interchangeable parameters and describe a unique property of the surface. These surface parameters are also considered for the effect analysis.

T-test: The discrimination ability and randomness of the data are evaluated using R^2 and significance F. Here, the significance of process variable effect on the shortlisted significant parameters are evaluated using the t-test. For confidence interval of 95%, if the p-value is less than 0.05, then the influence of the process variable on that specific surface parameter is significant.

$$t - statistic, \qquad T_0 = \frac{\widehat{\beta_J}}{se\ (\widehat{\beta_J})}$$

Where, $\widehat{\beta_J}$ is the least squares estimator of regression coefficient, *j*= 0, 1, 2, …, k in a multiple regression model is different linear combination of process variables and *se* is the standard error. For 95% confidence interval, p-value is approximated from the t-statistic distribution table. The calculation for $\widehat{\beta_J}$ and *se* $(\widehat{\beta_J})$ in a multiple regression problem is briefly described in [115].

Regression coefficients are used to interpret how the input variables or independent variables affect the response of dependent variables [123]. Here, it is used to model and predict the surface parameters with respect to the materials and manufacturing process variables. Regression coefficients are associated with standard error and confidence interval [124].

For simple linear model with one process variable,

$$\widehat{S_x} = \beta_0 + \beta_1 A + \epsilon$$

Where, $\widehat{S_x}$ is the predicted value of surface parameter S_x, A is the process variable, β_0 is the intercept when the process variable is zero, β_1 is the predicted coefficient calculated using the equation below and ϵ is the model error.

$$\beta_1 = \frac{\sum(A_i - A_m)(S_{x_i} - S_{xm})}{\sum(A_i - A_m)^2}$$

Where, A_i is the process variable for i^{th} observation; A_m is the mean value of the process variable A; S_{x_i} is the 'x' surface parameter; S_{xm} is the mean surface parameter.

For regression model with multiple process variables,

$$\widehat{S_x} = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \cdots + \beta_n n + \epsilon$$

Where, $\widehat{S_x}$ is the predicted value of surface parameter S_x; A, B, C, …, n are the process variables; β_0 is intercept when the process variables are zero; $\beta_1, \beta_2, \ldots, \beta_n$ are the predicted coefficients and ϵ is the model error.

For multiple regression with interaction effect is modelled as,

$$\widehat{S_x} = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 AB + \epsilon$$

Where, $\widehat{S_x}$ is the predicted value of surface parameter S_x; A, B are the process variables; β_0 is the intercept when the process variables are zero; $\beta_1, \beta_2, \beta_3$ are the predicted coefficients and ϵ is the model error.

Signal-to-noise (SN) ratio: Taguchi's Signal-to-noise ratio is used to identify the contribution of controllable variables to the variation of response [127]. Signal-to-noise ratios can be categorized into three investigations; lower-the-better, higher-the-better, and nominal-the-better [127, 128]. In lower-the-better investigations, the aim is to reduce both the mean and the variance, and the ideal SN ratio is zero. Whereas in higher-the-better studies, there is no pre-determined target value, and the aim is to have higher values of SN ratio. In this thesis, nominal-the-better, as in equation 3, is used to quantify the effects of process variables on the variation of significant surface parameters. It helps to identify the influence of process variable on distinctive surface topographical features. Signal-to-noise ratio is calculated for each experimental run *i* using the following equation.

$$SN_i = 10\log\left(\frac{mean_i^2}{variance_i^2}\right) \tag{3}$$

4.3.3 Limitations and assumptions

The variations in the surface topographical features influenced by materials and manufacturing process are quite complex to evaluate and predict. The research methods discussed in this chapter help to capture the probable variation of these topographical features represented by standard surface parameters. The research methods have the following limitations and assumptions with respect to the data measurement and analysis primarily to the scope of the study along with time constraint:

Sampling interval: The surface measurements are taken probabilistically independent from each other and analyzed, and the sampling size is decided as mentioned in Chapter 3. It is not practical and efficient to capture an entire manufactured surface. The sampling interval and population size is decided on whether the measurements capture the manufacturing footprints. In this study, the captured surfaces are assumed to be representative of the manufactured surface.

Outliers: Surface measurements may include outliers, either due to the measuring limitations or the surface inclusions which are not part of the investigations. Outliers can spike the regression statistics and lead to incorrect interpretations. Therefore, the surface data are carefully post-processed and examined for outliers. Hence, it is assumed that the surfaces are free from outliers, or that they do not have a considerable effect on the surface data.

Noise factors: Noise factors may include material inhomogeneity, manufacturing process, surface measurements, environmental conditions, or human error. The effect of uncontrollable variables or noise is not part of the investigations. It is assumed that this effect is negligible and does not have considerable influence on the surface measurements.

Linear approach: Linear approaches are straight-forward, simpler for interpretations and help assess the randomness using R^2. Linear regression assumes a linear relationship between the dependent and independent variables and is sensitive to outliers. Whereas non-linear approaches require better understanding of the physical phenomenon and scientific models that provide accurate relationship between the dependent and independent variables. In non-linear approaches, R^2 might not provide accurate information on the randomness. So, the linear approach is efficient and effective for the addressed investigation.

Extrapolation: Regression models are intended to interpolate the independent variables within the design space. Extrapolation outside the experimented range of process variables might be inaccurate and should be cautiously assessed.

Residual plots: The residual plots help to validate the model and if the spread of the data is random, then the data is said to be homoscedastic and unbiased. Homoscedasticity refers to dependent variables having the same variance in their errors, regardless of the process variables. For surface analysis, the assumption of equal variance is assumed, though the surface parameters might have a wide range of variances.

Multi-Collinearity: In regression, multicollinearity occurs when there are correlated independent variables, and this affects the regression model. Too many process variables and its interaction terms might also affect the predicted coefficients.

5 RESULTS AND DISCUSSIONS

This chapter summarizes the key research findings and its interpretations from the appended papers on surface characterization and analysis. The application of research methodology to different manufacturing systems and its results are discussed. Finally, the research questions are answered using the results from the appended papers.

5.1 Synthesis of research results

Surfaces produced by different manufacturing systems under varied process conditions are subjected to the research methodology to identify the deterministic information represented by significant surface parameters. To understand the application of research tools and answer the research questions, the results from the appended papers are classified into the following research objectives.

1. *Surface roughness specification*: This is evaluated based on the surface discrimination capability of significant surface parameters. By thresholding the coefficient of determination, R^2 and validating the randomness of the data using the test statistic- F_0, significant surface parameters are identified.

2. *Surface discrimination and effect analysis*: By using significant surface parameters, the effects of process variables are evaluated. To validate the effect of process variables on significant surface parameters and to quantify the effects, test statistic- T_0 and signal-to-noise ratio are employed.

3. *Multi-scale characterization and analysis*: Scale-limited surface analysis is supported by multi-scale analysis. Scale-sensitive fractal analysis is used for identifying the important scales of observation and to identify the surface representable measurement size. Power spectral density plots are used to decompose and identify the deterministic surface features.

4. *Modelling and prediction*: The significant surface parameters are modelled and predicted using regression coefficients. This modelling of surface parameters helps to optimize the process and to predict the intended surface functional behavior.

The numerical characterization by significant surface parameters represents the surface topographical features that are altered by the manufacturing process. These surface parameters are further assessed to quantify the effects of process variables. The use of advanced characterization methods to support scale-limited surface analysis is investigated. Finally, the significant surface parameters are predicted and modelled which can be later used for control and optimization. The appended papers with diverse research topics use the research tools, explained in Chapter 3 and 4, to achieve the research objectives and answer the research questions. This connection of research questions, appended papers and achieved objectives are illustrated in figure 28.

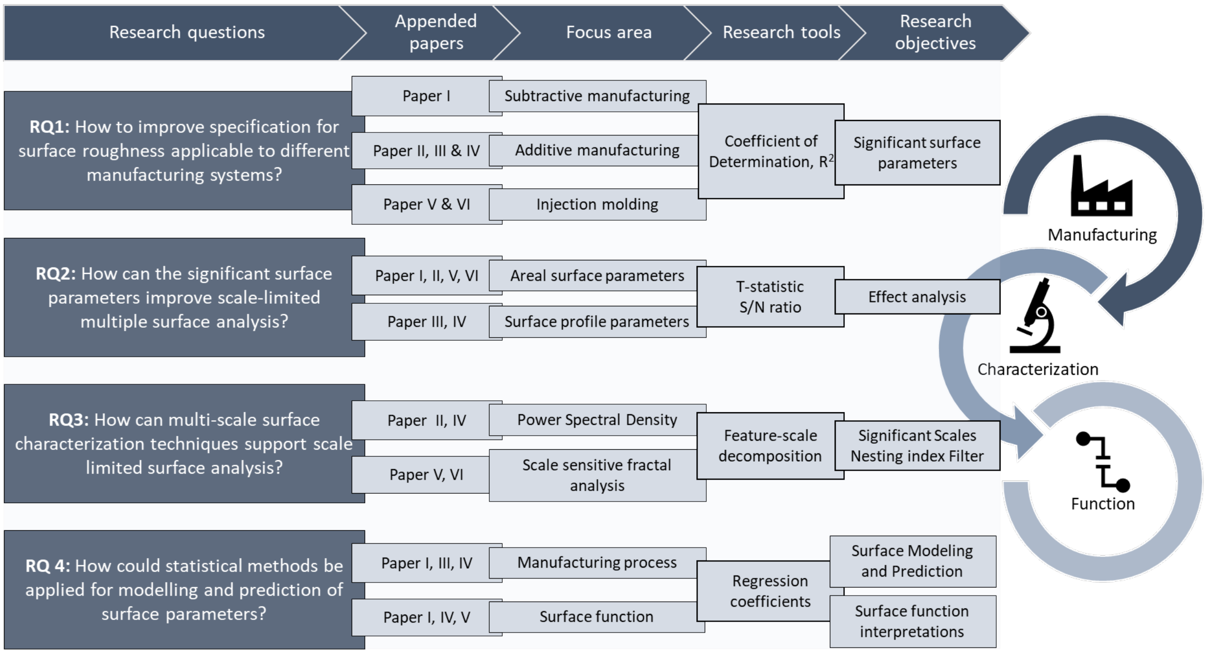


Figure 28: Contributions of appended papers to the research questions and objectives

5.2 Surface roughness specification

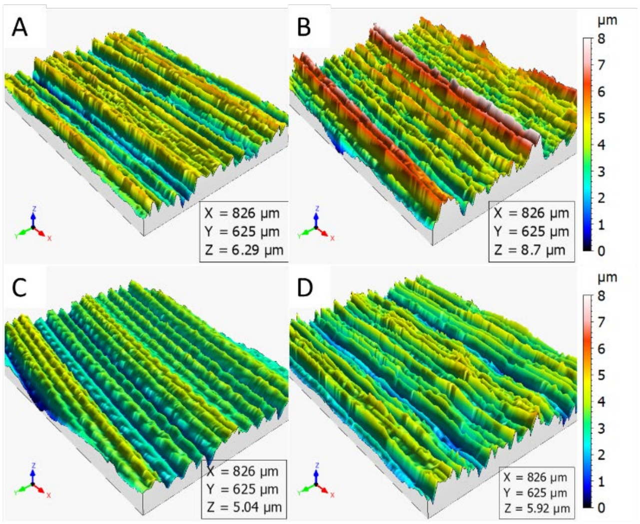
RQ1: *How to improve specification for surface roughness applicable to different manufacturing systems?*

With potential benefits, the interest in specification of surface roughness with different surface parameters has gradually increased in the industrial sector [9, 10]. It is not straightforward and efficient to include all the surface parameters for specification of surface roughness. Suitable methods are required to identify the critical surface parameters that can be used as the criteria to control the manufacturing process and surface function. The results of applying research methods to improve the surface roughness specification applicable to different manufacturing systems are discussed in this section.

5.2.1 Subtractive manufacturing: Paper I

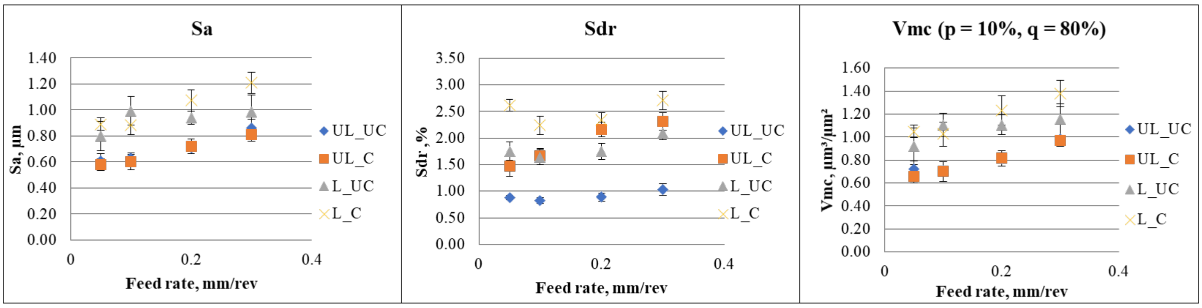
Paper I: Surface topography characterization of brass alloys: lead brass ($CuZn_{39}Pb_3$) and lead-free brass ($CuZn_{21}Si_3P$)

Considering the adverse consequences of lead contamination, the lead content in brass and brass alloys is replaced with a lead-free alternative. During the manufacturing of lead brass components, the lead gets dispersed on the surface topography and reduces the cutting force during turning operation [20], and results in lower production cost and time compared to lead-free brass [129]. Hence, it is sought-after to develop sustainable techniques to improve the manufacturability and functionality of brass alloys without lead [129]. Investigations on surface topography of turned lead- and unleaded brass samples with different cutting tool coating and process conditions were analyzed. This study was part of the project which aims at controlling the surface integrity of unleaded brass alloys substituting lead with silicon. Qualitative analysis from SEM and areal surface images, as observed in figure 29, suggest higher asperities on lead brass compared to unleaded brass. The surfaces are captured using optical interferometer and areal surface parameters are considered for characterization of surface topography. A full factorial experimental design includes cutting feed, cutting tool coatings and the material as independent variables and areal surface parameters as the dependent variables.



A. Lead brass machined at 0.1mm/s,
B. Lead brass machined at 0.3mm/s,
C. Unleaded brass machined at 0.1 mm/s
D. Unleaded brass machined at 0.3mm/s

Figure 29: Surface topography of turned brass alloys [125]



UL_UC: unleaded brass machined using uncoated tool, UL_C: unleaded brass machined using coated tool
L_UC: lead brass machined using uncoated tool, L_C: lead brass machined using coated tool

Figure 30: Significant surface parameters of brass alloys [125]

Using multiple regression analysis, the significant surface parameters are identified for discriminating the study samples surface topography. With coefficient of determination, R^2> 70% as the threshold, height parameters Sa, material ratio related parameters Smc, Sdc, Vmc, Vv and hybrid parameters Sdq, Sdr are shortlisted as significant. These significant surface parameters are used to define the surface roughness and understand the variation in the surface topography caused by the manufacturing process. Figure 30 shows that the surfaces of lead brass have higher arithmetic mean height (Sa) and core material volume (Vmc) compared to its lead-free counterpart. The increase in feed rates has led to increase in most of the significant surface parameters. These surface parameters represent deterministic feature distribution on the surface topography which is observed to improve the specification of surface topography produced by turning operations.

5.2.2 Additive manufacturing: Paper II, III, IV

Paper II: Topography characterization of Fused Deposition Modelling surfaces
Paper III: Study on surface texture of Fused Deposition Modelling
Paper IV: Influence of different post-processing methods on surface topography of Fused Deposition Modelling samples

Additive manufacturing is in a state of transition from rapid prototyping to manufacturing. But there are still concerns regarding the quality of output, especially the surface quality. Surface quality produced by additive manufacturing varies depending on the manufacturing technique, materials and process conditions [28]. The research on additive manufacturing, discussed in Papers II, III and IV, is focused on polymer based FDM to identify the critical variables and methods to improve or optimize the output surface topography. In paper II and III, the objective is to characterize and analyze the surfaces produced from FDM using surface parameters and Power Spectral Density (PSD). In paper IV, the surfaces produced by the FDM process are subjected to different post processing techniques and the resulting surfaces are analyzed to identify the ideal post-processing combination and conditions to replicate the surfaces of its injection molded counterpart.

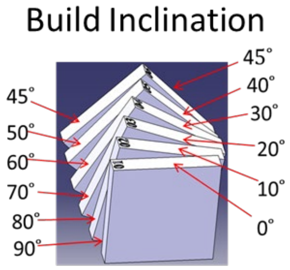


Figure 31: Truncheon artefact with varying build inclination

In paper II, the test artefact, as shown in figure 31, is built at different build inclination and layer thickness. The dominant features are identified using the dominant spatial frequency in PSD plots and significant surface parameters identified using regression analysis. In paper II, the dominant spatial frequency and the significant surface parameters helped to capture the variation in the surface topography observed in figure 32. In paper III, the objective was to analyze and model the surfaces produced by the FDM process, hence test samples are produced with varying build orientation, layer thickness, material infill and print quality. Taguchi's orthogonal array DoE is employed to study the influence of these process variables on the surface texture. A stylus profilometer is used to measure the surface profiles and the standard surface profile parameters are used for characterization. In paper IV, the surfaces of FDM are post processed by acetone vapor smoothening, shot blasting and laser finishing techniques. These post processed surfaces are characterized and analyzed using surface profile parameters. In both papers III and IV, the profile parameters are subjected to multiple regression analysis and the significant profile parameters are shortlisted using a threshold for R^2. The shortlisted parameters include Rp, Rv, Rz, Ra, RSm, Rdc and RPc in paper III, and Rp, Rv, Rz, Rdq and Rdc in paper IV. These specifications can be used for the description and discrimination of the study sample's surface roughness produced by FDM.

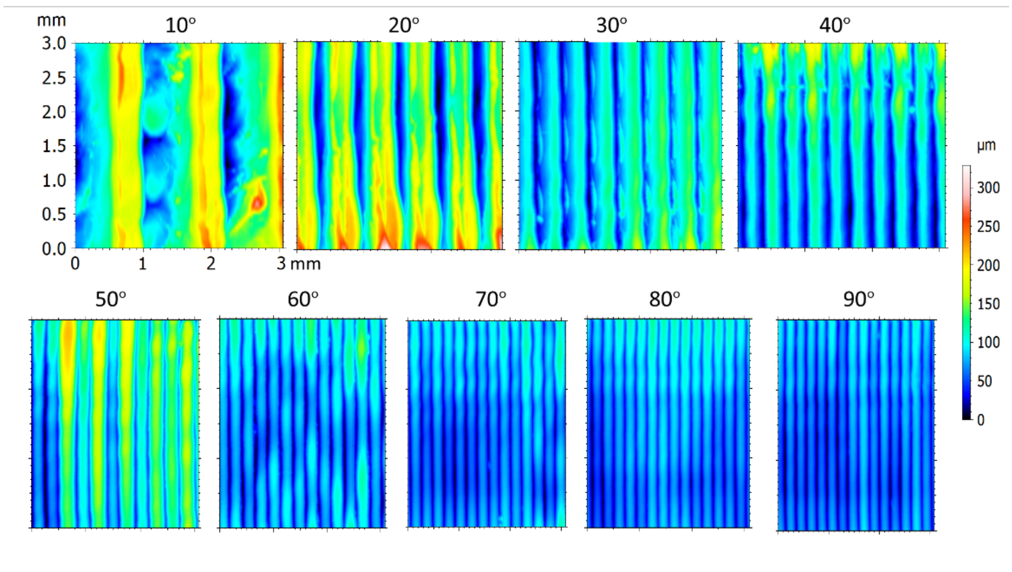


Figure 32: Surface topography of FDM samples with varying inclination [130]

5.2.3 *Injection molding: Paper V, VI*

Automotive interior components are deliberately designed with surface texture to imitate leather surface appearance and improve scratch resistance. It is important to control the replication of this surface texture from the mold tool to maintain uniformity in texture, gloss and in color [49, 56, 131]. The investigations on surface topography of textured automotive components discussed in Paper V and VI focus on identifying the robust set of surface parameters to define the surface variation caused by the critical process variables. In Paper V, the surfaces of PC-ABS samples with two different surface textures, as shown in figure 33, are investigated. Full factorial DoE and multiple regression analysis are applied with tool temperature, injection speed and holding pressure as the process variables and areal surface parameters as the response variables. Further the correlations between surface parameters and gloss measured using a glossmeter are evaluated.

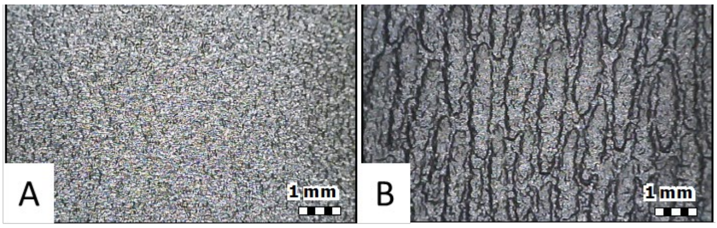


Figure 33: A. Fine texture, b. Coarse texture [132]

Surface investigations revealed that the effect of process variables has significant influence on the replication of surface topography from the mold tool. As observed from surface images in figure 34, the process variables affected the micro-surface topography. The results from MRA suggest that a different set of surface parameters should be selected as significant for different textured surfaces. For fine grain surfaces, significant surface parameters include Sq, Sal, Sdq, Sk and Spd while for coarse grain surfaces, Sdq and Spd are observed to be significant. The degree of replication is evaluated by comparing these surface parameters with their mold tool surface counterparts.

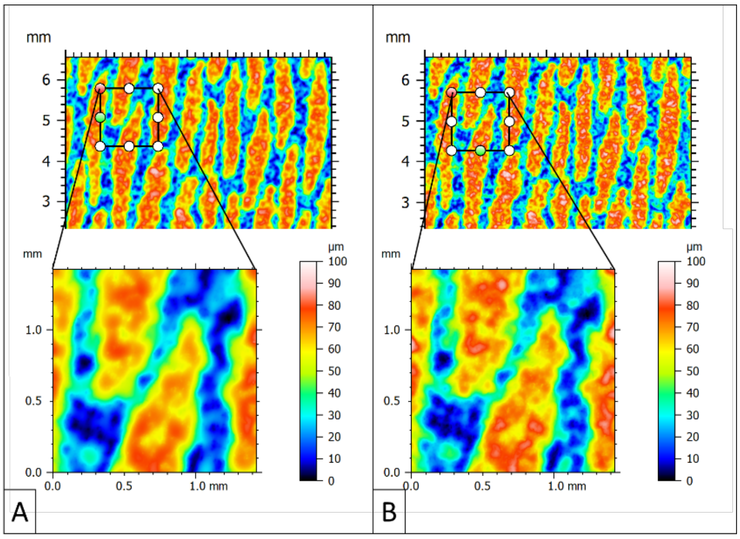


Figure 34: Injection molded surfaces produced at A. Injection speed of 80mm/s, holding pressure of 200 bar and tool temperature of 60°C. B. Injection speed of 240mm/s, holding pressure of 410 bar and tool temperature of 90°C

In paper VI, textured ABS and PP samples produced at different levels of melt temperature, tool temperature and injection speed are investigated for inflicted variation in surface topography. Relocated surface measurements are captured using an optical interferometer. The differences are observed in micro-surface topography and scales between which the differences are maximum is identified using SSFA. The corresponding robust Gaussian filter is applied, and the filtered surfaces are characterized using areal surface parameters. MRA is applied to identify the significant surface parameters that can help discriminate the surfaces and results suggest Sa, Sdq, Vmc and Sk vary significantly with respect to process variables. The significant surface parameters in both Paper V and VI are found to improve the specification of surface roughness produced by injection molding process with valuable information on the surface topography.

5.3 Surface discrimination and effect analysis

RQ2: *How can the significant surface parameters improve scale-limited multiple surface analysis?*
As discussed in chapter 3, surface parameters represent different topographical features produced by the tool-workpiece interaction under specific manufacturing conditions. Hence, the variation in surface parameters represents the variation caused by the material and manufacturing process conditions. This variation helps to capture the individual effects of process variables and helps in understanding the physical phenomena causing such effects. But not all surface parameters vary concurrently, and in some cases, certain parameters remain constant. In this section, some of the results from the appended papers on evaluating and analyzing the influence of process variables are discussed.

5.3.1 t-statistic

The significance of a process variable's influence on the surface parameters is statistically tested using the t-test. In the appended papers, process variables with p-value lesser than 0.05 for a confidence interval of 95% are accepted as significant for that specific surface parameter. In paper I, the surface parameters Sa, Sxp, Sdr, Sdq, Smc, Vmc and Vv help to statistically evaluate the lead and lead-free brass surfaces machined at different cutting feed and with different cutting tools. It is observed from the results that material and feed rates have statistically significant influence on all the significant surface parameters. Whereas the influence of tool coatings is found to be insignificant on surface parameters Smc and Vv. The lead brass samples are observed to have higher values of surface parameters compared to those of unleaded brass. This is primarily due to the segmentation of chips caused by the lower cutting forces offered by lead brass at the tool-workpiece interface. This segmentation of chips causes a ripping effect and results in higher surface asperities compared to the continuous chip formation while cutting unleaded brass [133]. Higher feed rates tend to increase the values of screened surface parameters and due to the wider contact area between the tool-workpiece resulting in higher tool forces.
In paper III, the influence of process variables, build inclination, layer thickness, material infill and print quality on surface profile parameters are investigated. Surface profile parameters Rp, Rv, Rz, Ra, RSm, Rdc and RPc are screened to be significant. From t-tests, it is observed that the influence of print quality governed by print speed is insignificant on all profile parameters and it is the same for print infill except for the peak count parameter, RPc. Layer thickness is found to be significant for all significant parameters and it is the same for build inclination except for valley depth, Rv. Further, a significant interaction effect is observed between layer thickness and build inclination. In paper III, the shortlisted profile parameters helped to understand the variation caused by the build inclination, layer thickness and the print quality. As observed in figure 35, The profile parameter, mean width of roughness elements, RSm, is lower at higher build inclination and increased with increase in layer thickness. Whereas, the peak count, RPc is observed to be higher at higher build inclination and decreases with

increased layer thickness. The surfaces built between 10° to 30° build inclination consisted of surfaces having both stair-steps effect and raster pattern.

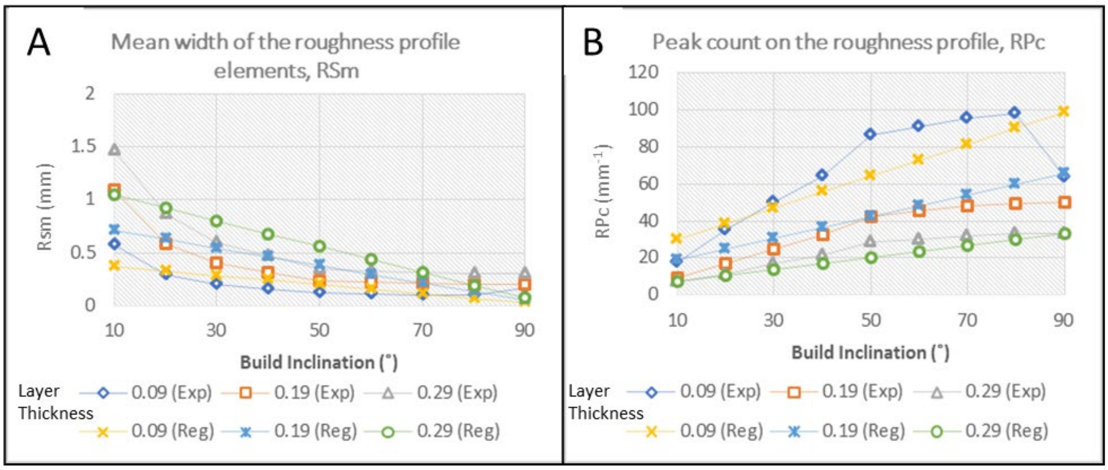


Figure 35: Profile parameters of FDM surfaces with respect to build inclination and layer thickness. A. Mean width of roughness elements, RSm B. Peak count, RPc (Exp- experimental values, Reg- regression values) [134]

In paper IV, the surfaces produced by different post processing techniques are analyzed using the surface profile parameters. For the laser assisted finishing technique, the effect of laser power, laser speed and resolution on the surface profile are investigated. Laser speed is the speed of the laser's lateral movement during the melting of the top layer and corresponds to the contact time of the laser beam and the sample's surface. Laser power corresponds to the amount of power output by the laser. From the t-tests, it is observed that laser power and laser speed had a higher effect on the significant profile parameters, Rp, Rz, Rv, Rdq and Rdc, compared to laser resolution. The higher the laser speed, the lower the contact time and less removal of material resulted in higher values of Rp, Rz and Rv. In case of laser power, the surface parameters are lower at high laser power. This can be observed from the surface profiles shown in figure 36 along with the peak height parameter Rp.

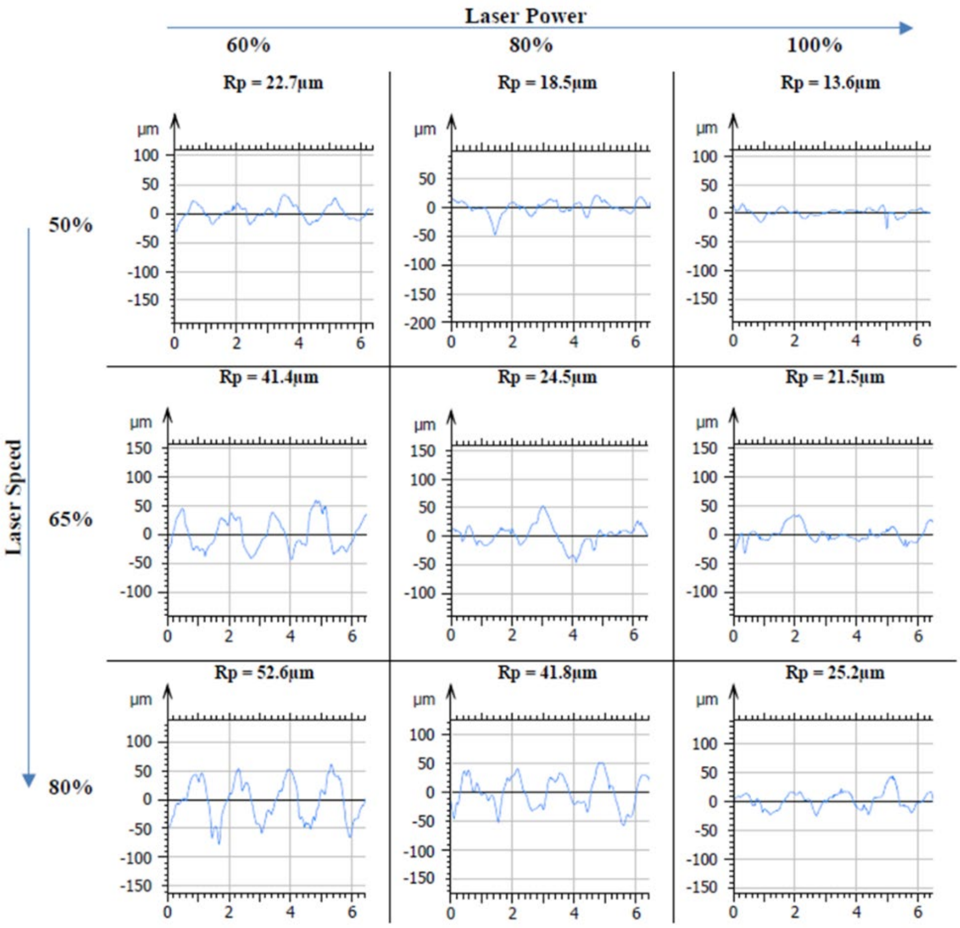
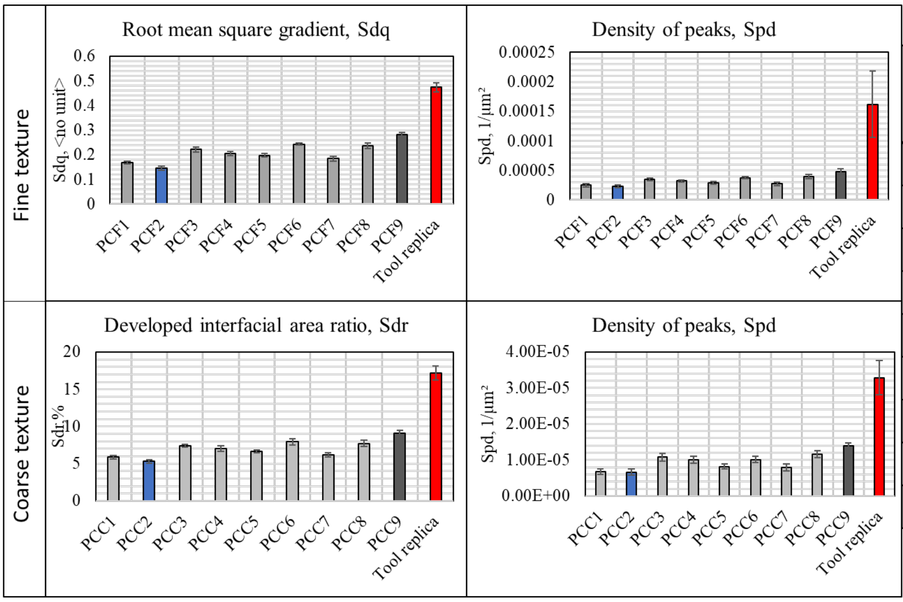


Figure 36: Surface profiles produced at varying laser speed and laser power [135]

In paper V, the significant surface parameters identified with the application of research methodology to the injection molded surfaces are further reduced by *correlation with categorization*, explained in section 4.3.2. Surface parameters Sq, Sal, Sdq, Sk and Spd are shortlisted for fine surfaces and, Sdr and Spd for coarse surfaces are used to compare and evaluate the influence of process variables. From statistics from the t-test shown in table 4, the effect of injection speed, holding pressure and tool temperature is found to be significant for both textured surfaces. The degree of replication, represented by the significant surface parameters, is found to be higher for surfaces produced at higher injection speed, tool temperature and holding pressure, as observed in PCF9 and PCC9 figure 37. Higher injection speed leads to higher shear rates and prevents skin layer formation with reduced polymer viscosity. Higher holding pressure leads to higher push of material into the mold's surface topography, thereby improving the surface replication. Higher tool temperature helps in elevating the temperature of molten material and improving the replication during its flow over the molten material. Further, the interaction effect of holding pressure and tool temperature is found to be significant.

Table 4: p-values of injection molding process variables [132]

p-value		Injection Speed (IS)	Holding Pressure (HP)	Tool temperature (T)	IS*HP	IS*T	HP*T
Fine grain	Sq	1.33E-24	1.32E-11	6.45E-22	0.29	0.001	0.001
	Sal	1.10E-24	7.22E-07	9.14E-22	0.008	2.39E-05	0.002
	Sdq	7.18E-38	1.85E-27	9.21E-38	0.009	0.009	1.46E-11
	Sk	6.46E-26	6.71E-12	8.15E-22	0.68	0.13	2.26E-06
	Spd	2.74E-23	9.90E-13	4.79E-25	0.19	2.65E-07	0.0002
Coarse grain	Sdr	6.34E-32	1.31E-21	2.43E-28	0.10	0.06	1.56E-10
	Spd	4.63E-29	3.39E-08	2.50E-17	0.35	0.87	4.07E-05



Sample	Tool temperature [°C]	Injection speed [mm/s]	Holding pressure [bar]
PC1	60	80	200
PC2	60	80	410
PC3	60	240	200
PC4	60	240	410
PC5	75	120	305
PC6	90	80	200
PC7	90	80	410
PC8	90	240	200
PC9	90	240	410

Figure 37: Significant surface parameters of coarse and fine textured surfaces [132]

5.3.2 Signal-to-noise ratio

Quantifying the effect of process variables helps in understanding the effects of process variables on the selection or distribution of the surface features and better control over the manufacturing process. Signal-to-noise ratio with nominal-the-better [127] equations are used in paper III and V to quantify the effects on significant surface parameters. In paper III, the influence of FDM process variables, build inclination, layer thickness, material infill and print quality on significant profile parameters, Rp, Rv, Rz, Ra, RSm, Rdc and RPc are evaluated as shown in figure 38. The effect of build inclination and layer thickness are observed to be the largest. The build inclination has a higher effect on mean width of roughness elements, RSm and peak count, RPc while print quality is found to have the least effect.

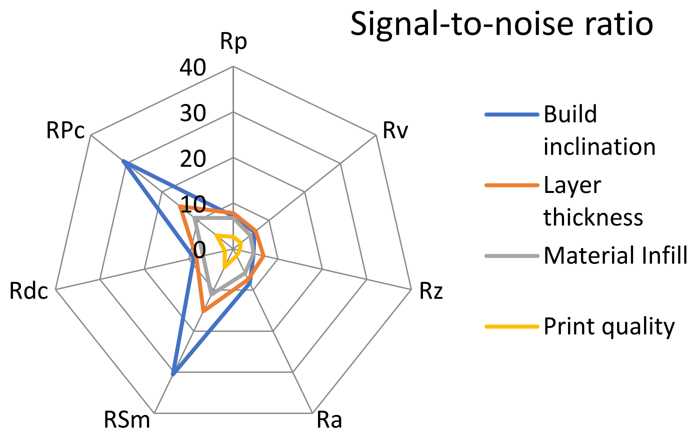


Figure 38: Signal-to-noise ratio of significant profile parameters with respect to FDM variables [134]

In paper V, the effects of injection molding process variables on the shortlisted surface parameters are evaluated using SN ratio. As observed in figure 39, for PC-ABS fine textured surfaces, tool temperature has a higher influence on the surface parameters, Sq, Sal and Sk, that represent the larger wavelength features. Holding pressure on hybrid parameter, Sdq and injection speed on density of peaks, Spd has higher influence. Similarly, for coarse textured surfaces, holding pressure has greater effect on hybrid surface parameter, Sdr, followed by tool temperature and injection speed. Injection speed has a higher effect on density of peaks, Spd followed by tool temperature.

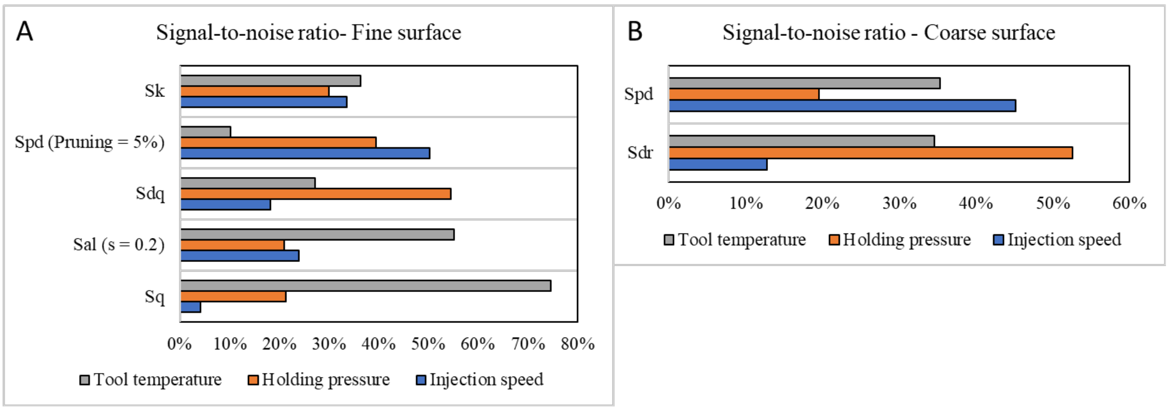


Figure 39: Signal-to noise ratio A. Fine textured surfaces B. Coarse textured surfaces [132]

5.4 Multi-scale characterization and analysis

RQ3: *How can multi-scale surface characterization techniques support scale-limited surface analysis?*

In surface investigations, it is important for the surface measurement to be representative of the manufactured surface and to include the features of interest. As the name suggests, scale-limited surface analysis is restricted to the captured measurement scale and size. It is a time consuming and tedious task to identify the suitable scale and size. This limitation of scale-limited approach can be supported by multi-scale analysis. Power Spectral Density (PSD) and Scale-sensitive fractal analysis are the multi-scale decomposition approaches utilized in the appended papers to identify the significant scales of observation.

5.4.1 *Power Spectral Density (PSD)*

Power Spectral Density resolves different spatial frequencies present on the surface. Decomposing the surface topographical features as a function of spatial frequency is important to identify the significant wavelengths and understand their occurrence. In paper II, PSD is calculated for build inclinations starting from 10° till 90° in steps of 10°, to identify the dominant features and their respective wavelengths. Spatial frequencies of surface features are extracted in profile and printing direction as shown in figure 40. Profile direction is the direction in which the stacking of layers takes place and printing direction is the travel direction of print head in each layer. The dominant wavelengths in the profile direction are identified as shown in figure 41 for different build inclinations. This information is later used to calculate the theoretical layer thickness, explained in section 5.5.1.

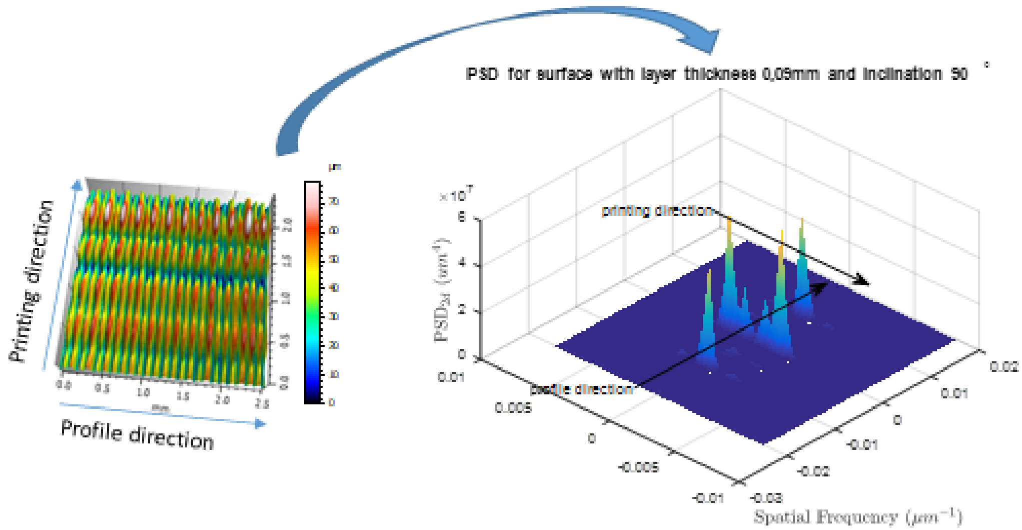


Figure 40: 3D PSD of FDM surface [130]

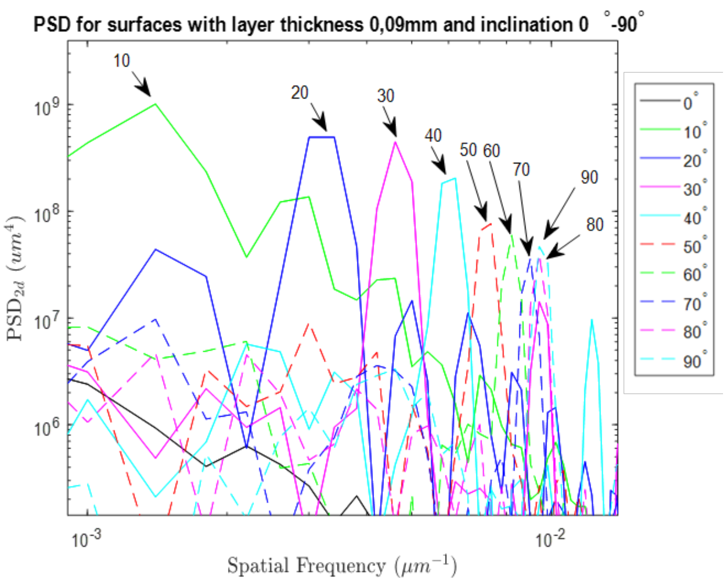


Figure 41: Power Spectral Density plots of FDM surface with different build inclination [130]

In paper IV, the PSD plots are used to compare different post-processing techniques and identify the differences in distribution of features as a function of spatial frequencies. It is observed from the results that there has been significant reduction in strength of features after application of post processing techniques. It is observed that the combined effect of two post processing techniques, acetone smoothening and shot blasting, has produced surface roughness much closer to the reference surface roughness produced by injection molding.

5.4.2 Scale Sensitive Fractal Analysis (SSFA)

Scale sensitive fractal analysis (SSFA) is a multi-scale characterization technique that decomposes the surface topographical features as a function of scales. In the appended paper, the area scale method is employed to analyze the surface areal features. In this method, relative area and complexity are calculated and plotted as a function of scale. As discussed in Chapter 3, relative area is the ratio of calculated area to the nominal area and complexity is obtained by taking the slope of the relative area plot. In paper V, the complexity plots are utilized to determine the scales of interest and calculate the evaluation area. In figure 42, complexity plots are for coarse surfaces (PCC) and fine surfaces (PCF) manufactured at higher (PCC9 and PCF9) and lower (PCC1 and PCF1) injection speed, holding pressure and tool temperature. As observed from figure 42, the complexity plots plateaus above the identified scales for fine and coarse textured surfaces. The surface topographical features below this threshold are considered to represent the study samples surface topography. The L-filter nesting index is calculated as the side of equilateral triangle. For fine textured surfaces, the curve plateaus at 1×10^6 mm^2 and the corresponding L-filter nesting index is 1.41 mm. Similarly for coarse textured surfaces, the curve plateaus at 1×10^7 mm^2 and the corresponding L-filter nesting index is 4.5mm. An evaluation area of $2 mm^2$ and $5 mm^2$ is representative of fine and coarse textured surfaces respectively.

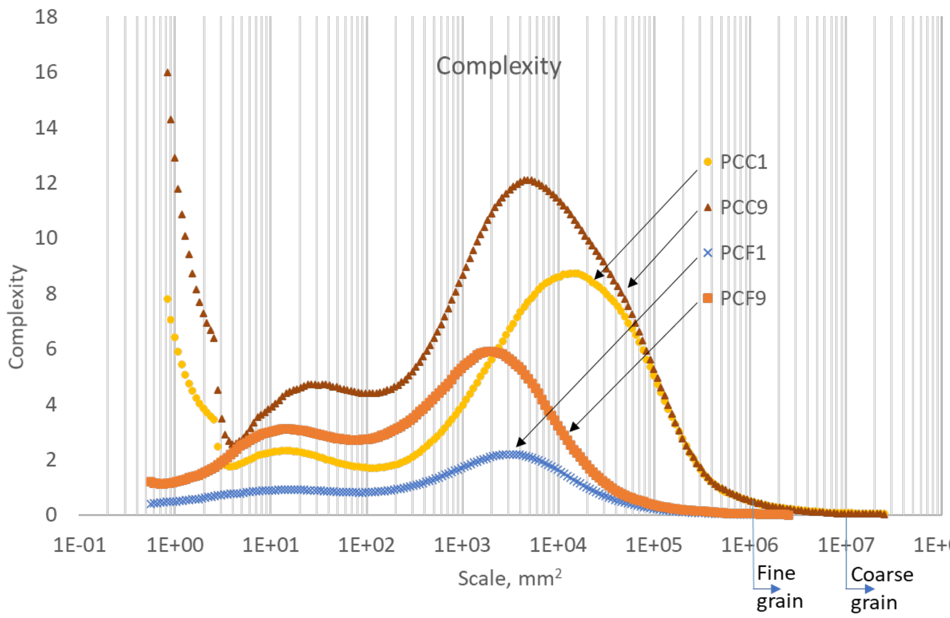


Figure 42: Complexity plots as function of scale for PC-ABS samples [132]

5.5 Modelling and prediction of surface parameters

RQ4: *How could statistical methods be applied for modelling and prediction of surface parameters?* Modelling and prediction of significant surface parameters are important for the following reasons: to optimize the manufacturing process, to provide input for further machining or post processing and to predict its function. By predicting the surface functional behavior, ideal process conditions for manufacturing a surface can be determined and optimized for production. Probabilistic variation of surface topography can be determined, and strategies can be developed for further machining or post-processing to achieve the intended surface topography. With modelling and prediction, the surface topography can potentially be tailored for specific application. In the appended papers, regression coefficients are used to model the significant surface parameters. Using these models, comparative analysis is conducted between the different surface topographies and probable surface functional behavior is discussed. Accuracy of the model is affected by the type of modelling (linear or quadratic) and in the appended papers, linear models are employed to predict the significant surface parameters.

5.5.1 Manufacturing process

In Paper III, regression coefficients are used to predict the significant profile parameters of FDM surfaces and compared with the experimental results. The regression model follows a similar trend to the experimental results and helps to capture the probabilistic variation. As observed from the graphs in figure 43, the profile parameters at lower layer thickness (0.09mm) are predicted better compared to higher layer thickness (0.29mm).

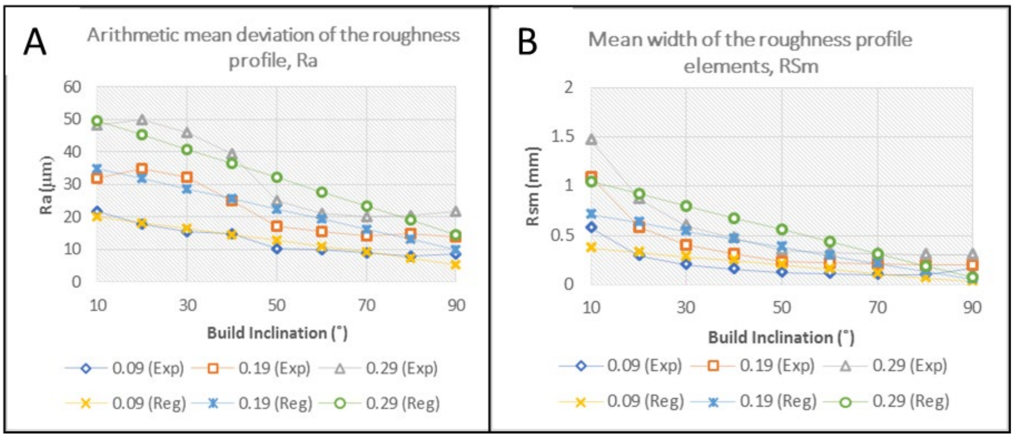


Figure 43: Experimental versus regressed values of profile parameters of FDM surfaces with respect to build inclination and layer thickness in mm. A. Arithmetic mean height, Ra B. Mean width of roughness elements, RSm (Exp- experimental values, Reg- regression values) [134]

In paper IV, the profile parameters of surfaces from laser assisted finishing, a post processing technique for FDM surfaces, is modelled and predicted using the regression coefficients. An example of a regression equation for peak height, Rp, is shown in equation 4.

$$Rp = 17.264 - 0.265BI - 0.087LP + 0.189LS + 0.0067R \tag{4}$$

Where, BI – Build Inclination in degrees, LP – Laser Power in %, LS – Laser Speed in %, and R – Resolution in ppi (pixel per inch)

The effect of process variables can be interpreted as a decrease in Rp as the build inclination and laser power increases. Laser speed and resolution have a positive effect, though the effect of resolution is low.

5.5.2 Surface functional behavior

Surface topographical features on the manufactured part or product affect its surface functional behavior. Different surface parameters relate to different functions and the functional importance of surface parameters is briefly discussed in the literature [10, 97, 98]. Correlation of surface function with scientific reasoning can determine the usefulness of the surface parameter to predict the surface function. In paper I, the surface functions of the turned lead- and unleaded brass samples are predicted based on their probabilistic variation in the significant surface parameters. This variation and the predicted surface function is summarized in figure 44.

Probabilistic variation ⇩ *: Lower* ⇧ *: higher ; Difference:* ● *: high* ○ *: low.* **/**: *No significant impact*

Significant Surface parameter	Independent variables: Unleaded brass		Lead brass	Uncoated tool		Coated tool	Feed rates	Comments: Higher the parameter value,
Smc (p = 10%)	⇩	●	⇧	⇩	/	⇧	●	Surface exhibits an increase in the fluid retention and debris entrapment
Vv (p = 10%)	⇩	●	⇧	⇩	/	⇧	●	
Sdq	⇩	○	⇧	⇩	●	⇧	○	Better wettability and sealing properties
Sdr	⇩	○	⇧	⇩	●	⇧	○	
Vmc (p = 10%, q = 80%)	⇩	●	⇧	⇩	○	⇧	●	Higher the load withstanding capacity in the material ratio ‘p’ and ‘q’.
Sdc (p = 50%, q = 97.5%)	⇩	●	⇧	⇩	○	⇧	○	
Sa	⇩	●	⇧	⇩	○	⇧	●	Higher the roughness, higher asperities and decrease in wear resistance

Figure 44: Illustrations of probabilistic variation and the difference in influence of the significant parameters and the predicted surface function [125]

In paper V, the measured gloss is correlated with the surface parameters of injection molded coarse and fine textured surfaces. Based on the correlation coefficient, R, between the surface parameters and measured gloss shown in figure 45, it is observed that the significant surface parameters selected based on the manufacturing process variables correlate well with the measured gloss (highlighted in figure 45). The measured gloss of fine textured surface is observed to be higher compared to that of the coarse grain. This may be a result of the presence of higher and lower wavelength features in coarse texture increasing the diffuse scattering. For fine textured surfaces, surface parameters Sq, Sdq and Sk exhibit negative correlation which implies higher measured gloss for lower values of these parameters whereas Sal exhibits positive correlation. For coarse textured surfaces, it is observed that Sdr and Spd have negative correlations with measured gloss.

Surface parameters	Measured Gloss	
	Fine	*Coarse*
Sq	-88.40%	-27.16%
Ssk	-32.58%	34.07%
Sku	52.23%	-58.43%
Sp	-34.39%	-22.53%
Sv	-56.43%	-33.31%
Sz	-52.31%	-38.03%
Sa	-87.36%	-8.25%
Sal (s = 0.2)	85.54%	37.04%
Str (s = 0.2)	-14.52%	34.13%
Sdq	-90.21%	-83.91%
Sdr	-87.59%	-86.76%
Spd (Pruning = 5%)	-78.18%	-83.09%
Spc (Pruning = 5%)	13.23%	24.26%
S10z (Pruning = 5%)	-74.97%	24.02%
S5p (Pruning = 5%)	-55.21%	24.02%
S5v (Pruning = 5%)	-79.65%	24.03%
Sda (Pruning = 5%)	79.19%	74.99%
Sha (Pruning = 5%)	77.80%	85.30%
Sdv (Pruning = 5%)	51.45%	27.69%
Shv (Pruning = 5%)	27.64%	79.44%

Surface parameters	Measured Gloss	
	Fine	*Coarse*
Smr (c = 1 µm below highest peak)	28.50%	19.79%
Smc (p = 10%)	-83.11%	-9.27%
Sdc (p = 10% q = 90%)	-87.68%	-34.47%
Vm (p = 10%)	-70.09%	-52.42%
Vv (p = 10%)	-83.13%	-11.91%
Vmp (p = 10%)	-70.09%	-52.42%
Vmc (p = 10% q = 80%)	-82.80%	-11.68%
Vvc (p = 10% q = 80%)	-80.46%	0.49%
Vvv (p = 80%)	-25.24%	-59.06%
Sk	-84.69%	-15.00%
Spk	-51.24%	-63.16%
Svk	15.58%	-15.59%
Smrk1	-32.80%	-64.17%
Smrk2	-38.73%	-39.04%

Figure 45: Correlation coefficient, R, between measured gloss and areal surface parameters [132]

5.6 Industrial relevance and contribution

In manufacturing industry, the KPIs (Key Performance Indicators) are well defined quantifiable metrics that measure the performance of manufacturing operations. Surface parameters, in a similar way, may be used to optimize the process efficiency or define the performance of the manufactured surface or product. As mentioned before, identifying the surface parameters that are important for optimizing the process and function is not straight-forward and requires experimentation. This thesis summarizes methods to experiment and identify significant surface parameters applicable to different manufacturing systems. This experimentation helps to address the engineering requirements and to further expand and develop knowledge in the respective domain, as illustrated in figure 46. Consequently, it helps to achieve autonomy in knowledge management for smart manufacturing described in [136].

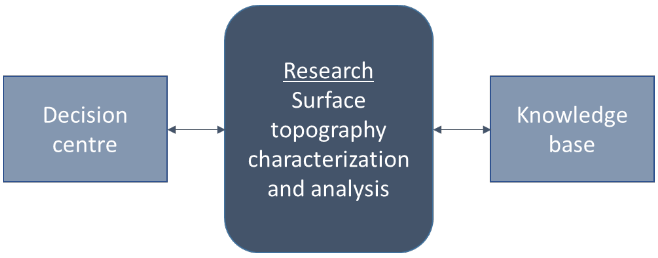


Figure 46: Research connection with business needs and knowledge base

Investigations on surface topography of turned brass samples in Paper I contributed to the project of sustainable manufacturing of lead-free brass components by verifying the possibility to manufacture and achieve the surface topography of brass in a lead-free alternative. Further, the studies suggest better surface functional behavior of lead-free brass compared to its leaded counterpart. Investigations on the Fused Deposition Modeling process in Paper II, III, IV has shown the variations in surfaces and their relationship with the process variables. The results confirmed the possibility to reduce the cusp height and achieve better surface finish either by controlling the process variables or by post-processing. This valuable information supports the manufacturing industry’s vision of adapting the FDM technology to complement its existing manufacturing processes. Research investigations on injection molded textured surfaces in Paper V and VI help in understanding and controlling the influence of process variables on surface replication from mold tools. These results contribute towards developing strategies to produce textured surfaces of injection molded automotive interiors efficiently with recycled and bio-based materials.

6 CONCLUSIONS AND FUTURE WORK

In this chapter conclusions from the research results and discussions are presented by summarizing the results corresponding to the research questions. The future work including the continuation of the present work on practical implementation in industry and further improvements are discussed in this chapter.

6.1 Conclusions

Surface topography characterization and analysis helps in establishing the relationship between the manufacturing process and the performance of the manufactured part. The surface parameters provide a quantitative measure of the surface and help to understand and control this relationship. There are several surface parameters available in the ISO standards that define and represent different topographical features and their distributions. But the use of these surface parameters in manufacturing industry are limited with only few, such as Ra and Sa, are used for specification of surface roughness. Arithmetic mean height of roughness elements, Ra or Sa, may provide elementary insights on the manufactured surface or adequate explanations on a few applications. But to gain comprehensive advantage, it is important to investigate the suitability of surface parameters for the specific processes and application. Research questions are framed on this applicability of different surface parameters for characterizing surfaces produced by different manufacturing systems.

In this thesis, the research questions are addressed with experimental investigations on the surfaces produced by subtractive, additive, and formative manufacturing processes. This thesis proposes research methodology that can help to identify the important surface parameters representing deterministic surface features using statistical methods. The simple and effective statistical strategies discussed in this thesis help to evaluate the relationship between the material, manufacturing process conditions and surface parameters. Further, the methodology helps to analyze the effects, model, and predict the surface parameters based on the process variables. This can subsequently be used for process and functional optimization. This thesis also discusses the importance of multi-scale characterization for a scale-limited surface analysis. Here, a summary of the results pertaining to the research questions are presented.

Research Question 1: *How to improve specification for surface roughness applicable to different manufacturing systems?*

In the appended papers, surface roughness produced by different manufacturing systems with multiple process variables are investigated. Areal and profile parameters are used for the characterization of manufactured surfaces and multiple regression analysis is employed with surface parameters as the dependent variables. Coefficient of determination, R^2, is used as the criterion to identify the significant surface parameters that discriminate between the study surfaces. Based on the study results from appended papers, it is observed that specification of surface roughness is not limited to a single surface parameter representing the average roughness, but a combination of surface parameters that represents the different topographical features and their distribution affected by the process variables. Also, different sets of surface parameters qualify depending on the surface investigation. The characterization and analysis of surface topography by using significant surface parameters is observed to be well supported by the qualitative assessment using surface images. Hence, the use of significant surface parameters is observed to improve the specification of surface roughness. This identification of the significant features helps to improve our understanding of the manufacturing principle and its process signature.

Research Question 2: *How can the significant surface parameters improve scale-limited multiple surface analysis?*
In a scale-limited surface analysis, the surfaces produced are investigated at a particular scale which represents the surface effects including the manufacturing process signature. Using t-tests, the validation of the independent variable effect on the significant surface parameter is assessed. The results from the t-test provide information on the significance of the effects on different topographical features and their distribution represented by significant surface parameters. It is observed from the results that the contribution of process variables towards these surface effects vary. This improved specification of surface roughness helps to discriminate between the study samples and helps to identify the critical process variables. In paper III and V, signal-to-noise ratio is employed to quantify the effects and rank the process variables. Identifying and quantifying the effects of critical process variables helps to interpret the underlying physical phenomenon causing the resultant surface.

Research Question 3: *How can multi-scale surface characterization techniques support scale-limited surface analysis?*
In general, multi-scale characterization and analysis can be utilized in different case scenarios of surface investigation. In the appended papers, Power Spectral Density (PSD) and Scale-Sensitive Fractal Analysis (SSFA) are utilized to identify the significant wavelengths and scales of importance respectively. In paper II, PSD is plotted as a function of spatial frequency to characterize the surfaces of FDM and to identify the effect of build inclination and layer thickness. In paper VI, SSFA is used to identify the scale of features which are representative of the surface and the evaluation area is calculated based on this. These investigations affirm that the scale-limited surface analysis can be supported by multi-scale analysis.

Research Question 4: *How could statistical methods be applied for modelling and prediction of surface parameters?*
Modeling and prediction of surface parameters helps to identify the ideal conditions to manufacture a surface. In appended papers I, III, IV, the regression coefficients are effectively utilized to model and predict the significant surface parameters for the range of process variables investigated. These predicted surface parameters help to analyze the variation in the surface topography at different manufacturing conditions. The resulting surface functional behavior may also be predicted connecting these interpolation variation and correlation studies with the specific surface function.

6.2 Future work

With advancement in manufacturing technologies and surface metrology, the requirement for effective and reliable methods for characterization and analysis will increase. Moreover, to develop application specific surfaces, control over manufacturing process is paramount. In this thesis, manufactured surfaces are investigated using controlled experimental design and methods for identifying important surface parameters and application of these parameters for evaluating the surface effects are proposed. The modelling and prediction of surface parameters helps to identify the ideal conditions for manufacturing a surface. However, implementation of these strategies in the industrial sector will require more complex models due to the influence of a large number of controlled and uncontrolled variables. Modeling a surface control loop, as shown in figure 47, would require sophisticated characterization and analysis algorithms. Future work should include developing methods to model this surface control loop and analyze the surface data in real time. This may require complex machine learning algorithms to identify, model and predict the significant surface parameters that connect process and product's performance.

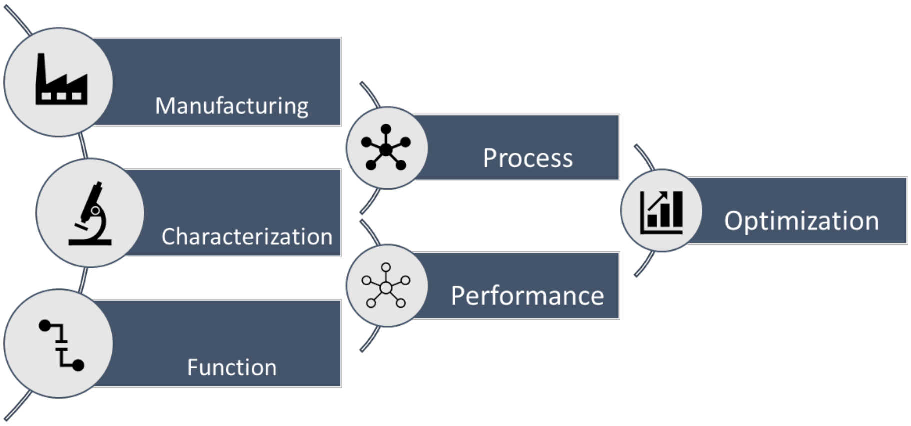


Figure 47: Process and performance optimization with surface control loop

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