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Uncertainty Measurement and Analysis for Quality and Reliability in Manufacturing Process

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Abstract. The variation and uncertainty existed in every process and considered as an essential element in precise, accurate and high-quality manufacturing, especially in the Industry 4.0 era. Manufacturing quality and reliability is affected by variations and uncertainties in different process parameters and influencing factors. The variations and uncertainties are considered very critical in measurement and monitoring process, i.e., prediction or prognostics. These variations and subsequent uncertainties are needed to be identified, quantified, analyzed and controlled. This paper presents an approach to uncertainty measurement and analysis in manufacturing. The key characteristic parameter is identified which is critical for final product quality and reliability. To determine the uncertainty in the specific parameter, the uncertainty factors of both the manufacturing process and measurement process are determined. The combined uncertainty is determined by considering the influencing factors both in manufacturing and measurement process. The relation of each factor to the key parameter is analyzed and the sensitivity coefficient is determined mathematically or experimentally. The combined and expanded uncertainty is determined considering all related factors. The proposed approach has been applied to an additive manufacturing technique, and useful results are achieved.

1. Introduction

The industrial manufacturing is proliferating leading towards Industry 4.0. Internet of things, cyber-physical systems, intelligent manufacturing, cloud manufacturing, additive manufacturing, big data analytics are important element technologies in Industry 4.0 [1–3]. Industry 4.0 need fast, accurate, precise, reliable, flexible and holistic measurements using advanced measurement technologies and determine measurement uncertainty which describes the accuracy of measurement results quantitatively [4].

The development of new technologies has shifted the quality and reliability from corrective and preventive to predictive and prognostic approach. Therefore, many prognostic techniques are being deployed in the manufacturing sector [5]. The monitoring and measurement constitute a significant part of prognostics and uncertainty in measuring parameters are very critical for effective action [5,6].



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The importance and need for uncertainty measurement is also recognized in aerospace measurement processes [7].

Additive manufacturing (AM) is a major key player element in Industry 4.0 which offers rapid, efficient, customization and intelligent solution for building complex products through automation and digitization [8,9]. It is rapidly adopting by aerospace, military, automobile, oil and gas, and medical sectors which demand high accuracy, precision, and reliability, along with desired repeatability and reproducibility [10]. Therefore, research in AM quality and reliability has a particular focus and an active research area [11].

Most uncertainty measurement and analysis research work focused on testing and calibration domain and it has not explored for other manufacturing processes. Therefore, there is a necessity to explore and develop some quantitative approaches for manufacturing.

In this research paper, an approach is proposed for dealing with uncertainty measurement and analysis for quality control and reliability in manufacturing. In the first step key quality and reliability, the characteristic is identified. Secondly, uncertainty factors or sources and uncertainties are determined for the manufacturing or production process and measurement or testing/ inspection process. Experimental data of manufacturing process parameters are obtained to develop a mathematical equation between each input and output parameters. Regression modelling and analysis is performed using MATLAB or MINITAB software. Similarly, data of measurement or testing process is obtained. The sensitivity coefficient for each input quantity and output is determined from the mathematical equation. The A-Type and B-Type uncertainties are estimated for the manufacturing process and measurement or testing process. Finally, the combined and expanded uncertainty is estimated. Based on the estimated uncertainties, the sensitivity analysis and control strategy is suggested. The proposed is applied to Selective Laser Melting (SLM) additive manufacturing technique.

2. Manufacturing process variations, uncertainties, quality and reliability

Manufacturing process variations and product quality and reliability have a close relationship. The reliability degradation in the final product is caused by quality variation in the manufacturing process [12]. The quality and reliability can be improved by targeting key characteristics and analysing critical process parameters in manufacturing [13]. These manufacturing process variations regarded as sources of errors and uncertainties in the system. During the manufacturing process, reliability can be assured by analysing and controlling the influencing factors or parameters, process variations and uncertainties [12,14].

Modern quality and reliability control systems are based on predictive and prognostic techniques. Accurate measurement and monitoring is an essential need for these predictive quality control and prognostic system. In manufacturing the key process, parameters are monitored and tracked for variation detection and subsequent action by predictive quality or prognostic system [5,6,15]. The uncertainty is an essential part of these measurements and monitoring.

Uncertainty exists in every measurement being performed during manufacturing. It is a critical factor which is significant as accuracy and precision. The realization and requirement for uncertainty measurement and analysis are emerging in manufacturing systems. Therefore, new approaches are required for quantification, measurement and analysis of manufacturing uncertainties.

3. Methodology

The methodology is based on a proposed approach which is explained below. The first general scheme of the proposed approach is defined. Then the quantitative treatment for uncertainty measurement and, sensitivity analysis and control for influence or contributing process parameters, sources, and uncertainties is explained.

3.1. General approach

The proposed approach is described in Figure 1. In general, the proposed approach has four steps. The first step includes identification of key characteristics or features which is critical for product or process quality and reliability. Secondly, determine contributing uncertainty factors and their uncertainties of both the manufacturing process and measurement process. Thirdly estimation of combined and expanded uncertainty, and finally perform sensitivity analysis for controlling and improving the uncertainties.

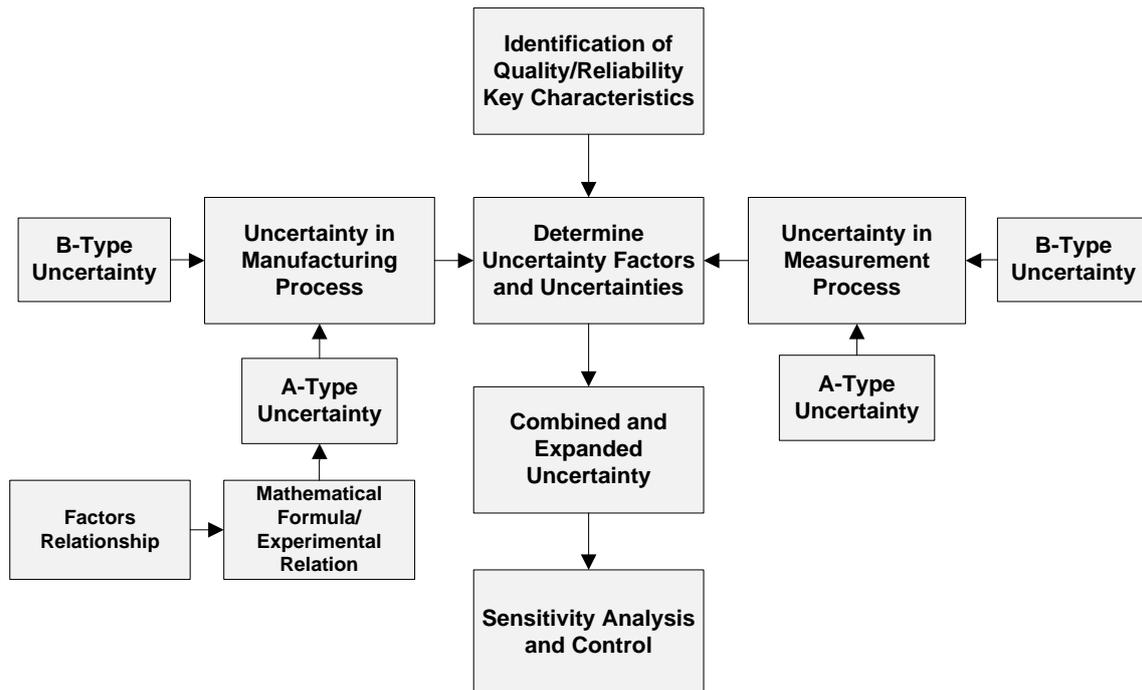


Figure 1. General approach

3.2. Identification of key characteristics

The product or process quality and reliability are associated with certain key characteristics. To improve quality and reliability, the key characteristics are needed to be identified, monitored and controlled during manufacturing, i.e., strength, stiffness, dimensional accuracy, surface finishing, etc. There are different originating sources of these key characteristics which include design and operational requirements, environmental conditions, field performance data, validation data, maintenance, quality, and reliability analysis, i.e., FMMEA, Failure Analysis, DOE, QFD, etc. In the first step, we need to identify and define the key characteristic(s) which is needed to be controlled during the manufacturing process.

3.3. Determination uncertainty factors and uncertainties

In this step, we need to determine sources of error and factors contributing to the uncertainty in the identified key characteristics. In general, different sources of errors and uncertainties originate from man, machines, materials, environment, procedures/ techniques, etc. We have divided the overall uncertainty into two parts, one includes uncertainties in the manufacturing process, and second are uncertainties in the measurement process. The numerical values of identified uncertainties are determined by formulas as defined in Guide for Uncertainty Measurement (GUM) and other reference guidelines developed for uncertainty measurement [16–20]. The uncertainties of the factors which are controlled, in a limit that they do not affect output, are not included in the uncertainty budget. The uncertainty can be overestimated and should not be underestimated.

3.3.1. Uncertainty in the manufacturing process: There are different manufacturing or production process parameters which affect the quality and reliability. The variation in these input process parameters contributes significantly to the uncertainty of the output quantity. We have two possibilities to estimate the uncertainties. In the first case, if we have a mathematical formula or relationship between process input and output quantities, then we can estimate the uncertainty in output due to variation or uncertainty in input quantities using this relation. In the second case if we do not have any formula or relationship between inputs and output, then we have to do experimentation in a systematic way, such as the design of experiment (DOE). We take different input setting values and determine output response against change in inputs. From data collected we develop a mathematical model or equation which gives the relationship between each input and output by using MATLAB or MINITAB software. The regression and correlation analysis can be done for correlated input quantities. Using developed equations, we determine the sensitivity coefficients, which are used to transform the numerical value of each input quantity into the output.

3.3.2. Uncertainty in the measurement process: The measurement process is an integrated part of manufacturing which exists in the form of testing, inspection, and calibration. All the measurable quantities are realized, verified, validated and qualified through this process. This process is used to compare the process or product output against standards or some references. The uncertainties originate from the measurement process, testing, inspection or calibration, itself. The major sources, but not limited these, include measuring or testing instruments, reference standards and materials, calibrations, traceability, environmental conditions, methods and procedures, sampling, instrument properties, i.e., resolutions, drift, stability, etc., maintenance and personnel performing measurement tasks [16–20].

3.3.3. A-Type and B-Type uncertainties: The uncertainties are determined as A-Type and B-Type. A-Types uncertainties are those which are estimated from data set values of input quantities and estimated using equation (1). The B-Type is estimated for those quantities which do not have data values. For such quantities, we estimate their standard uncertainty from a single available value. For each uncertainty component, we need its numerical value of uncertainty with the unit, distribution (normal, rectangular, triangular or U-shape) with respective divisor ($1, \sqrt{3}, \sqrt{6}$ or $\sqrt{2}$) and sensitivity coefficient. Examples of A-Type include repeatability or reproducibility performed by using a set of data values. The B-Type includes instrument resolution (taken as half value of resolution), calibration, drift, standard reference certificate value, etc. The numerical treatment and methodology for A-Type and B-Type uncertainties are addressed in detail in different uncertainty measurement standards and guides [16–20].

$$u(X) = \frac{\sigma}{\sqrt{n}} = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n(n-1)}} \quad (1)$$

Where $u(X)$ is the A-Type uncertainty, X_i is an i^{th} measured value, \bar{X} is the mean value, σ is the standard deviation and n is the number of measurements or values taken for quantity X .

3.4. Combined and expanded uncertainty

The combined uncertainty $u_c(y)$ included estimated A-Type and B-Types uncertainties which are resulted from both manufacturing and measurement process. It is calculated by using equation (2) or (3) for uncorrelated and correlated input quantities respectively [15,16]. Equation (4) is useful when the uncertainties are required to be measured in fractions or percentage.

$$u_c(Y) = \sqrt{\sum_{i=1}^n \left(\frac{\partial Y}{\partial X_i} \right)^2 u^2(X_i)} \quad (2)$$

Where $u_c(Y)$ is the combined uncertainty in output quantity (Y), $\partial Y / \partial X_i = C_{xi}$ is the sensitivity coefficient of i^{th} quantity, and $u(X_i)$ is the standard uncertainty in i^{th} quantity.

$$u_c(Y) = \sqrt{\sum_{i=1}^n \left(\frac{\partial Y}{\partial X_i}\right)^2 u^2(X_i) + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \frac{\partial Y}{\partial X_i} \frac{\partial Y}{\partial X_j} u(X_i, X_j)} \quad (3)$$

$$\frac{u_c(Y)}{Y} = \sqrt{\sum_{i=1}^n \frac{u^2(X_i)}{X_i}} \quad (4)$$

The estimated uncertainties have a 68% confidence level. The final expanded uncertainty U is determined, at 95% confidence level (coverage factor $k=2$), by using equation (5) [16,20].

$$U = k u_c(Y) \quad (5)$$

3.5. Sensitivity analysis and control

The sensitivity analysis of estimated uncertainties will provide a way to study the impact and degrees of variation in influencing inputs parameters and the resulting variation in the uncertainty of the output quantity. It helps in targeting, controlling and improving the different uncertainty contributors or sources. We can reduce the uncertainty by either reducing or eliminating the sources having a higher contribution in overall uncertainty. A control strategy can be developed to control and improve target uncertainties.

4. Case application

The additive manufacturing or 3D printing process case is taken to demonstrate the proposed approach. For this purpose, data of Selective Laser Melting (SLM) is taken for study. In this technique, the object is built by using a laser beam which targets powder material and solidifies it layer by layer by using an automated programme. This technique is being used to manufacture different complex parts and rapidly expanding in different sectors including in the aerospace sector.

There are different process parameters which affect the product quality and reliability. The key quality or reliability characteristics of the product, e.g., surface finishing, part density, hardness, strength, etc., depends on the properties of the material used and input process parameters settings. In order to get the best results, these input parameters settings are optimized.



Figure 2. Selective laser melting system SLM 280 HL

In this study results of 27×3 samples of $8 \times 6 \times 10$ mm size are analyzed which were fabricated on SLM 280 HL system, as shown in Figure 2, using gas-atomized AlSi10Mg powder material provided by SLM solutions. The surface roughness of the samples measured using Mitutoyo surface roughness tester SurfTest SJ-210.

4.1. Identification of key characteristics and critical parameters

The manufactured parts have key characteristics which are linked with the quality and reliability of the final product. In this case, we have taken front surface roughness (R_a) as a key characteristic or critical output parameter. The input manufacturing process parameters laser power, scan rate, hatch distance, beam angle and layer thickness are considered as critical input parameters. The surface roughness measurement or testing process parameters, i.e., repeatability of roughness tester are taken as critical.

4.2. Determine uncertainty factors and uncertainties

The uncertainty factors and uncertainties based on critical parameters are determined both in manufacturing process and measurement or testing process. The known or available factors and uncertainties are included in the uncertainty budget.

4.2.1 Uncertainty factors and uncertainties in the manufacturing process: There are different input parameters in the SLM manufacturing process which includes laser power, scan rate, hatch distance, beam angle, and layer thickness. The relationship between these input factors and output parameter, the surface roughness is not available. Therefore, we need to determine the relationship between these inputs and output parameters. We have taken laser power, scan speed and hatch distance as three uncertainty factors and beam angle and layer thickness are fixed. First, considering independent input quantities, we perform experimentation and develop a linear equation as defined in equation (6). Then the sensitivity coefficient for each input is determined using relation (6).

$$Y = a + C_{xi} X_i \quad (6)$$

Where Y is the output, “ a ” is the y-intercept of the line, C_{xi} is the slop, which is called the sensitivity coefficient, corresponding to the i^{th} parameter and X_i is the i^{th} input. The sensitivity coefficient will be determined with the following relation by using equation (6);

$$C_{xi} = \frac{\partial Y}{\partial X_i} \quad (7)$$

The layer thickness fixed as $30\ \mu\text{m}$, vertical orientation or building direction and scanning strategy at 67° . There were twenty-seven settings of input parameters and three samples were developed at each setting. The laser power, scan speed and hatch distance (inputs) were varied in range as mentioned in Table 1, and average surface roughness (output) of the samples was determined at each setting.

Table 1. Manufacturing process parameters value selection for determination of the relationship.

Inputs (X_i)			Output (Y_i)
Laser Power (kW)	Scan Speed (m/s)	Hatch Distance (μm)	Surface Roughness (μm)
LP	SS	HD	R_a
0.32 ~ 0.40	0.60 ~ 0.90	81 ~ 116	3 ~ 10

If the surface roughness R_a is output, then the corresponding equations with each input will be in the following form;

$$R_a = a + C_{LP} LP \quad (8)$$

$$R_a = a + C_{SS} SS \quad (9)$$

$$R_a = a + C_{HD} HD \quad (10)$$

The mathematical equations are developed and sensitivity coefficients are determined, as defined in equations (8) – (10), using MATLAB or MINITAB software. The equations and estimated coefficients are mentioned in Table 2.

Table 2. Mathematical relationships and sensitivity coefficients.

Inputs	Equation	Sensitivity Coefficients C_{xi}		
Laser Power	$R_a = -8.088 + 37.36 LP$	C_{LP}	37.36	$\mu\text{m} / \text{kW}$
Scan Speed	$R_a = 9.887 - 6.031 SS$	C_{SS}	6.031	$\mu\text{m} / \text{m/s}$
Hatch Distance	$R_a = -6.497 + 0.1285 HD$	C_{HD}	0.1285	$\mu\text{m} / \mu\text{m}$

The optimum value of surface roughness is observed at laser power value 0.32 kW. In the samples developed at laser power 0.32kW setting, the average surface roughness is $R_a = 4.23 \mu\text{m}$. The A-Type standard uncertainty in surface roughness is estimated as $0.48 \mu\text{m}$ (11.39 %) from repeatability which is due to variation in surface roughness in these samples. For A-Type uncertainty, the formula defined as equation (1) is used. The variation in surface roughness at the same parameters is due to variations in the manufacturing process that may be caused by some other random or assignable factors. The B-Type uncertainties are due to system resolution of laser power, scan speed, and hatch distance. The value of these uncertainties is taken as half of the resolution.

Table 3 shows the uncertainty factors and uncertainties in the SLM manufacturing process. For each factor, the numerical value of uncertainty with its type, distribution, and the divisor is identified.

Table 3. Uncertainty factors and uncertainties in SLM manufacturing process

Component of Uncertainty	Unit	Type	Uncertainty U_{xi}	Distribution, Divisor
Repeatability-Variation in Surface Roughness	μm	A	0.48	Normal, 1
Resolution of Laser Power	kW	B	5×10^{-7}	Rectangular, $\sqrt{3}$
Resolution of Scan Speed	m/s	B	5×10^{-7}	Rectangular, $\sqrt{3}$
Resolution of Hatch Distance	μm	B	0.05	Rectangular, $\sqrt{3}$

4.2.2. Uncertainty factors and uncertainties in the measurement process: The surface roughness of the samples is measured by using surface roughness tester of Mitutoyo SurfTest SJ-210. The A-Type uncertainty in surface roughness tester is determined by repeatability by using precision reference specimen provided by Mitutoyo (Precision Reference Specimen No. 178-602). The value of precision reference specimen is the value of $2.91 \mu\text{m}$ or $115 \mu\text{in}$. The resolution of surface roughness tester is taken as B-Type uncertainty factor. Half value of resolution is taken. The both A and B Type uncertainties in measurement/ testing process are mentioned in Table 4.

Table 4. Uncertainty factors and uncertainties in measurement process

Component of Uncertainty	Unit	Type	Uncertainty U_{xi}	Distribution, Divisor
Repeatability of Surface Roughness Tester using Precision Reference Specimen	μm	A	0.031	Normal, 1
Resolution of roughness meter	μm	B	0.0005	Rectangular, $\sqrt{3}$

4.3. Combined and expanded uncertainty

The combined uncertainty by considering both manufacturing process uncertainties and measurement process uncertainties is determined by using equation (3). The results are mentioned in Table 5. The standard uncertainty of each factor is determined by multiplying its uncertainty value with its sensitivity coefficient.

Table 5. Combined uncertainty estimations

Component of Uncertainty	Type	Uncertainty U_{xi}	Distribution	Divisor d	Sensitivity Coefficient C_{xi}	Standard Uncertainty $u_{xi} = (U_{xi}/d) \times C_{xi}$	Unit
<i>Manufacturing Process</i>							
Repeatability -Variation in Surface Roughness	A	0.48	Normal	1	1	0.48	μm
Resolution of Laser Power	B	5×10^{-7}	Rectangular	$\sqrt{3}$	37.36	0.0000032	μm
Resolution of Scan Speed	B	5×10^{-7}	Rectangular	$\sqrt{3}$	6.031	0.0000005	μm
Resolution of Hatch Distance	B	0.05	Rectangular	$\sqrt{3}$	0.1285	0.0111284	μm
<i>Measurement Process</i>							
Repeatability of Surface Roughness Tester using Precision Reference Specimen	A	0.031	Normal	1	1	0.0310	μm
Resolution of roughness meter	B	0.0005	Rectangular	$\sqrt{3}$	1	0.000866	μm
Combined Standard Uncertainty $u_c =$						± 0.523	μm
Coverage Factor $k =$						2	
Expanded Uncertainty $U = (u_c \times k)$						± 1.05	μm

The estimated combined standard uncertainty in surface roughness is $\pm 0.523 \mu\text{m}$ which is at 68% confidence level. The estimated expanded uncertainty in surface roughness is $\pm 1.05 \mu\text{m}$ which is at 95% confidence level ($k=2$).

4.4. Sensitivity analysis and control

The sensitivity coefficient of laser power has the highest value of $37.36 \mu\text{m}/\text{kW}$ as compared to all three input parameters. It means a change of 1 kW in power can change surface roughness value to $37.36 \mu\text{m}$. Similarly, one unit change in scan speed of 1 m/s and hatch distance $1 \mu\text{m}$ can vary the surface roughness value to $6.031 \mu\text{m}$ and $0.1285 \mu\text{m}$ respectively.

The estimated combined uncertainty provided overall uncertainty which has a cumulative effect of both manufacturing process uncertainties and measurement or testing process uncertainties. The manufacturing process uncertainties (93.91%) have a higher contribution as compared to measurement process uncertainties (6.09%) in combined uncertainty.

Figure 3 shows the percentage contribution of each factor in overall uncertainty. The variation in surface roughness – repeatability due to manufacturing process variation has the highest contribution

of 91.78% in overall uncertainty value. These process variations are due to some random or systematic errors and assignable causes of other factors, i.e., material, laser beam properties, gas properties, etc. The second major contributor is the repeatability of surface roughness tester using a precision reference specimen which contributes 5.93% in overall uncertainty. The third is the resolution of hatch distance.

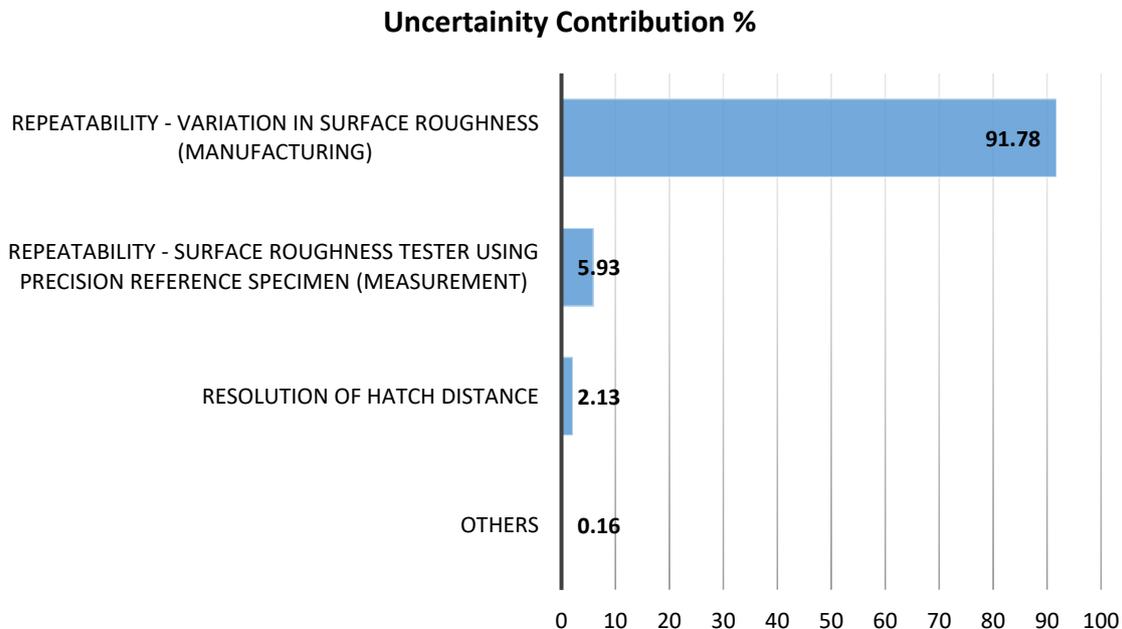


Figure 3. Contribution (%) of sources to the overall uncertainty

To achieve higher accuracy and minimize the value of uncertainty, we need to control and improve the significant uncertainty contributors. The SLM manufacturing process further needs to be analyzed, and assignable causes can be eliminated to improve the uncertainty in the surface roughness. Utilizing a higher resolution of scan speed can also reduce uncertainty.

5. Conclusions

The quality and reliability are one of the essential concerns of modern manufacturing. The key characteristics of quality and reliability are linked with different manufacturing process parameters. The estimation and analysis of uncertainty in the output value of key characteristic value and input process parameters need a quantitative approach.

The proposed approach for uncertainty measurement and analysis has found to be very practical and useful in implementation. It provides an insight view of critical parameters or factors and their uncertainties affecting product or process quality and reliability.

The uncertainties are estimated by considering both manufacturing process parameters and measurement process parameters. The uncertainty contribution from the manufacturing process is much higher as compared to the measurement process. Higher accuracy can be achieved by minimizing and targeting the primary uncertainty contribution sources.

6. References

- [1] Xu L Da, Xu E L and Li L 2018 Industry 4.0: state of the art and future trends *Int. J. Prod. Res.* **56** 1–22
- [2] Zhong R Y, Xu X, Klotz E and Newman S T 2017 Intelligent Manufacturing in the Context of Industry 4.0: A Review *Engineering* **3** 616–30
- [3] Arfan Majeed, Jingxiang Lv T P 2018 A framework for big data driven process analysis and

- optimization for additive manufacturing *Rapid Prototyp. J.* **25** 308–21
- [4] Imkamp D, Berthold J, Heizmann M, Kniel K, Manske E, Peterek M, Schmitt R, Seidler J, Sommer K and Vde-gesellschaft V D I 2016 Challenges and trends in manufacturing measurement technology – the “ Industrie 4 . 0 ” concept *J. Sensors Sens. Syst.* **5** 325–35
- [5] Vogl G W, Weiss B A and Helu M 2019 A review of diagnostic and prognostic capabilities and best practices for manufacturing *J. Intell. Manuf.* **30** 79–95
- [6] Atamuradov V, Medjaher K, Dersin P, Lamoureux B and Zerhouni N 2017 Prognostics and Health Management for Maintenance Practitioners-Review , Implementation and Tools Evaluation *Int. J. Progn. Heal. Manag.* **8** 060
- [7] Abollado J R, Shehab E, Rose M and Schr öter T 2017 Uncertainty Assessment for Measurement Processes in the Aerospace Manufacturing Industry *Procedia CIRP* **60** 326–31
- [8] Jos é Horst D, Adriano Duvoisin C and De Almeida Vieira R 2018 Additive Manufacturing at Industry 4.0: a Review *Int. J. Eng. Tech. Res.* **8** 3
- [9] Dilberoglu U M, Gharehpapagh B, Yaman U and Dolen M 2017 The Role of Additive Manufacturing in the Era of Industry 4.0 *Procedia Manuf.* **11** 545–54
- [10] Hoejin Kim, Yirong Lin T-L B T 2018 A Review on Quality Assurance in Additive Manufacturing *Rapid Prototyp. J.* **24** 645–69
- [11] Berumen S, Bechmann F, Lindner S, Kruth J P and Craeghs T 2010 Quality control of laser- and powder bed-based Additive Manufacturing (AM) technologies *Phys. Procedia* **5** 617–22
- [12] Yao J, Xiong B, Zhou Y and He Y 2016 Research on relationship between manufacturing process quality variation and product reliability *Proceedings of 2016 Prognostics and System Health Management Conference, PHM-Chengdu 2016* pp 1–6
- [13] He Y and Chang W 2009 Systematical Design Quality Control model based on Key Quality Characteristics *2009 16th International Conference on Industrial Engineering and Engineering Management* pp 1208–12
- [14] Wang W, Ren Y and Lv J 2016 Research on the assurance of reliability during the manufacturing process of mechanical products *Proceedings of 2016 Prognostics and System Health Management Conference, PHM-Chengdu 2016* pp 1–5
- [15] Gu H, Zhang S and Ma L 2012 Process Analysis for Performance Evaluation of Prognostics Methods Orienting to Engineering Application *2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering* pp 681–6
- [16] ISO 2017 *ISO/IEC 17025:2017 General requirements for the competence of testing and calibration laboratories*
- [17] ISO 2012 *ISO/IEC 17020:2012 Conformity assessment -- Requirements for the operation of various types of bodies performing inspection*
- [18] BIPM, IEC I and ILAC, ISO, IUPAC I and O 2008 *JCGM 200:2008 International vocabulary of metrology — Basic and general concepts and associated terms (VIM)*
- [19] BIPM, IEC, IFCC, ISO, IUPAC, IUPAP O 2008 *JCGM 100:2008 Evaluation of measurement data — Guide to the expression of uncertainty in measurement*
- [20] UKAS 2012 *M3003 The Expression of Uncertainty and Confidence in Measurement 3rd Ed.*