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Technological maturity assessment of advanced metal subtractive manufacturing process

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Abstract

The degree of maturity of subtractive manufacturing technology (SMT) which has evolved over ages has not been established anywhere in the competitive manufacturing and quality hierarchy, including the latest advanced manufacturing computer and numerical control (CNC) digital machining. Having been applied in the advanced metal additive manufacturing technology, this paper adopted and implemented artificial intelligent-based generic semi-direct technological maturity assessment methodology (SDTMAM) model; EbereDimMT001 on the advanced metal SMT along its process capability variable of product quality (PQ). Started with major five adopted to the expanded eighteen-number process product quality parameters. Also adopted is a set of 28 sub-parametric manufacturing process performance indices, a set of 26 research statement and propositions coined from the performance indices each as applicable to the technological maturity assessment project were as well adopted. As required, the set of 26-questionnaire was designed based on artificial intelligence principle Fuzzy logic and Set theories, and were coupled for the experts' survey to source the research data from the target 150-expert respondents. Data analytics models were utilized progressively and systematically as generic scientific tools to assess and analyze the maturity level of the advanced metal subtractive manufacturing technology. A continuous capability maturity model integration (CMMI) model was adopted as a reference maturity profile for the technological maturity experts' survey ranking and assessment results. The PQ technological maturity assessment of the advanced metal SMT is found at 3.94 maturity level (ML) being the mean result of the fuzzy experts' survey result, which falls within the quantitatively managed maturity level 4 of 5, therefore at 78.8% maturity. Simulation of the result was consistently found at the mean value, and within the quantitatively managed maturity level of 4 of 5. Therefore, justifies the seamlessness and validity of the model; EbereDimMT001, as well, represents the maturity level of the advanced metal subtractive manufacturing technology based on product quality. However, sourcing of data and application of the model in this research is a private effort. So, it is recommended that the questionnaire should be further administered up further, at the upper echelon of advanced (metal subtractive) manufacturing industries and research institutions of the world for research data and implementation for a possible variation or improved result.

Keywords: Product Quality; Maturity Profile; Subtractive manufacturing; Linguistic Variables; Data Analytics; Artificial Intelligence; Parametric Variables; Performance Indices; Fuzzy System; Process Capability Area

1. Introduction

Obviously, subtractive manufacturing technology is a very old traditional and conventional manufacturing technology that has evolved over ages and has continued to evolve technologically for better to date. [1, 2, 3] Presently are the cutting-edge advanced manufacturing technology, digital manufacturing technology, the computer and numerical control CNC machining technology, industrial automation and robotics system and application, intelligent mechatronics

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systems and technology with target results of improved product quality, process dependability and reliability [3]. These advancements have been attained with little or few data or established figures on the technology lifecycle and the technological maturity assessment of advanced metal subtractive manufacturing technology. [3] Therefore, there is a need for a product quality-based technology maturity assessment, to ascertain the current level of technology advancement. Especially in the advanced metal subtractive manufacturing technology (AMSMT) of high-performance engineering components or parts for the high-risk field of aerospace, medicine and automotive industry sectors of economy, a data-based status, and the need to assure and reassure both the existing and prospective government agencies, academia, and industry investors of the industry reality through research, development, seminars, conferences, workshops and publications. [1, 2, 3, 4]

2. Methodology

The Semi-Direct Technology Maturity Assessment model, EbereDimMT001 adopted is non-laboratory experimental research that involves applications of knowledge of advanced manufacturing, artificial intelligence, Fuzzy logic system, data analytics and software engineering to product quality technology maturity assessment of an advanced metal subtractive manufacturing technology, in the steps. [1, 2, 3, 4, 5, 6]

2.1. Algorithm of the Product Quality Technological Maturity Assessment of Advanced Metal Subtractive Manufacturing Technology (MSMT)

The algorithm of product quality technological maturity assessment (TMA) of advanced metal subtractive manufacturing technology (AMSMT), is shown in figure 1 below as explained in the schematic illustration in table 1. [3]

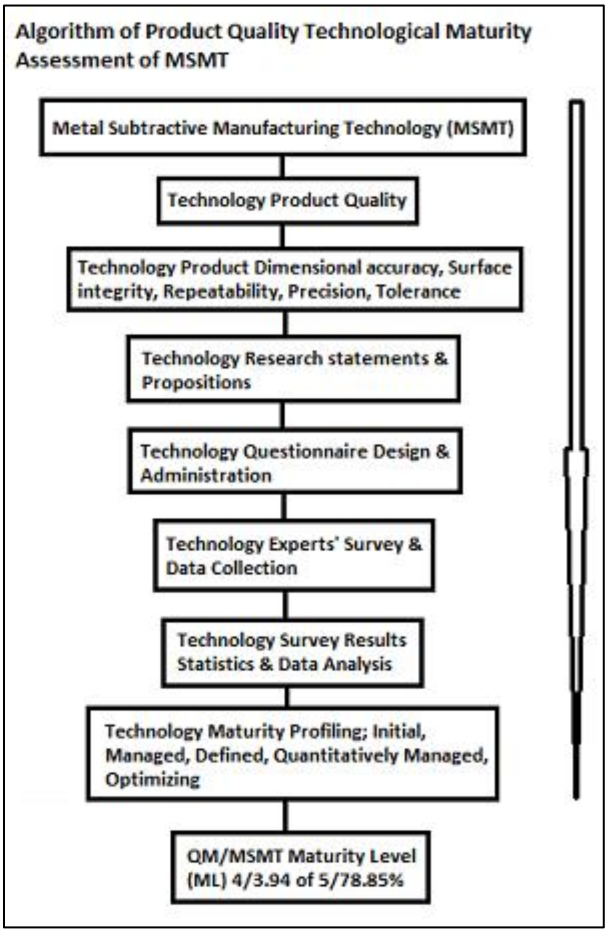

Figure 1 The Algorithm of Product Quality TMA of MSMT

2.2. The Schematic Representation of The Semi-Direct Technological Maturity Assessment Methodology (SDTMAM) Model for MSMT

Table 1 shows steps for the newly formulated generic model for technological maturity assessment of the advanced metal subtractive manufacturing technology which were drawn from the SDTMAN algorithm of figure 1. [1, 2, 3]

Table 1 Schematic Representation of the Semi-Direct Technological Maturity Assessment Methodology for MSMT

Serial No.	Steps	Description of activities
1.	Step1.	The strategic processes common capability areas of metal hybrid manufacturing technologies were determined
2.	Step2.	Processes performance indices were identified, and the performance indicators were established
3.	Step3.	The type of data, source and collection techniques was determined
4.	Step4.	Research propositions with respect to the processes were generated
5.	Step5.	A set of research questionnaire or survey interface tool was developed and designed
6.	Step6.	Technological maturity assessment maturity profile was determined
7.	Step7.	A digital technology and artificial intelligence (AI) Fuzzy logic and Fuzzy set theories were applied in the questionnaire design and administration programme.
8.	Step8.	Expert's technology maturity survey was carried out, data collected and analysed with results
9.	Step9.	Technology maturity assessed data was ranked on the CMMI profile according to the maturity levels with results
10	Step10.	Product Quality technology maturity level result established
11	Step11.	Simulation of result in fuzzy logic system in MATLAB Toolbox to confirm and validate result.
12	Step12.	Presentation and analysis of result

2.3. Experts' Fuzzy Survey Questionnaires and Design for the MSMT Product Quality Technology Maturity Assessment.

The vague nature of the linguistic variable; the maturity, necessitated and as considered in the development, planning, and design of a set of questionnaires peculiar to the process for the expert survey, and research data collection. [3, 5, 6, 7, 8, 9] As a result of the semi-direct technological maturity assessment methodology approach of the assessment, the challenging vague and irregular nature of the linguistic variable, product quality and parameters, the expanded metal subtractive process parameters, performance indices and the associated maturity profiling reality necessitated the introduction of artificial intelligence based fuzzy logic principle in the design, planning and administration of a set of 26-number experts' survey questionnaires, for collation and processing of research data.[3, 5, 6, 7, 8, 9]

Also, to bridge to checkmate the chances or situation of bias throughout the questionnaire planning and administration system, and results, it was ensured that there is no information in the questionnaire system that can suggest exactly to the participating experts and professionals, the actual or intended use and purpose of the project, neither the data nor their responses. With this approach, the possible sentiments and bias influences are eliminated in the questionnaire system. [1, 2, 3]

Thus, a model was developed ready for the advanced metal subtractive manufacturing process product quality technological maturity assessment (TMA). [1] It comprises of research statements jointly produced from various metal subtractive manufacturing studies and literature, experience and engineering practice. Therefore, meaning that they are subject to continuous scrutiny and review of the process capability performance areas, characteristics, propositional statements, and questionnaire design to suit maturity assessment of a target technology at a time. [1, 2, 3]

2.4. Administration of Questionnaires to the Selected Experts' Respondents and Collation

Survey was conducted with 150 questionnaires administered, the data collected and processed in the process class frequency distribution tables. To further checkmate the chances or situation of bias during questionnaire administration and data collation, it was again ensured that the participating experts and professionals do not know the intended use or the actual purpose of the questionnaire exercise, neither the data nor their responses. With this approach as well, the possible remaining sentimental and bias influences are farther eliminated from the entire process. [1, 2, 3]

Similarly, to ensure and improve the reliability and confidence of research, the questionnaire was directly emailed to the targeted professionals and experts' respondents drawn from the field of advanced metal subtractive manufacturing technologies. [1,2, 3] A situation where, based on the research variable of PQ, and importance of specialty, the related quality and manufacturing engineers and technologists in the midst were marked and sub-grouped as main target. Then, applying principal component analysis, and to achieve a better manageable data size, the 63 questionnaires returned within the stipulated time frame were sorted and classified under three employers' groups within the first; academia, second; industry, and third; research institutes of the respondents. [1, 2, 3] This was based on the employment data provided in the questionnaires, which includes current position and titles of the respondents.

2.5. Introduction of Fuzzy Logic Theory and Model Application

Fuzzy logic utilized in the EbereDimMT001, Semi-Direct Technological Maturity Assessment Methodology (SDTMAM) model, [1, 2, 3] is a multiple valued logic that is obtained from a fuzzy set to consider and utilize the intermediate or approximate values instead of the only actual binary or two truth precise values; True and False. Thus, it brings about infinite number of truth values between true and false, where the true can be represented as ''1'', and false by ''0'', and any truth value between the true and false lies in between ''0'', and ''1'', such as ''0.2, 0.3, 0.6, 0.9'' are the approximate values rather than the precise values. In comparison, looking at a Crisp logic, it uses binary sets and binary logic of 1 for true and 0 for false in handling precise or exact information, but in contrary to that, Fuzzy logic is not limited to the values, 0 and 1, rather it has the degree of truth proposition or statement that fall between 0 and 1. [8]

However, it has also been realized that the capability maturity model (CMM) is a linguistic variable, which means that knowledge of fuzzy theory will be needed to transform the variables into numerical variables. Fuzzy logic like other artificial or machine intelligence tools is a comprehensive or more valid way of collecting research data and information outside the conventional quantitative method. [1, 2, 3, 7, 8, 9]

However, the inputs can be either crisp or fuzzy, and the outputs as well can be either crisp or fuzzy, depending on the system and operation under study. Hence, when the input is crisp, it is defuzzified. Then, when output is crisp, it is applied or used directly, but if the output is fuzzy, it is defuzzified. [1, 2, 3, 7, 8, 9]

2.6. Metal Subtractive Manufacturing (CNC Machining) Process Product Quality Parameters

Manufacturable product characteristics and quality which are considered for the technology capability parameters of the MSMT include (i) dimensional accuracy (ii) surface roughness (iii) precision or repeatability and (iv) tolerance. [1, 2, 3] The product quality technology capability parameters which were further expanded or extended up to 18 in number covering various possible aspects of the technology operational phenomenal conditions in the advanced metal subtractive manufacturing processes through relationship-based classification, grouping and matches. [3, 10, 11, 12]

2.7. Metal Subtractive Manufacturing Process Product Quality Capability Performance Indices

Measurable performance indices of 28 in number with objective checks as evident, were sourced from metal subtractive manufacturing literature and studies, experience and engineering practice covering the technology or process challenging goals and conditions of manufacture. [3, 13, 14] These performance indices provide for a set of about 28 well-articulated and purposefully coined propositional research statements meticulously generated for the experts' survey. However, these metal subtractive manufacturing process product quality performance indices are subject to a continuous scrutiny and review of its capability areas, characteristics, propositional statements, including the questionnaire to suit maturity assessment of the target technology at a time. [1, 2, 3]

2.8. Maturity Modelling and Profiling for the Product Quality TMA of the MSMT

Maturity levels (MLs) used in this research are the evolutionary steps towards achieving a continuous mature process. They are five with a continuous representation, marked by the numbers 1 to 5. Each maturity level provided a layer in the foundation for continuous process improvement. [1, 2, 3] However, technology maturity in metal subtractive manufacturing technology is a measurement of the ability of the process or its product quality to achieve a continuous improvement in a particular capability area. Maturity levels of a MSMT are well-defined evolutionary plateau towards achieving an advanced or developed manufacturing process. Each maturity level provides a layer in the foundation for continuous process improvement which presents a way to describe the performance of a system. The maturity levels are calculated by the accomplishment of the specific and generic goals related to all predefined set of process work areas. [1, 2, 3]

Thus, the adopted maturity model for the technological maturity assessment of a metal subtractive manufacturing technology is the linguistic variables-based Capability Maturity Model Integration (CMMI) model by Carnegie Mellon University, Software Engineering Institute (SEI), USA. Each maturity level considers a given group of reference metal subtractive manufacturing process work areas, where achievement of a capability level in those metal subtractive manufacturing process work areas allots a particular maturity level to the process technology as seen in the table 2 below. [1, 2, 3]

Table 2 The Capability Maturity Model Integration (CMMI Maturity Levels) Model

S/No	Levels	Maturity Levels Term (Linguistic)	Maturity Levels Qualification and Description
1	Level 5	Optimizing	Industry continually improves the processes with respect to a good quantitative understanding of the common causes of variation
2	Level 4	Quantitatively Managed	Industry and the technologies establish quantitative objectives for process quality performance, and use them as bases in managing processes
3	Level 3	Defined	Technologies are well defined and understood, proactive, and are described in standards, procedures, tools, processes, and methods
4	Level 2	Managed	Technologies are planned and executed in accordance with the process discipline reflected by maturity level
5	Level 1	Initial	Technologies are normally ad hoc and chaotic, whereby success depends on the competence of the personnel

3. Results and discussion

Survey was conducted, the data collected and processed in the process class frequency distribution tables. The maturity assessment results are analyzed and presented with the mean, median, mode, range, standard deviation (S), and the variance, for the process capability areas experts' survey result.

3.1. Product Quality Technological Maturity Data Profiling of Metal Subtractive Manufacturing Technology

The adapted capability maturity model integration (CMMI) is applied as the maturity profile for a scientific technology maturity assessment survey. The result in the table 3 below, is the maturity assessment survey outcome for the product quality technological maturity assessment of a metal subtractive manufacturing technology. Thus, the representation shows that in the current performance capability maturity status as seen in table 3 of the process product quality capability maturity results profiling or ranking framework for MSMT, 11 out of the 26 numbers of research survey statements of the questionnaire as coded with numbers, made it to the 5th stratum of the CMMI maturity profile. 10 made it to the 4th stratum, while the remaining 5 machining concerns are found on the 3rd stratum. Where there is none on the 2nd stratum. The 1st stratum of the CMMI maturity profile has no process area, which means that it did not come into assessment, hence overqualified for maturity level 1.

Thus, the representation shows that in the current performance capability maturity status of the MSMT manufacturing process and products, attention is needed with respect to each of the research statements to find out what is required to be done to ensure a continuous and sustainable movement up ranks of the few on the 3rd stratum into the 4th stratum, and the same thing will be expected of those on the 4th stratum to move into the 5th stratum, while the 5th continues to optimize.

Table 3 MSMT Product Quality Capability Maturity Framework and Survey Primary Results Profiling

Levels	Focus	Process Capability Area	Result
5. Process Optimizing	Continuous Process Improvement	4, 5, 6, 7, 8, 10, 12, 16, 23, 24, 26	-
4. Process Quantitatively Managed	Process Quantitatively Managed	1, 3, 13, 14, 17, 18, 19, 21, 22, 25,	
3. Process Defined	Process Standardization	2, 9, 11, 15, 20	
2. Process Managed	Basic Process Management	-	-
Process Just Initiated	Process Taken off, Informal and Adhoc	Process Area not Exsting	

Table 4 Statistical results of Product Quality TMA of the MSMT

Variable	Total Count	Percent	Mean	StDev	Variance	Sum	Minimum	Q1	Median
MPPQ Maturity	26	100	3.936	0.574	0.329	102.330	3.000	3.585	4.000
Variable	Q3	Maximum	Range						
MPPQ Maturity	4.330	4.670	1.670						

In table 4 above are the statistical results of the experts' survey showing the Minimum (mini) maturity level (ML) of the metal subtractive manufacturing technology, the 1st Quartile (Q1), the Median, 3rd Quartile (Q3), and the Maximum (max) ML of the MSMT, with a range of 1.670, and the interquartile range (IQR), 0.745 This means that the middle 50% of the maturity spread only has a variability of 0.745ML.

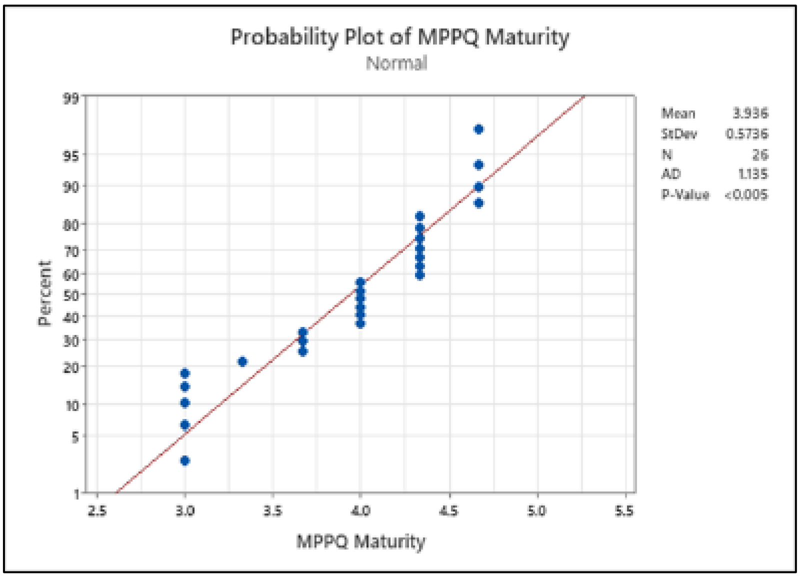

Figure 2 The normal probability test plot of CNC MPPQ maturity data on Minitab.

Figure 2 shows the normal probability test results for Anderson-Darling (AD). The probability value; P-Value is 0.005 and less than the significant level of 0.05. This means strong evidence against the null hypothesis (H_0). Also, the data do not follow a normal distribution and H_0 is rejected. Thus, the test is statistically significant. Standard deviation of 0.5736 was recorded.

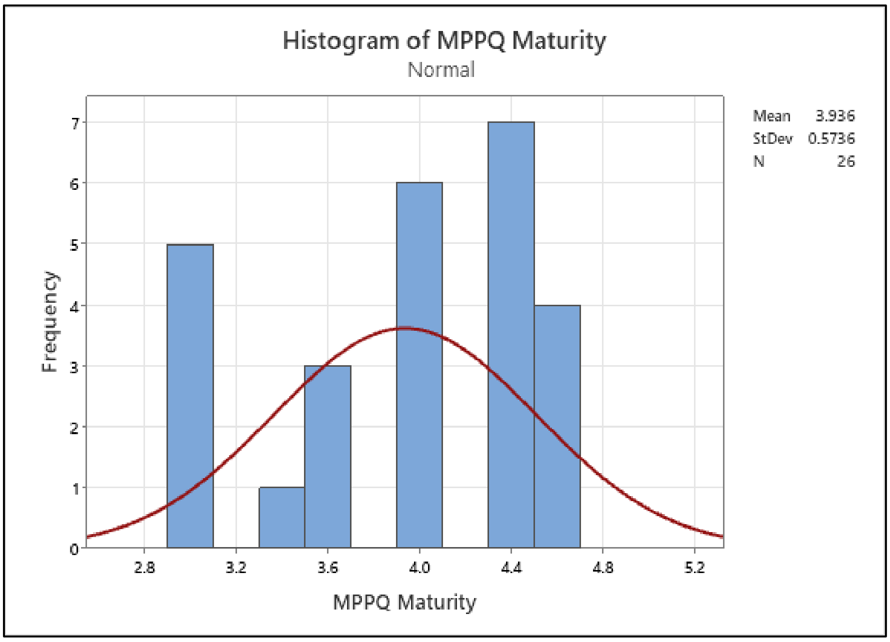

Figure 3 Histogram of CNC MPPQ maturity graph

Figure 3 is the histogram representation of the results of the 26-number sample size experts survey of the product quality technological maturity assessment of the metal subtractive manufacturing technology. The mode is 4.4, where the mean maturity level 3.936, and the standard deviation (STD) 0.5736.

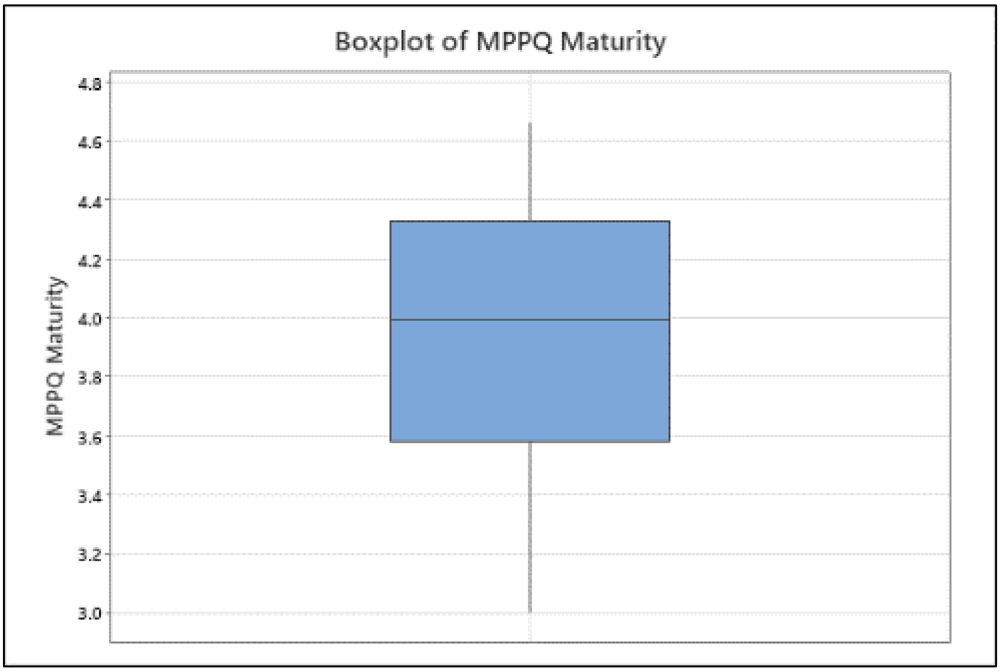

Figure 4 Boxplot of CNC MPPQ maturity.

However, the boxplot of figure 4 shows the maturity data spread. It means that the CNC Machining PPQ maturity data is concentrated in the shaded area, which shows the Variability (V) of the CNC MPPQ maturity, where the Range (R) 1.670, shows the extent CNC MPPQ maturity data spread out, while the Interquartile Range (IQR) 0.745 meaning that the middle 50% of CNC MPPQ maturity data spread has 0.745ML variability. Where the Median (M) 4.000ML, with a Mean (M) 3.936 Maturity.

Therefore, by the statistical analysis of the Fuzzy experts' survey results of the metal subtractive manufacturing technology, the maturity levels and the percentage maturity of the process is the cluster mean as in the table 5 below.

Table 5 MSMT Product Quality TMA Results

Process Product Quality Maturity Level	
MSMT	
ML	%tage
3.94	78.8

Table 5 shows the result of the product quality technological maturity assessment of metal subtractive manufacturing technology (MSMT) at 3.94 of 5CMMI maturity profile, which is equivalent to 78.8% maturity.

3.2. Contributions to Knowledge

The novel generic technology maturity assessment model, EbereDimMT001, designed was implemented successfully on the product quality technology maturity assessment of metal subtractive manufacturing process with impressive and consistent result, which validates the model. Thus, the research has been able to make significant contribution to the field of advanced manufacturing engineering in general.

The generic technology maturity assessment model for metal subtractive manufacturing technology, EbereDimMT001, a semi-direct technology maturity assessment model was implemented on the metal subtractive manufacturing process, with an impressive and consistent result of 3.94 maturity level (ML) of 5CMMI maturity profile, which is 78.8% maturity. and within the Quantitatively Managed (QM) maturity level, which is a novel contribution to the field.

4. Conclusion

A novel generic model for maturity assessment of subtractive manufacturing technology was expressed. The metal SMT maturity level for PQ showed 3.94 of 5CMMl maturity profile at 78.8% maturity level, with the application of the model. This model x-rays that the metal subtractive manufacturing technology is therefore at the quantitively managed (QM) maturity level. Again, the novelty opens doors for further research in the advanced manufacturing technologies with the knowledge and experience in artificial intelligence fuzzy logic system and the SEI CMMI model.

Thus, the results representation shows that in the current process product quality performance capability maturity status of the MSMT and products, attention is also needed with respect to each of the research survey statements to find out what is required to be done to ensure a continuous and sustainable movement of those on the 3rd stratum into the 4th stratum. The same thing will be expected of those on the 4th stratum to move into the 5th stratum, while those already on the maturity level 5 go through and maintain continuous optimization process. Moreover, in table 4 the outcome of the experts' survey shows the Minimum (mini) maturity level (ML) of the metal subtractive manufacturing technology, the 1st Quartile (Q1), the Median, 3rd Quartile (Q3), and the Maximum (max) ML of the MSMT, with a range of 1.670, and the interquartile range (IQR), 0.745, which means that the middle 50% of the maturity spread only has a variability of 0.745ML.

Thus, from the statistical analysis results of the MSMT, the maturity levels and the percentage maturity of the process is the cluster mean as in the table 4 above. Then, the metal subtractive manufacturing technology (MSMT) product quality technological maturity level 3.94ML equals 78.8% maturity as in table 5 above.

Limitations

- Difficult to access the target high place industry expert questionnaire respondents.
- It was a private effort project
- Limited funding opportunity
- The process capability area, parameters, maturity indicators (PMI), performance indices were solely identified and determined from studies and literature.

4.1. Recommendations and Future Work

Experts' survey questionnaire should better target respondent quality and manufacturing engineers and technologists at the upper echelon of advanced manufacturing industries, institutions and societies such as the Mazak Corporation, DMG MORI, Manufacturing Technology Centre (MTC), UK, American Society of Mechanical Engineers (ASME), American Society for Testing and Materials (ASTM) for a more reliable, valid and dependable technology maturity research data.

More study and research are necessary around the model to optimize the product quality technology maturity assessment and results of metal subtractive manufacturing technology. At the same time embark on the design of maturity assessment model for hybrid manufacturing technology.

EbereDimMT001 generic technological maturity assessment model should as well be applied in the product quality technological maturity assessment of the ceramics and plastics additive manufacturing technologies to ascertain the maturity level of the cutting-edge 4.0IR manufacturing technology.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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