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Implementation of Advanced Generic Product Quality Technological Maturity Assessment Model, EbereDimMT003 by Membership Function on Metal Additive Manufacturing Process

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Abstract
The requirement for more quality and higher performance engineering components has brought about the quest for more research for advanced generic semi-direct product quality technology maturity assessment methodology model, EbereDimMT003 by membership function aimed for reliable and wider acceptable advanced metal additive manufacturing technology industry maturity assessment results. The research therefore aimed to adapt to implement the advanced generic technology maturity assessment model on metal additive manufacturing technology (MAMT) first along the process capability area of product quality (PQ). Five manufactured product achievable characteristics of dimensional accuracy, surface roughness, precision or repeatability, and tolerance were considered for the technology capability parameters, while the capability maturity model integration (CMMI) maturity profile of the Software Engineering Institute (SEI), Carnegia Mellon University, USA was adopted for maturity profiling of the scientific technology maturity assessment of additive manufacturing technologies. The digital technology, intelligent mechatronics systems, artificial intelligence (AI), robotics and automation engineering, data and software engineering driven Semi-Direct Technological Maturity Assessment Methodology (SDTMAM) model; Ebere Dim MT003 was applied with membership function based on the primary result of the foundational generic model, EbereDimMT001. The models were systematically coupled in series and was implemented on a laser powder bed fusion (LPBF) MAMT for the product quality technology maturity assessment results set using fuzzy graphical inference rules. The MAMT LPBF product quality technology maturity after research and results simulation in the Fuzzy logic system in the MATLAB Toolbox was consistently found at the quantitatively managed maturity level of 3.19 maturity level (ML) of 5CMMI maturity profile, where the technology maturity level of a MAMT for the PQ is 63.75% maturity. This justifies the model advancement, thus represents the maturity level of the metal additive manufacturing technology based on product quality (PQ), which validates the new advanced model.
Keywords: *Digital Manufacturing, Additive Manufacturing, Advanced Manufacturing, Maturity Profile, Metal Powder, Artificial Intelligence, Data Analytics, Software Engineering, Process Area, Process Capability, Performance Index*

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I. INTRODUCTION

Additive manufacturing technology is a manufacturing technology in which products are produced as a whole and single unit part through additive manufacturing means and process of product design, material selection, modelling and data filing, and 3-D Printing processes proper, in a solid material or metal powder, wire feedstock forms, and additive manufacturing process design and implementation, in layers to produce engineering components of a more complex geometries and of high performance demand. Additive manufacturing technology (AMT) therefore, has continued for a long time been referred to as a new technology in all publications and assemblies to date. A technology of over 20years since inception, still being introduced and described as emerging technology each time. However, a model, EbereDimMT001 has been designed recently and was successfully implemented on both metal subtractive and additive manufacturing (AM) processes based on the product quality technological maturity assessment (TMA) with impressive and consistent results. Notwithstanding, there is room for competition, more research for improvement as the model has been extended in the EbereDimMT003 and implemented successfully on a metal subtractive manufacturing process with good and consistent outcome. Therefore, it is good it is similarly run on a metal additive manufacturing process based on the product quality TMA too as there is a need for a devoted and continued technological assessment programme, the level of technology advancement in the AMT, a data-based status, and the best means and available modalities to achieve that. Also, there is a need to update the existing and prospective government agencies, academia, and industry private investors of the industry technology maturity level, and about a new or improved technology maturity assessment methodology models. Especially with the high demand of AM materials and parts from the strategic high-risk engineering fields of aerospace, automotive, medicine and defense industry sectors of world economy. [1], [2], [3], [4], [5]

II. METHODOLOGY

Algorithm of the Advanced Generic Technology Maturity Assessment Model, EbereDimMT003 Application on MAMT

The algorithm of product quality technology maturity assessment (TMA) of metal additive manufacturing technology (MAMT), with the advanced generic semi-direct technology maturity assessment model, EbereDimMT003 is shown in figure 1 below as explained in the schematic illustration in table 1. [1], [2], [3], [4], [5]

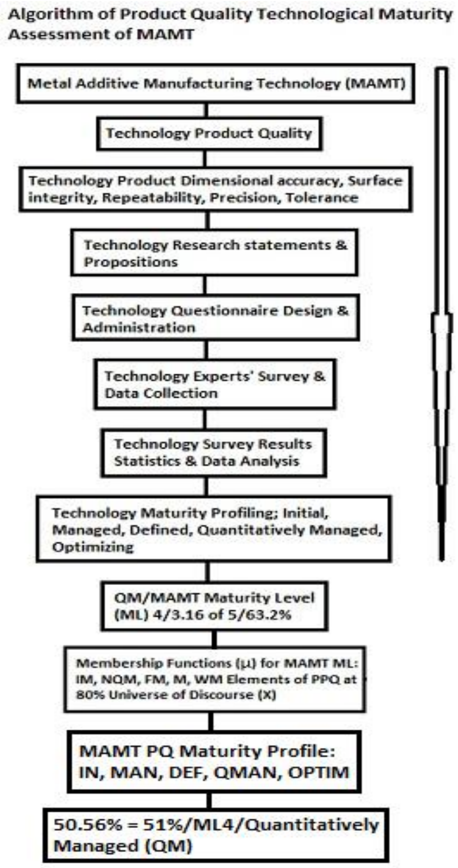

Figure 7. The algorithm of the metal additive manufacturing technology product quality TMA

The Schematic Representation of the Advanced Generic Technology Maturity Assessment Methodology, EbereDimMT003 Model

Table 1 shows procedural implementation steps for the new advanced generic model for technology maturity assessment of the metal additive manufacturing technology which were drawn from the SDTMAM algorithm of figure 1. [1], [2], [3], [4], [5]

Table 1 Schematic representation of the advanced generic technological maturity assessment model

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 survey was carried out, data collected and analysed
9.	Step9.	The Input/Output maturity results were independently fuzzified into five subsets each
10.	Step10.	Membership functions were created and assigned to the Input/Output fuzzy subset.
11	Step11.	Application and execution of Fuzzy graphical inference rules on process subset with result
12	Step12.	Defuzzification of the result was carried out with engineering mathematical model for exact maturity level results by applying a centroid defuzzification method with result
13	Step13.	Simulation of result in fuzzy logic system in MATLAB Toolbox by artificial intelligence (AI) fuzzy command line functions, and by using a graphical user interface for the simulated result from AI for confirmation and validation of result
14	Step14.	Presentation and analyses of final result

Experts' Fuzzy Survey Questionnaire and Design for MAMT Product Quality TMA

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. [1], [3], [6] As a result of the semi-direct technology maturity assessment methodology approach of the research project, the challenging vague and irregular nature of the linguistic variable, product quality and parameters, the expanded metal additive 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. [1], [3], [6] Also, to close to checkmate the chances 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, 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], [4], [5]

Therefore, questionnaire model was developed ready for the metal additive manufacturing process product quality technology maturity assessment. [1], [7] It comprises research statements jointly produced from various metal additive manufacturing studies and literature, experience and engineering practice. Therefore, meaning that they are subject to continuous scrutiny and review of the process capability performance indicators, characteristics, propositional statements, and questionnaire design to suit maturity assessment of a target technology each time as necessary. [1], [7], [8]

Administration of the MAMT Product Quality Questionnaires to the Selected Experts' Respondents and Collation

To ensure and improve the reliability, integrity and confidence of research, the questionnaire was directly emailed to the targeted experts' respondents drawn from the field of additive manufacturing technology. A situation where, based on the research variable of the product quality, 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 the principles of principal component analysis, 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. This was based on the employment data provided in the questionnaires, which includes current positions of the respondents. [1], [2], [3], [4], [5]

Introduction of Fuzzy Logic Theory and Model Application

The L. A. Zadeh's Fuzzy logic theory utilized in the EbereDimMT003, a Semi-Direct Technological Maturity Assessment Methodology (SDTMAM) model, [1] 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. [1], [2], [3], [4], [5], [6]

However, it has also been noted that the capability maturity model (CMMI) 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. [3], [6], [8]

Defuzzification

Defuzzification is the process of producing a quantifiable result in fuzzy logic. Fuzzy set will have number of rules that transform a few or several variables into a resultant fuzzy set. Thus, the resultant Fuzzy set is the set whose elements have degree of membership. [7] 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], [4], [5], [6]

Metal Additive Manufacturing Process (LPBF) Product Quality Parameters

Metal manufacturable product characteristics and quality which are considered for the technology capability parameters of the MAMT include dimensional accuracy, surface roughness, precision or repeatability and tolerance. [1], [3] [9], [10] The 5-number product quality technology capability parameters which are further expanded up to 18 in number to cover various possible aspects of the technology operational phenomenal conditions in metal additive manufacturing processes through relationship-based classifications, groupings and matches. [11]

Metal Additive Manufacturing Process Product Quality Capability Performance Indices

Measurable performance indices of 28 in number with objective checks as evident were sourced from metal additive manufacturing literature and studies, experience and engineering practice covering the technology or process challenging goals and conditions of manufacture. [1], [12], [13] These performance indices provide for a set of about 28 well-articulated and purposefully coined propositional research statements meticulously generated for the experts' survey as suitable. However, these metal additive 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], [4], [5],

Maturity Modelling and Profiling for the Product Quality TMA of the MAMT

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], [14] However, technology maturity in metal additive 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 MAMT 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], [14]

Thus, the adopted maturity model for the technological maturity assessment of a metal additive 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 additive manufacturing process work areas, where achievement of a capability level in those metal additive manufacturing process work areas allots a particular maturity level to the process technology as seen in the table 2 below. [1], [2], [3], [14]

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

III. SURVEY RESULT AND DISCUSSION

Survey was conducted, the data collected and processed in the process class frequency distribution tables. [1] The maturity assessment result of the metal additive manufacturing process is analyzed and presented with the mean, median, mode, range, standard deviation (S), and the variance, for the process capability areas experts' survey result. [1], [2], [3], [4], [5],

Product Quality Technological Maturity Data Profiling of MAMT

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's now primary outcome for the product quality technology maturity assessment of a metal additive manufacturing technology by EbereDimMT003 model. Thus, the representation shows that in the current performance capability maturity status as seen in table *3* of the process product quality capability maturity result ranking framework for MAMT, 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 AM 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. [1], [2], [3], [14]

Thus, the representation shows that in the current performance capability maturity status of the MAMT 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. [1], [2], [3], [14], [15], [16], [17], [18]

Table 3 MAMT product quality capability maturity framework and survey primary result profiling

Level	Focus	Process Capability Area	Result
5 Process Optimizing	Continuous Process Improvement	-	-
4 Process Quantitatively Managed	Process Quantitatively Managed	1, 5, 9, 17, 18, 19, 26	
3 Process Defined	Process Standardization	2, 3, 4, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 20, 21, 22, 23, 24, 25	
2 Process Managed	Basic Process Management	-	-
1 Process Initiated	Process is informal and Adhoc	No Process Area	

Table 4 Primary statistical results of product quality MAMT LPBFPPQ

Variable	Total Count	Percent	Mean	StDev	Variance	Sum	Minimum	Q1
LPBFPPQ Maturity	26	100	3.1546	0.4441	0.1972	82.0200	2.6700	3.0000

Variable	Median	Q3	Maximum	Range
LPBFPPQ Maturity	3.0000	3.4150	4.0000	1.3300

In table 4 above are the statistical primary result of the experts' survey showing the Minimum (mini) maturity level (ML) of the metal additive manufacturing technology survey ranking, the 1st Quartile (Q1), the Median, 3rd Quartile (Q3), and the Maximum (max) ML of the MSMT, with a range of 1.330, and the interquartile range (IQR), 0.4150. This means that the middle 50% of the maturity spread only has a variability of 0.4150ML. [1], [3], [9], [10], [11]

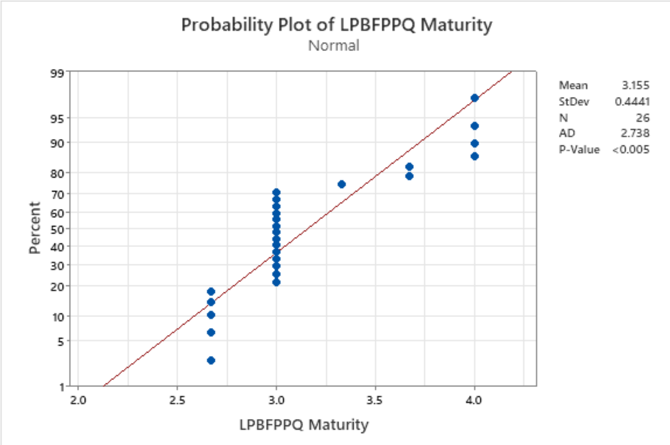

Figure 2 The normal probability test plot of MAMT LPBFPPQ maturity data on Minitab.

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 0.4441 was recorded. [1], [3], [9], [10], [11]

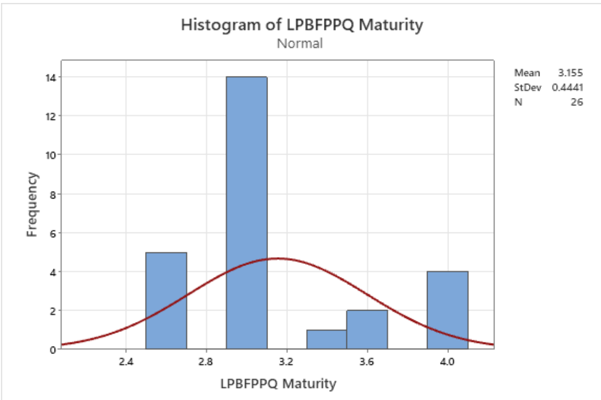

Figure 3 Histogram of MAMT LPBFPPQ maturity graph

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 additive manufacturing technology. The mode is 4.4, where the mean maturity level 3.155, and the standard deviation (STD) 0.4441. [1], [3], [9], [10], [11]

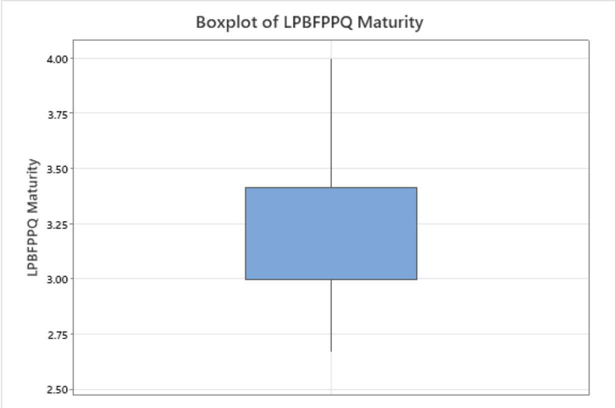

Figure 4 Boxplot of MAMT LPBFPPQ maturity.

The boxplot figure 4 above shows the maturity data spread. It means that the MAMT LPBFPPQ maturity data is concentrated in the shaded area, which shows the Variability (V) of the LPBFPPQ maturity, where the Range (R) 1.3300, shows the extent LPBFPPQ maturity data spread out, while the Interquartile Range (IQR) 0.4150 meaning that the middle 50% of MAMT LPBFPPQ maturity data spread has 0.4150ML variability. Where the Median (M) 3.000ML, with a Mean (M) 3.155 Maturity. [1] Therefore, by the statistical analysis of the Fuzzy experts' survey primary data result of the metal additive manufacturing technology, the maturity levels and the percentage maturity of the process is the cluster mean as in the table 5 below. [1], [3], [9], [10], [11]

Table 5 Product quality MAMT TMA primary results

Process Product Quality Maturity Level	
MAMT	
ML	%tage
3.16	63.2

Therefore, if the classical or crisp maturity level is as obtained, then there is a need to also determine the degree or the extent of truth in it or the extent that it is true. This leads to the introduction of the membership functions.

Determining the Membership Functions for the Metal Additive Manufacturing Technology Maturity Level

As the primary maturity level of the metal additive manufacturing technology laser powder bed fusion (LPBF) has been found, yet, there is a need to also find out how true or the degree of truth in the maturity level found. Thus, a set of maturity subsets are established with some familiar descriptors, to determine the membership functions of the subsets as in the figure 5 below. Defining the membership functions for the set of MAMT Input descriptors, a triangular membership function is applied in the fuzzy subset. The MAMT subset descriptors; IM, NQM, FM, M, WM. Where equation of a straight line is used to determine the membership functions for all the descriptors and corresponding membership values as follows. [1], [2], [3]

$$\frac{y_2-y_1}{x_2-x_1} = \frac{y-y_1}{x-x_1} \quad \text{--(i)}$$

Where $y = \mu$ and $x = x_m$ (Input Variable or the element which must belong to the universe of discourse (X))

MAMT Input (1)

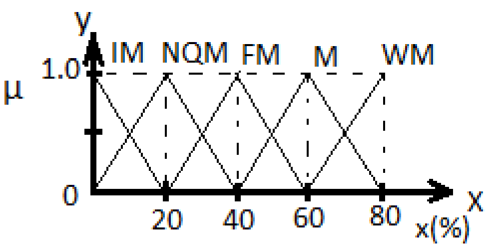

Figure 5 Element of the MAMT LPBPPQ Input 1 universe of discuss

Accordingly, the membership function of the MAMT Input is as determined and summarized below. Now we have. [1], [2], [3]
μIM = 20 –x/20 [0,20]
μNQM = x/20 [0,20], 40 – x/20 [20,40]
μFM = x - 20/20 [20,40], 60 – x/20 [40,60]
μM = x - 40/20 [40,60], 80 – x/20 [60,80]
μWM = x - 60/20 [60,80]
Then, applying the percentage of the crisp maturity values of the MAMT (Input 1) against the current chosen universe of discourse (X), the elements of the subsets and membership functions (μ). [1], [2], [3]
If the maturity of the Input (1) is = 63.2%, then, the membership function (μ) from the graph will be at the 63.2% of 80 (Universe of discourse).
Which implies; 63.2/100 x 80 = 51
Thus, it falls between the range [40,60] as illustrated above

Therefore, striking out the rest in Input (1), it implies that,
μFM = 60 – x/20 [40,60], where x = 51
μM = x - 40/20 [40,60], where x = 51
Therefore, the membership functions of MAMT Input (1); FM and M will be as stated below.
μFM = 60 – x/20 = 60 – 51/20 = 0.45
μFM = 0.45
Then,
μM = x - 40/20 = 51 – 40/20 = 0.55
μM = 0.55
Therefore,

→ 63.2% of 80 = 50.56% ≈ 51%

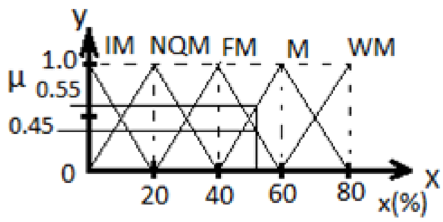

Figure 6 Membership values of the MAMT LPBFPPQ ML [1], [2], [3]

Product Quality MAMT Maturity Assessment Results Simulations in Fuzzy Logic System in MATLAB Toolbox

Simulation of the technological maturity assessment result of the metal subtractive manufacturing technology was performed in a fuzzy logic system MATLAB Toolbox and the result is as shown in the numerical figure 7 below. [1], [2], [3]

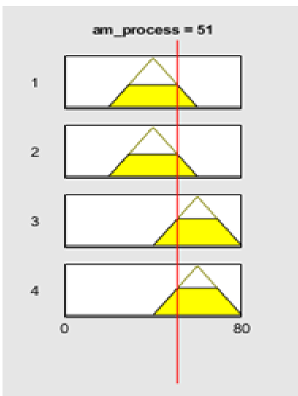

Figure 7 The Rule Viewer MAMT LPBFPPQ maturity level format in a fuzzy logic system toolbox in MATLAB

In summary, figure 7 above shows a dynamic inference process for the fuzzy product quality metal additive manufacturing technology maturity assessment process, with the maturity value of the MAMT.

Result and Analysis of Processes Product Quality ML of the MAMT by EbereDimMT003 Model

The technology maturity level of the metal additive manufacturing technology with respect to the process product quality (PQ) is as follows in the table 6 below in percentage.

MAMT LPBF: the maturity level is 3.19 maturity level (ML) of 5CMMI ML, which is 63.75% maturity.

Table 6 Process product quality ML of MAMT LPBFPPQ

Process Product Quality Maturity Level	
MAMT LPBF	
ML	*%*
3.19/5	63.75

Contributions to Knowledge

The optimized generic technology maturity assessment model, EbereDimMT003, designed was implemented successfully on the product quality technology maturity assessment of metal additive 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.

The optimized generic technology maturity assessment model for metal additive manufacturing technology, EbereDimMT003, a semi-direct technology maturity assessment model with membership function was implemented on the metal additive manufacturing process, with an impressive and consistent result of 3.19 maturity level (ML) of 5CMMI maturity profile, which is 63.75% maturity. and within the Quantitatively Managed (QM) maturity level, which is a novel contribution to the field.

Limitation

1. The most target high place industry experts and stakeholders' questionnaire respondents were not within reach.
2. It was an intensive but solely private effort research project
3. Limited funding affected coverage
4. The process capability areas, parametric variables and performance maturity indicators (PMI) were solely identified and generated from literature and studies.

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). Also, Metal Additive Manufacturing (METAL AM), Wohlers Associates, VoxelMatters, Formnext and others for a more involved, reliable, valid and dependable technology maturity research data.

EbereDimMT003 generic technological maturity assessment model should as well be applied in the product quality technological maturity assessment of hybrid manufacturing technology to ascertain the maturity level of the cutting-edge 4.0IR manufacturing technology.

IV. CONCLUSION

An optimized generic model for technology maturity assessment of metal additive manufacturing technology, EbereDimMT003 was expressed. The MAMT maturity level for PQ showed 3.19 maturity level (ML) of 5CMMl maturity profile at 63.75% maturity. Really, the optimization of the model is evident in the algorithm and the new result. Thus, model has shown that the metal additive 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, set theory, the SEI CMMI model, data and software engineering.

Thus, the result representation shows that in the current process product quality performance, capability maturity status of the MAMT 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 additive manufacturing technology, the 1st Quartile (Q1), the Median, 3rd Quartile (Q3), and the Maximum (max) ML of the MAMT, with a range of 1.3300, and the interquartile range (IQR), 0.4150, which means that the middle 50% of the maturity spread only has a variability of 0.4150ML.

The model, EbereDimMT003 has been used to determine the maturity level of MAMT in terms of PQ at the quantitatively managed maturity level (QMML), which is a novel contribution to the field. Thus, from the statistical analysis results of the MAMT, the maturity levels and the percentage maturity of the process is the cluster mean as in the table 6 above, where the metal additive manufacturing technology (MAMT) product quality technological maturity level 3.19ML, which is 63.75% maturity.

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