Organizing the Internal Manufacturing Complexity Elements in Adaptation of Current Manufacturing Environment: A Fuzzy Approach

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ABSTRACT

Manufacturing industry has been developed outrageously during the past decade. The scenario also applies on Malaysian industry where 22.3% of the economy is generated from the manufacturing industry. Numerous latest concepts and technologies have been implemented by manufacturing firms to increase their productivity, product variety and efficiency. However, these changes also provide certain challenges by increasing manufacturing complexity and decreasing sustainability. Generally, manufacturing complexity is classified into internal and external complexity. This research intends to arrange the elements of internal manufacturing complexity (IMC) according to the priority through the period of enhancing sustainability. IMC elements were clustered into organizational, operational and productivity complexity. Fuzzy analytic hierarchical process was implemented in this research as multi criteria decision making method in IMC management. The

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results found that IMC priority sequence started with productivity, followed by organizational and operational complexity. Productivity complexity with dominant weightage of 0.5302 was emphasized by three elements which are quality inspection process, cost reduction and time reduction respective to the sequence. Meanwhile, organizational complexity slightly led operational complexity by a difference of 0.059. The results show that the Malaysian manufacturing industry is very keen on the product quality and conforms to the requirements. This research could aid firms and researchers to focus on more important elements in decision making for bigger impact on overall performance.

Keywords: *Internal Manufacturing Complexity; Fuzzy Analytic Hierarchical Process; Malaysian Industry; Prioritizing the More Important Element*

Introduction

The world is moving towards a revolution that constituted with internet of things which provides increase in productivity, quality and capability of manufacturing firms [1]. Industrial revolution 4.0 happened due to the development of technology like machine learning, real-time optimization and cyber-physical system [2], [3]. Nowadays, manufacturing firms are able to reduce all associated wastes easily compared to the conventional method [4], [5]. A case study has proven that the development of new concepts guide firms towards better product values while improving employees and customers' satisfaction [6].

However, this adaptation of technology impacted on the addition of elements involved in manufacturing practices. For example, the implementation of additive manufacturing (AM) is still a critical phase where standardisation is yet developed, and issues on intellectual properties and its environmental impact are still uncertain. These new considerations that appear with AM implementation require extra effort to fully optimise its benefits [7]. The situation directly causes manufacturing complexity level to increase.

Meanwhile, the need to contribute on sustainability through manufacturing practices also has been raised. The main drive towards the implementation is the enforcement of law and regulations [8]. In Malaysia, the agreement pledged in 2015 to achieve 17 Sustainable Development Goals (SDG) has led towards a bigger transformation in manufacturing industry [9]. Sustainability also happened to be agitated by the recent COVID-19 global pandemic which apparently has urged more sustainable related policies to be introduced [10].

Manufacturing complexity

Manufacturing complexity (MC) results from multiple factors depending on manufacturing operational characteristics such as technology innovations, shorter product life cycle and political issues [11]. It is defined as an interrelationship between components involved within manufacturing practices that impacted on overall system behavior [12]. Normally, firms have initial negative perspective on MC [13]. Nevertheless, driven by research and innovation, this perception is encountered by numerous fresh, hybrid and integrated concepts such as anarchic manufacturing [13], integration of social responsibility with human resources management [14] and structure for technical scheme by complexity level [15].

In the context of MC management, it best classified into internal and external MC [12], [16]. Internal and external MC are separated by a clear barrier where internal MC is related to areas that are directly manageable while external MC is related to areas that have significance on manufacturing practices but could not be directly managed by manufacturing firms [17]. In addition, both classifications are related to each other with bi-directional influence [18]. From management level perspective, internal MC has been highlighted to be emphasized before external MC [16], [19].

Internal manufacturing complexity

As this research emphasized on internal manufacturing complexity (IMC), the determination of its elements are essential. Based on published articles related to Malaysian manufacturing industry, initially IMC has 30 elements. Nevertheless, after a series of analyses, IMC can been grouped into three clusters, namely operational, productivity and organisational complexity [16], [20]. These clusters have their own elements as presented in Table 1.

According to [16], aided by data reduction and factor analysis, 13 remaining elements were found to be of significance towards IMC. These elements were adapted from published articles but the clusters' name have been revised to avoid any misinterpretation upon unsuitable words used [21]. The words organisational, operational and productivity complexity have been chosen referring to their respective elements and suggested by several researchers [11], [22], [23].

This research intends to organize these IMC clusters and their elements according to the priority. Any insignificant elements should be eliminated from the list in order to provide clearer management areas to be concentrated upon. The final result will present the organized IMC clusters with significant elements with respect to the priorities.

Table 1: Internal manufacturing complexity elements [16]

	Cluster	Abbr.	Element
Internal Manufacturing Complexity	Organisational Complexity	IMC1	Sufficient and effective employee training
		IMC2	Information flow management
		IMC3	Fulfill key performance index (KPI)
		IMC4	Managing employees' behavior
		IMC5	Improve organizational culture
		IMC6	Establish standard operation procedures (SOP)
	Operational Complexity	IMC7	Materials handling system
		IMC8	Inventory management
		IMC9	Production records system
		IMC10	The needs to use simulation
	Productivity Complexity	IMC11	Reduce production time
		IMC12	Reduce production cost
		IMC13	Quality inspection equipment

Materials and Methods

There are various management principles suitable to be adapted in this research. Among them, fuzzy analytic hierarchical process (FAHP) was chosen from the multi-criteria decision making methods available. FAHP has several advantages to be adapted in this research: similarly understandable across the world, fuzzy integration suitable to be used with purposive sampling in exploratory research, small sample size with limit reachability of reliable respondents, and that fuzzy aided the high possibility of vagueness and ambiguous responds collected [24], [25]. Figure 1 presents the flow of FAHP.

In this research, FAHP is divided into three phases: pair-wise comparison matrix, fuzzification process and prioritisation arrangement, as illustrated in Figure 1. These phases are according to the steps and its purposes. The end outcome is normalized weightage of elements' importance level. In this research, the fuzzy element is represented by triangular fuzzy number (TFN) where a number is expanded into a set of three numbers as guided in this section [26]. All equations and steps involved are adapted from standard steps in FAHP.

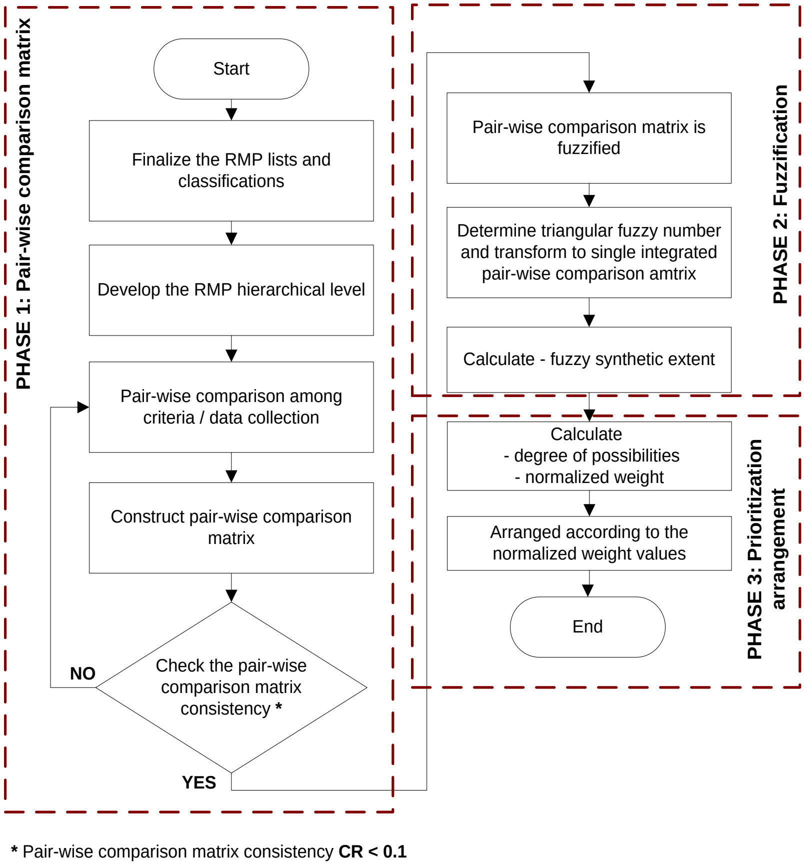

Figure 1: Fuzzy analytic hierarchical process flow [24], [26]

The input data for FAHP were collected during interview sessions with selected experts from the managerial level of Malaysian manufacturing industry. The experts should be either currently employed at related managerial level in industry, or lecturers with past experience. They should also possess knowledge and qualification on the research subject and be willing to cooperate with honest judgment [27], [28].

According to the review done by [29], 80% of research with FAHP method involved between four to nine experts. This is due to the accessible number of reliable experts to make pair-wise comparison between the elements during the research where each expert's judgment is very valuable. Thus, six experts are involved in this research.

By having IMC as the highest hierarchy level, FAHP here involves four matrices: IMC, organizational, operational and productivity complexity with matrix dimensions of 3x3, 6x6 and 4x4. There are eight equations with table of guidelines involved through the FAHP as listed in next section.

Phase 1

Equations (1) and (2) involved in Phase 1 are stated below [24].

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

The completion of Phase 1 is the formation of sets of consistent pair-wise comparison matrices. Each expert's responses are presented by four matrices as described above.

Phase 2

The second phase is dedicated to transform the matrices into fuzzy TFN number matrix form. Equation (3) until (7) is implemented [24]. Table 2 is implemented as guidelines for Equation (3).

$$\tilde{A} = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix} \tag{3}$$

where $a_{ij} = \left(b_{ij}^{-}, b_{ij}, b_{ij}^{+}\right)$ and $a_{ji} = \frac{1}{a_{ij}}$

Table 2: Guidelines to convert TFN numbers [30].

Scale	**Description**	**TFN**	**Reciprocal Triangular Fuzzy Number (*l, m, u*)**
1	Equally important	1,1,2	$\frac{1}{2}, 1,1$
3	Moderately more important	2,3,4	$\frac{1}{4}, \frac{1}{3}, \frac{1}{2}$
5	Strongly more important	4,5,6	$\frac{1}{6}, \frac{1}{5}, \frac{1}{4}$
7	Very strongly more important	6,7,8	$\frac{1}{8}, \frac{1}{7}, \frac{1}{6}$
9	Extremely more important	8,9,9	$\frac{1}{9}, \frac{1}{9}, \frac{1}{8}$
2, 4, 6, 8 * (x = 2, 4, 6 or 8)	Intermediate references (as above)	x – 1, x, x + 1	$\frac{1}{x+1}, \frac{1}{x}, \frac{1}{x-1}$

Once the TFN matrices have been constructed, the calculation continues with implementation of Equation (4) until (7) as below [26].

$$\bar{b}_{ij} = \frac{\left(b_{ij}^{-} + 4b_{ij} + b_{ij}^{+}\right)}{6} \tag{4}$$

$$S_i = \sum_{j=1}^{m} \bar{b}_{ij} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} \bar{b}_{ij}\right]^{-1} \tag{5}$$

$$\sum_{j=1}^{m} \bar{b}_{ij} = \left(\sum_{j=1}^{m} b_j^{-}, \sum_{j=1}^{m} b_j, \sum_{j=1}^{m} b_j^{+}\right) \tag{6}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} \bar{b}_{ij} = \left(\sum_{i=1}^{n} b_i^{-}, \sum_{i=1}^{n} b_i, \sum_{i=1}^{n} b_i^{+}\right) \tag{7}$$

These five equations included in the second phase aimed to provide a TFN matrix for a single hierarchy that have been pair-wise compared. All six experts' responses will be integrated into a single response.

Phase 3

Finally, the third phase will provide the solution as needed in this research. The degree of possibilities value is calculated using Equation (8) [26].

$$(S_2 \geq S_1) = \begin{cases} 1 & \text{, if } b_2 \geq b_1 \\ 0 & \text{, if } b_1^- \geq b_2^+ \\ \dfrac{b_1^- - b_2^+}{(b_2 - b_2^+) - (b_1 - b_1^-)} & \text{, otherwise} \end{cases} \tag{8}$$

The findings from the calculation will be used to determine the normalized weight values that represent the prioritized weight of each element involved in IMC. This step will be adopting the basic normalization calculation as per 100%.

Results

This section is organized according to the flow in Figure 1 by discussing the outcome of each phase. The pair-wise matrices involved here are IMC, organizational, operational and productivity complexity clusters. Throughout this section, only one matrix from one expert will be used as the example which is cluster operational complexity.

As the data collection from experts were completed, six sets of matrices were developed. However, only one sample of matrix is shown here where the final findings is the involvement of all six experts' responses. Table 3 shows a sample of pair-wise comparison matrix for operational complexity as responded by Expert 1 (E1).

Table 3: Operational complexity pair-wise matrix for E1

	IMC7	IMC8	IMC9	IMC10
IMC7	1	4	2	0.5
IMC8	0.25	1	0.333	0.25
IMC9	0.5	3	1	1
IMC10	2	4	1	1

*Abbreviations defined in Figure 1

The observation in Table 3 explained that generally all elements in this cluster from E1 response have a similar level of importance. Nevertheless, IMC8 is found to be the least important where all its importance level compared to others are in decimal points or reciprocal.

Before proceeding to TFN numbers, it is important to examine the matrices' consistency. Table 4 summarizes the consistency ratio values for the matrices by applying Equation (3).

Table 4: Consistency test results

Pair-wise matrix	**CI**	**CR**
IMC	0.009	0.03
Organizational	0.076	0.061
Operational	0.057	0.063
Productivity	0.001	0.002

With the requirement of CR < 0.1, results in Table 4 certified that all matrices here are consistent and none of them need to be reassessed [31].

As the progress has reached phase 2, it is important to realize its outcome which is integrated matrices presenting all experts as one. As an example, Table 5 show a sample of TFN matrix resulted from Equation (3) and Table 2 guidelines.

Table 5: Operational complexity TFN matrix for E1

	IMC7	**IMC8**	**IMC9**	**IMC10**
IMC7	1,1,2	3,4,5	1,2,3	$^{1}/_{3},^{1}/_{2},1$
IMC8	$^{1}/_{5},^{1}/_{4},^{1}/_{3}$	1,1,2	$^{1}/_{4},^{1}/_{3},^{1}/_{2}$	$^{1}/_{5},^{1}/_{4},^{1}/_{3}$
IMC9	$^{1}/_{3},^{1}/_{2},1$	2,3,4	1,1,2	$^{1}/_{2},1,1$
IMC10	1,2,3	3,4,5	1,1,2	1,1,2

The matrix transformation could be observed by comparing matrices in Table 4 and Table 5 where ingle numbers were converted to TFN numbers as guided by Table 2 guidelines. In completion, the rest of the pair-wise matrices were also transformed as above.

After that, each matrix will be implemented Equation (4) until (7) to produce the desired outcome of Phase 2. Along the processes, fuzzy synthetic extent is determined before producing the integrated matrices. Table 6 presents a sample of integrated TFN matrices.

Table 6: Integrated TFN matrices for operational complexity

	IMC7	**IMC8**	**IMC9**	**IMC10**
IMC7	1,1,2	0.5,0.6,1.3	0.6,1.3,1.8	$^{1}/_{3},^{1}/_{2},1$
IMC8	$^{1}/_{5},^{1}/_{4},^{1}/_{3}$	1,1,2	$^{1}/_{4},^{1}/_{3},^{1}/_{2}$	$^{1}/_{5},^{1}/_{4},^{1}/_{3}$
IMC9	$^{1}/_{3},^{1}/_{2},1$	2,3,4	1,1,2	$^{1}/_{2},1,1$
IMC10	1,2,3	3,4,5	1,1,2	1,1,2

To make it clear, like the matrix presented in Table 6, there are three matrices. The remaining matrices are for the other two clusters namely organizational and productivity complexity. These remaining matrices are not shown in this article, because it is believed that the sample was adequate and well-understood and emphasized on the main outcome from this research [31].

Finally, the real discussion that is intended to be emphasized is the degree of possibilities and normalized weight values for each of the elements and clusters. The elements require their degree of possibilities to be determined before the final values could be provided using Equation (8). Tables 7 and 8 show the sample calculation.

Table 7: Sample degree of possibilities

		Condition A, $m_1 \geq m_2$	**Condition B, $l_2 \geq u_1$**	**Condition C, *otherwise***	**V, The minimum value (A, B , C)**
IMC 7	IMC7 ≥ IMC8	False	False	0.3899	0.3899
	IMC7 ≥ IMC9	False	False	0.872	
	IMC7 ≥ IMC10	1	False	False	
IMC 8	IMC8 ≥ IMC7	1	False	False	1
	IMC8 ≥ IMC9	1	False	False	
	IMC8 ≥ IMC10	1	False	False	
IMC 9	IMC9 ≥ IMC7	1	False	False	0.5289
	IMC9 ≥ IMC8	False	False	0.5289	
	IMC9 ≥ IMC10	1	False	False	
IMC 10	IMC10 ≥ IMC7	False	False	0.342	0
	IMC10 ≥ IMC8	False	0	False	
	IMC10 ≥ IMC9	False	False	0.21	

Table 8: Sample of normalized weight calculation

Element	V	Normalized weight, W (V÷∑V)	Priority
IMC7	0.3899	0.2032	3
IMC8	1	0.5212	1
IMC9	0.5289	0.2756	2
IMC10	0	0	4
∑	1.9188		

Eventually, as presented in Table 9, the normalized weight values prior to their level of importance are calculated.

Table 9: Complete normalized weight value for internal manufacturing complexity

Cluster	Abbr.	Element	Normalized weight
Productivity complexity (0.5302)	IMC13	Quality inspection equipment	0.4284
	IMC12	Reduce production cost	0.3896
	IMC11	Reduce production time	0.1821
Organizational complexity (0.2646)	IMC6	Establish standard operation procedures	0.5729
	IMC4	Managing employees' behavior	0.2720
	IMC2	Information flow management	0.1108
	IMC1	Sufficient and effective employee training	0.0443
	IMC5	Improve organizational culture	0
	IMC3	Fulfill key performance index (KPI)	0
Operational complexity (0.2052)	IMC8	Inventory management	0.5212
	IMC9	Production records system	0.2756
	IMC7	Materials handling system	0.2032
	IMC10	The needs to use simulation	0

The final result as shown in Table 7 has been rearranged in descending order by importance level. The next section is the discussion and development of suitable framework based on these results.

Discussion

The discussion in this section is dedicated on the findings in Table 7. Among those three IMC clusters, productivity complexity leads by 0.5 in priority followed by organizational and operational complexity. Productivity complexity has been dominant cluster representing 50% of IMC. This result is aligned with researches done within the same scope for the Malaysian industry [32]. Looking deeper into productivity complexity, the quality inspection equipment has a very important role in productivity improvement. The Malaysian industry currently is developing automated quality inspection that will ensure improvement in productivity [33]. The condition of the inspection equipment must be good, periodically calibrated and applying the latest technology available. It is well-known that providing a great quality product is a major step towards excellence in business and customer satisfaction [34]. In addition, reducing cost and time is another well-known area for active improvement which is also included within the productivity complexity cluster [35].

Moving to the other two clusters, operational complexity emphasizes that a proper way of SOP development and revision will reduce IMC by largest impact compared to the other elements. It is undeniable the important role of SOP on overall firm's routines [36]. SOP is also considered as a tool to control employees' behavior to abide by firms' rules and regulations. Their relationship has been proven by employees' behavior occupying second place within the same cluster.

Lastly, the best operational practices must come with the best inventory management as the top priority. Integrated and hybrid techniques in inventory management are actively implemented and evaluated for improvement where internet of things (IoT) element is the most implemented to minimize inaccuracy [37]. The Malaysian industry in particular gradually adapted digitalization in SOP development and inventory management to reduce IMC [38]. The findings are summarized into a framework as illustrated in Figure 2.

As the presented framework in Figure 2 is directly extracted from experts' judgments and feedback, it has been presented to the experts for any feedback and improvement. Apparently, all experts agreed with the framework but insisted that extension research to be planned to improve the framework.

There are two highlighted areas to be noticed, firstly regarding elements with zero weight values which do not appear in the framework. According to

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[24], the zero value denotes unimportant elements which can be eliminated from the list. Secondly, as the research is done in Malaysia, it is believed that the framework needs further research before it can be implemented in other countries.

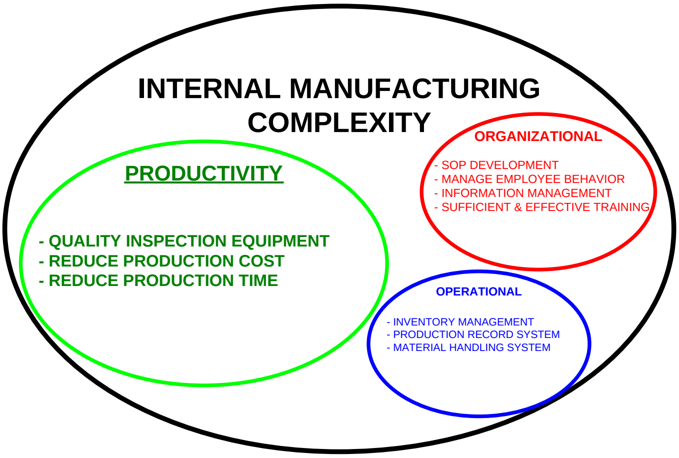

Figure 2: Internal manufacturing complexity framework

Conclusions

Reacting to the current competitive and aggressive market, actions have to be done effectively in order to manage manufacturing complexity. Basically, it is starts with managing the highest priority area as emphasized in this research. FAHP is implemented to transform IMC clusters and elements into an arrangement with hierarchy. This research finds that all clusters of IMC from literature are relevant, with productivity complexity as the top priority to be actively improved time after time. Malaysian manufacturing industry also has been proven to put product quality as top priority by using the best quality inspection equipment. The second cluster goes to organizational complexity where the fully utilized SOP should be implemented to manage this area's complexity. Lastly, as different product families experience different complexity, operational complexity is the lowest priority cluster due to variations in operation processes subjected to the particular product family. This research aims to guide industrialists and researchers before making any action in any situation faced. It is highly recommended that this research is done in other regions for comparison and a comprehensive theory and framework can be developed.

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Reference

[1] A. Szalavetz, "Industry 4.0 and capability development in manufacturing subsidiaries," *Technol. Forecast. Soc. Change*, vol. 145, no. May, pp. 384–395, 2019, doi: 10.1016/j.techfore.2018.06.027.

[2] M. Djerioui, M. Bouamar, M. Ladjal and A. Zerguine, "Chlorine soft sensor based on extreme learning machine for water quality monitoring," *Arab. J. Sci. Eng.*, vol. 44, no. 3, pp. 2033–2044, 2019, doi: 10.1007/s13369-018-3253-8.

[3] G. Eappen and T. Shankar, "Multi-objective modified grey wolf optimization algorithm for efficient spectrum sensing in the cognitive radio network," *Arab. J. Sci. Eng.*, vol. 46, pp. 3115-3145, 2021, doi: 10.1007/s13369-020-05084-3.

[4] M. N. H. M. Rosdi, M. R. Muhamad, W. H. W. Mahmood and M. H. A. Kadir, "Discovering the readiness of Malaysian industry in adaptation of industrial revolution 4.0 towards manufacturing sustainability," *Int. J. Recent Technol. Eng.*, vol. 8, no. 4, pp. 10994–10998, 2019, doi: 10.35940/ijrte.D5422.118419.

[5] E. P. Garina, A. P. Garin, E. V Romanovskaya, N. S. Andryashina and S. N. Kuznetsova, "Development of the enterprise process management system based on Total Productive Maintenance (TPM) technology," *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 10, pp. 6869–6872, 2020, doi: 10.30534/ijeter/2020/388102020.

[6] H. Rifqi, S. B. E. N. Souda, A. Zamma and S. Kassami, "Lean facility management 4.0: A case study," *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 10, pp. 7363–7370, 2020, doi: 10.30534/ijeter/2020/1138102020.

[7] M. K. Niaki, F. Nonino, G. Palombi and S. A. Torabi, "Economic sustainability of additive manufacturing: Contextual factors driving its performance in rapid prototyping," *J. Manuf. Technol. Manag.*, vol. 30, no. 2, pp. 353–365, 2019, doi: 10.1108/JMTM-05-2018-0131.

[8] A. Fadzlin, M. Zubir and N. F. Habidin, "The development of sustainable manufacturing practices and sustainable performance in Malaysian automotive industry," *J. Econ. Sustain. Dev.*, vol. 3, no. 7, pp. 130–139, 2012.

[9] N.-A. Hassan, N. H. Ahmad and R. Thurasamy, "Entrepreneurial leadership and sustainable performance of manufacturing SMEs in Malaysia: The contingent role of entrepreneurial bricolage," *MDPI Sustainability*, vol. 12, no. 8, p. 3100, 2020, doi: 10.3390/SU12083100.
[10] O. Renn, "The call for sustainable and resilient policies in the COVID-19 crisis : How can they be interpreted and implemented ?," *MDPI Sustainability*, vol. 12, no. 6466, pp. 1–5, 2020, https://doi.org/10.3390/su12166466
[11] D. Kohr, M. Ahmad, B. Alkan, M. K. Chinnathai, L. Budde, D. Vera, T. Friedli and R. Harrison, "Proposing a holistic framework for the assessment and management of manufacturing complexity through data-centric and human-centric approaches," in *3rd International Conference on Complexity, Future Information Systems and Riskd (COMPLEXIS 2018)*, 2018, pp. 86–93, https://doi.org/10.5220/0006692000860093
[12] W. M. W. Hasrulnizzam, M. N. H. M. Rosdi and M. R. Muhamad, "A conceptual framework in determining manufacturing complexity," *Appl. Mech. Mater.*, vol. 761, pp. 550–554, 2015, doi: 10.4028/www.scientific.net/AMM.761.550.
[13] A. Ma, A. Nassehi and C. Snider, "Anarchic manufacturing," *Int. J. Prod. Res.*, vol. 57, no. 8, pp. 2514–2530, 2019, doi: 10.1080/00207543.2018.1521534.
[14] J. Herrera and C. D. L. Heras-Rosas, "Corporate social responsibility and human resource management: Towards sustainable business organization," *MDPI Sustainability*, vol. 12, no. 841, pp. 1-24, 2020, doi: 10.1057/978-1-352-00403-8_14.
[15] V. Gruzin, A. Tulembayeva and A. Berdibekov, "Improvement of the structural scheme of technical and technological complex management," *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 10, pp. 7328–7336, 2020, doi: 10.30534/ijeter/2020/1098102020.
[16] M. N. H. M. Rosdi, W. H. W. Mahmood, S. R. Kamar, R. Tukimin and N. S. Ayuni, "Discovering the classification of manufacturing complexity from Malaysian industry perspective," *J. Adv. Manuf. Technol.*, vol. 14, no. 2, pp. 65–76, 2020.
[17] W. Vogel and R. Lasch, "Complexity drivers in manufacturing companies: A literature review," *Logist. Res.*, vol. 9, no. 1, pp. 1–66, 2016, doi: 10.1007/s12159-016-0152-9.
[18] M. N. H. M. Rosdi, M. R. Muhamad, W. H. W. Mahmood and M. Z. Yusup, "The relationship between internal and external manufacturing complexity," *J. Ilmi*, vol. 8, pp. 90–101, 2018.
[19] H. Panetto, B. Iung, D. Ivanov, G. Weichhart and X. Wang, "Challenges for the cyber-physical manufacturing enterprises of the future," *Annu. Rev. Control*, vol. 47, pp. 200–213, 2019, doi: 10.1016/j.arcontrol.2019.02.002.
[20] W. Vogel, "Complexity management in variant-rich product

development," PhD Dissertation, Faculty of Business and Economics, Technischen Universität Dresden, 2019.

[21] J. Drew and B. Dollery, "What's in a name? Assessing the performance of local government classification systems," *Local Gov. Stud.*, no. February, pp. 37–41, 2015, doi: 10.1080/03003930.2015.1007132.

[22] G. Schuh, G. Reinhart, J. P. Prote, F. Sauermann, J. Horsthofer, F. Oppolzer and D. Knoll, "Data mining definitions and applications for the management of production complexity," in *52nd CIRP Conference on Manufacturing Systems*, 2019, vol. 81, pp. 874–879, doi: 10.1016/j.procir.2019.03.217.

[23] B. Alkan, D. A. Vera, M. Ahmad, B. Ahmad and R. Harrison, "Complexity in manufacturing systems and its measures: A literature review," *Eur. J. Ind. Eng.*, vol. 12, no. 1, pp. 116–150, 2018, https://doi.org/10.1504/EJIE.2018.089883

[24] M. N. H. Mohd Rosdi, W. H. Wan Mahmood, M. N. Ab Rahman, M. A. Razik and S. R. Kamat, "Fuzzy arrangement of manufacturing sustainability practices priority levels : Exploratory research for Malaysian industry 4.0 revolution," *Technol. Reports Kansai Univ.*, vol. 62, no. 09, pp. 5479–5494, 2020.

[25] G. Kabir and M. A. A. Hasin, "Multi-criteria inventory classification through integration of fuzzy analytic hierarchy process and artificial neural network," *Int. J. Ind. Syst. Eng.*, vol. 14, no. 1, pp. 74–103, 2013, doi: 10.1504/IJISE.2013.052922.

[26] R. Tukimin, W. Hasrulnizzam, W. Mahmood, N. Mohamed, M. N. Hanif and M. M. Nordin, "Prioritization of supplier development practices: A fuzzy method," *Int. J. Recent Technol. Eng.*, vol. 8, no. 4, pp. 11020–11024, 2019, doi: 10.35940/ijrte.d5423.118419.

[27] M. R. Galankashi, A. Chegeni, A. Soleimanynanadegany, A. Memari, A. Anjomshoae, S. A. Helmi and A. Dargi, "Prioritizing green supplier selection criteria using fuzzy analytical network process," *Procedia CIRP*, vol. 26, no. April 2015, pp. 689–694, 2015, doi: 10.1016/j.procir.2014.07.044.

[28] S. N. Kamaruzzaman, E. C. W. Lou, P. F. Wong, R. Wood and A. I. Che-Ani, "Developing weighting system for refurbishment building assessment scheme in Malaysia through analytic hierarchy process (AHP) approach," *Energy Policy*, vol. 112, no. October 2017, pp. 280–290, 2018, doi: 10.1016/j.enpol.2017.10.023.

[29] A. Darko, A. P. C. Chan, E. E. Ameyaw, E. K. Owusu, E. Pärn and D. J. Edwards, "Review of application of analytic hierarchy process (AHP) in construction," *Int. J. Constr. Manag.*, vol. 19, no. 5, pp. 436–452, 2018, doi: 10.1080/15623599.2018.1452098.

[30] H. Vahidi, F. Ghazban, M. A. Abdoli, V. D. Kazemi and S. M. A. Banaei, "Fuzzy analytical hierarchy process disposal method selection for an industrial state; Case study Charmshahr," *Arab. J. Sci. Eng.*, vol. 39, no.

2, pp. 725–735, 2014, doi: 10.1007/s13369-013-0691-1.

[31] N. T. Pham, A. D. Do, Q. V. Nguyen, V. L. Ta, T. H. B. Dao, D. L. Ha and X. T. Hoang, "Research on knowledge management models at universities using fuzzy analytic hierarchy process (FAHP)," *MDPI Sustain.*, vol. 13, no. 809, pp. 1–16, 2021, [Online]. Available: https://doi.org/10.3390/su13020809.

[32] J. Y. Yong, M. Y. Yusliza, T. Ramayah, C. J. Chiappetta Jabbour, S. Sehnem and V. Mani, "Pathways towards sustainability in manufacturing organizations: Empirical evidence on the role of green human resource management," *Bus. Strateg. Environ.*, vol. 29, no. 1, pp. 212–228, 2020, doi: 10.1002/bse.2359.

[33] M. A. A. Rahman, M. H. Rahman, E. Mohamad, A. A. A. Rahman, M. R. Salleh and J. P. T. Mo, "Enhancing the automated quality inspection in manufacturing process through parameter optimization," *Univers. J. Mech. Eng.*, vol. 7, no. 6, pp. 1–5, 2019, doi: 10.13189/ujme.2019.071501.

[34] J. Hallencreutz and J. Parmler, "Important drivers for customer satisfaction–from product focus to image and service quality," *Total Qual. Manag. Bus. Excell.*, vol. 32, no. 5–6, pp. 501–510, 2021, doi: 10.1080/14783363.2019.1594756.

[35] G. Raj-Reichert, "Global value chains, contract manufacturers, and the middle-income trap: The electronics industry in Malaysia," *J. Dev. Stud.*, vol. 56, no. 4, pp. 698–716, 2020, doi: 10.1080/00220388.2019.1595599.

[36] S. De Treville, J. Antonakis and N. M. Edelson, "Can standard operating procedures be motivating? Reconciling process variability issues and behavioural outcomes," *Total Qual. Manag.*, vol. 16, no. 2, pp. 231–241, 2005, doi: 10.1080/14783360500054236.

[37] A. M. Braccini and E. G. Margherita, "Exploring organizational sustainability of Industry 4.0 under the triple bottom line: The case of a manufacturing company,"*MDPI Sustain.*, vol. 11, no. 36, pp. 1–17, 2018, doi: 10.3390/su11010036.

[38] M. A. Soomro, M. Hizam-Hanafiah and N. L. Abdullah, "Digital readiness models : A systematic literature review," *COMPUSOFT, An Int. J. Adv. Comput. Technol.*, vol. 9, no. Iiii, p. 3596, 2020.