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Comparative Analysis of Risk Management Strategies for Additive Manufacturing Supply Chains

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Abstract: Supplier selection is an important strategic decision to be made in additive manufacturing supply chains. This paper presents a hybrid Analytic Hierarchy Process-Preference Ranking Organization Method for Enrichment of Evaluations (AHP-PROMETHEE) algorithms-based Failure Mode and Effects Analysis (FMEA) for supplier selection in a risk-based environment. Our approach is contrasted with an FMEA based on a Fuzzy Analytic Hierarchy Process (FAHP) for modeling assessment and mitigation of risk. In the FAHP method, the selection of the best supplier is based on the value of the weighted RPN whereas, in the hybrid AHP-PROMETHEE method, the selection of the best supplier is based on the value of outranking. An illustrative case study is used for a comparative analysis between the two methods. The AHP-PROMETHEE algorithms-based FMEA was the preferred method based on ease of implementation, accuracy of results and higher decision-maker involvement as compared to the FAHP method. This research develops a hybrid AHP-PROMETHEE algorithms-based FMEA to incorporate risk criteria toward systematic evaluation of suppliers for supply chain management.

Keywords: Additive Manufacturing, Supply Chain Management, Risk Assessment, PROMETHEE, Analytic Hierarchy Process, FMEA

Introduction

Additive Manufacturing (AM) technologies are poised to transform manufacturing supply chains based on AM's highly customizable product variety. Popularly called 3D printing, AM will cause an increase in decentralized manufacturing over the next five to ten years (Durach *et al.*, 2017, Elhoone *et al.*, 2019). Companies can benefit from the positive contributions of AM to supply chains and the overall efficiency of manufacturing firms, while mitigating associated risks (Roger *et al.*, 2016). AM services may complement or replace current supply configurations, or even create entirely new supply configurations. AM offers unprecedented flexibility in terms of production volume, location, product customization and product complexity (Rylands *et al.*, 2016). For a realistic implementation of AM supply chains, close collaboration between material suppliers and machine suppliers is expected. In terms of supplier relations management, the categories to be addressed by AM are the procurement process, quality management by the focal firms and quality management by the supplier (Oettmeier and Hoffman, 2016). A risk management strategy is paramount if AM supply chains are to thrive. These include the evaluation of suppliers for their risk potential based on specific risk criteria that are applicable to the field of additive manufacturing.

In an effort to compete in the global marketplace, manufacturing firms are focusing on improving their performance in terms of cost, quality and flexibility (Ertugrul Karsak and Tolga, 2001). Supplier selection and evaluation is arguably one of the most important operational and strategic decisions to be made by Supply Chain Management (SCM). The problem of supplier selection is considered to be a complex Multi-Criteria Decision-Making (MCDM) problem by manufacturing firms ((Mahdiloo *et al.*, 2012; Ilangkumaran *et al.*, 2012; Ghosh *et al.*, 2012; Sandeep *et al.*, 2011). Supplier selection involves using both quantitative and qualitative factors when it is necessary to make a trade-off between suppliers. In addition, various factors have been used as criteria for supplier selection: price, delivery performance, reputation in the industry, size of enterprise, geographical location, quality, environmental compliance, capacity, lead-time, packaging, storage and transportation. As per the literature, these are the two most important aspects of the supplier selection process: (a) identifying key criteria to be used in evaluating potential suppliers and (b) determining the evaluation methods used to compare different suppliers. The criteria considered in the evaluation of suppliers are industry-specific, where the applicability of these criteria depends on the type of product or service (Almakaeel *et al.*, 2018). The problem of supplier selection has been studied extensively and many decision-making methodologies have been proposed to solve it. These methodologies include the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), Fuzzy Sets Theory (FST), the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), Elimination and Choice Expressing Reality (ELECTRE), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Oreste method and Multi-Attribute Utility Analysis (MAUT) (Huseyinozder, 2017; Almakaeel *et al.*, 2018).

The objective of this paper is to integrate the Failure Mode and Effects Analysis (FMEA) with hybrid AHP-PROMETHEE algorithms for supplier selection in additive manufacturing supply chains and contrast it with relevant MCDM approaches such as the FMEA based on the Fuzzy Analytic Hierarchy Process (FAHP). The rationale for focusing on these approaches is based on their applicability to solving supplier selection problems for in-field implementation.

Supplier Selection in a Risk-based Environment

In today's dynamic market, supplier selection is focused on providing an adequate service level while controlling the overall costs of the purchasing activities. The primary challenges facing modern supply chain are globalization, lack of communication across departments, lack of communication with external partners and lack of alignment between business goals and information technology (Henderson and Nadvi, 2011). These issues can be compounded by unpredictable demand, cost pressures, outsourcing, reliance on suppliers and international governmental intervention (Brindley, 2017; Waters, 2011; Craighead *et al.*, 2007; Harland *et al.*, 2003). Other factors that need to be considered include the increase in the intensity of disasters in recent decades, continental transportation, the economic environment and political stability. Li *et al.* (2012) stated that the distributed nature of factories and manufacturers requires inclusive coordination and cooperation among all the suppliers. In order to overcome the supply chain risk challenges and achieve higher efficiency, companies are forced to disintegrate their operations and cooperate with each other (Pereira, 2009). The continuing disintegration and the specialization of operations have made the supply chains vulnerable to disturbances from both internal and external influences. In particular, this specialization has led to lower visibility of operations that are now transferred to supply chain suppliers, with a consequent increase in the risk potential within the supply chain tiers (Gattorna and Jones, 1998). According to Soosay *et al.* (2008), inter-organizational relationships in supply chains have become increasingly important. Integrated and seamless logistics can play a crucial role in facilitating supply-chain processes (Banomyong, 2005). Therefore, applicable and effective supplier selection methodology is needed to capture the foreseeable supply risks in AM and encompass the relevant criteria for successful decision making.

Analytic Hierarchy Process (AHP) Method

The Analytic Hierarchy Process (AHP) breaks down a complex decision-making problem into a hierarchical structure composed of decision-making components (criteria and alternatives). This hierarchy involves at least three levels: (1) overall objective at the highest level; (2) multiple criteria that define alternatives at the intermediate level; and (3) alternatives at the lowest level. The second step involves comparison of alternatives and criteria. Once the problem is analyzed and the hierarchical levels are formed, preferences are determined at each level based on the relative importance of each criterion. At each level, pairwise comparison is made among the criteria to identify the impact of each criterion compared to certain criteria at the higher levels (Saaty, 1987). AHP has the ability to measure quality and quantity indicators by using mental preferences, expertise and objective information. AHP is a reliable method for calculating the weight of each criterion based on the decision-maker's viewpoint. A unique feature of AHP is the possibility of calculating the compatibility/incompatibility of decisions made by the decision maker (Desai *et al.*, 2012). Pairwise comparisons are carried out using Saaty's 9-point preference scale. A Consistency Ratio (CR) check is performed at the final step of the AHP to ensure that the pairwise matrix judgments are acceptable. A value of 10% is acceptable as the upper limit for the CR. If the CR is larger than this value, assessment must be repeated to improve consistency (Saaty, 1987).

Fuzzy Analytic Hierarchy Process (FAHP) Method

The FAHP method extends Saaty's AHP by combining it with fuzzy set theory. In the FAHP, fuzzy ratio scales are used to indicate the relative strength of the factors in the corresponding criteria. Therefore, a fuzzy judgment matrix can be constructed. The final scores of alternatives are also represented by fuzzy numbers. The optimum alternative is obtained by ranking the fuzzy numbers using special algebraic operators. In this methodology, all elements in the judgment matrix and weight vectors are represented by triangular fuzzy numbers. Fuzzy numbers are used to indicate the relative importance of one risk type over the other and a fuzzy judgment vector is obtained for each criterion (Nazam *et al.*, 2015). These judgment vectors form part of the fuzzy pairwise comparison matrix, which is then used to determine the weight of each criterion. The extent analysis method of Chang *et al.* (2007) has been used for determining weights from pairwise comparisons. The computational details of FAHP can be found in Islam *et al.* (2016).

Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) Method

PROMETHEE establishes a complete preorder among the alternatives and consists of building a valid outranking relation. The basic principle of PROMETHEE is based on a pair-wise comparison of alternatives. The implementation of the PROMETHEE method requires a determination of the weights of the criteria and preference functions (Balali *et al.*, 2014). PROMETHEE assumes that a decision-maker is able to weight the criteria appropriately. The preference function represents the difference between the evaluations obtained by two alternatives using the preference degree ranging from zero to one. The preference function formula is used to compute the degree of preference associated with the best action in the case of pairwise comparisons (Balali *et al.*, 2014). Weighting of the criteria during decision making and evaluation of these criteria by preference functions are performed simultaneously. The procedure of implementing PROMETHEE starts with determining deviations based on pair-wise comparisons. It is followed by using an associated preference function for each criterion in Step 2. A global preference index is calculated for each alternative in Step 3. Step 4 involves the procedure for calculating the leaving and entering flows for each alternative. This procedure is terminated in Step 5 by calculating the net outranking flow for each alternative. The highest value of net flow denotes the best alternative. The computational details of hybrid AHP-PROMETHEE can be found in Venkatesan and Kumanan (2012).

Illustrative Case Study

In this section, we present an illustrative case study to demonstrate the comparison between the proposed integration of FMEA with hybrid FMEA AHP-PROMETHEE algorithms and the Fuzzy AHP method. The criteria and alternatives of this case study were retrieved from the literature (Islam *et al.*, 2016). The six criteria and their twenty-six sub-criteria are shown in Table 1.

Failure Mode and Effects Analysis (FMEA)

In this comparative analysis, both methods implement the FMEA technique to assess the risk potential of suppliers. FMEA is a structured proactive method for evaluating the risks within a system and prioritizing the relative impact of different failures (Stamatis, 2003). The decision makers and the expert team score each risk criterion based on a scale rating of its severity (S), occurrence (O) and detection (D). S represents the effect of failure on the system, O represents the frequency of failure and D represents the probability of detecting the failure. Based on the case study (Islam *et al.*, 2016), this paper uses a 4-point scale to design the scheme.

Table 1: Criteria and their sub-criteria (Islam *et al*., 2016)

Number	Criterion	Reference	Sub-criterion
C_1	Cost	$C_{1.1}$	Product cost
		$C_{1.2}$	Inbound transportation cost
		$C_{1.3}$	Charge of support service
		$C_{1.4}$	Exchange rate
C_2	Quality	$C_{2.1}$	Input quality control
		$C_{2.2}$	Reliability
		$C_{2.3}$	Durability
		$C_{2.4}$	Defect rate
		$C_{2.5}$	Product line compliant rate
C_3	Deliverability	$C_{3.1}$	Production cycle
		$C_{3.2}$	On time delivery
		$C_{3.3}$	Delivery lead time
		$C_{3.4}$	Idle rate
C_4	Productivity	$C_{4.1}$	Productivity flexibility
		$C_{4.2}$	Amount of production
C_5	Organizational Behavior	$C_{5.1}$	Responsiveness
		$C_{5.2}$	Claim policy
		$C_{5.3}$	Social responsibility
		$C_{5.4}$	Research and Development
		$C_{5.5}$	Reputation
		$C_{5.6}$	Innovation
C_6	Environmental Assessment	$C_{6.1}$	Energy consumption
		$C_{6.2}$	Green packaging
		$C_{6.3}$	Waste management
		$C_{6.4}$	Recyclable/reusable product
		$C_{6.5}$	Emission

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Table 2: RPN calculation based on expert feedback (Islam *et al*., 2016)

	Supplier A				Supplier B				Supplier C			
Criterion	S	O	D	RPN	S	O	D	RPN	S	O	D	RPN
$C_{1.1}$	2	2	1	**4**	3	2	1	**6**	3	2	1	**6**
$C_{1.2}$	3	2	1	**6**	2	3	1	**6**	2	3	1	**6**
$C_{1.3}$	3	2	1	**6**	2	2	1	**4**	2	2	1	**4**
$C_{1.4}$	2	4	1	**8**	3	1	1	**3**	3	4	1	**12**
$C_{2.1}$	2	3	1	**6**	1	2	1	**2**	2	2	1	**4**
$C_{2.2}$	3	2	1	**6**	3	2	1	**6**	3	3	1	**9**
$C_{2.3}$	2	4	1	**8**	1	1	1	**3**	4	3	1	**12**
$C_{2.4}$	2	4	1	**8**	2	3	1	**6**	2	2	1	**4**
$C_{2.5}$	3	2	1	**6**	3	2	1	**6**	3	1	1	**3**
$C_{3.1}$	4	2	1	**8**	1	2	1	**6**	3	2	1	**6**
$C_{3.2}$	2	3	1	**6**	1	3	1	**3**	2	1	1	**2**
$C_{3.3}$	3	2	1	**6**	2	2	1	**4**	3	3	1	**9**
$C_{3.4}$	2	4	1	**8**	3	4	1	**12**	3	2	1	**6**
$C_{4.1}$	2	3	1	**6**	2	2	1	**4**	4	2	1	**8**
$C_{4.2}$	3	3	1	**9**	1	4	1	**4**	3	4	1	**12**
$C_{5.1}$	4	2	1	**8**	3	2	1	**6**	3	2	1	**6**
$C_{5.2}$	3	2	1	**6**	2	4	1	**8**	3	3	1	**9**
$C_{5.3}$	4	3	1	**12**	3	1	1	**3**	4	2	1	**8**
$C_{5.4}$	3	4	1	**12**	3	3	1	**9**	2	4	1	**8**
$C_{5.5}$	4	3	1	**12**	3	2	1	**6**	2	3	1	**6**
$C_{5.6}$	3	3	1	**6**	3	4	1	**12**	3	4	1	**12**
$C_{6.1}$	4	2	1	**8**	4	1	1	**4**	3	3	1	**9**
$C_{6.2}$	2	3	1	**6**	2	4	1	**8**	3	2	1	**6**
$C_{6.3}$	3	4	1	**12**	4	2	1	**8**	3	2	1	**6**
$C_{6.4}$	2	3	1	**6**	3	3	1	**9**	4	2	1	**8**
$C_{6.5}$	2	2	1	**4**	2	3	1	**6**	2	3	1	**6**
Total				**193**				**154**				**187**
Average				**7.42**				**5.92**				**7.19**

The determination of the Risk Priority Number (RPN) for failure modes is calculated based on expert feedback. The RPN is calculated using the following mathematical equation: RPN = S × O × D. Based on the RPN values, risks are prioritized. The highest RPN value is considered as a high priority and the lowest RPN value is considered as a low priority. The calculated RPN values for all suppliers are given in Table 2.

Comparative Analysis of the FAHP and the Hybrid AHP-PROMETHEE

Determining the Weights of Criteria

The AHP hierarchy model shown in Fig. 1 is applicable to both models considered in this research. At the highest level, it consists of the goal of selecting the supplier with the lowest risk to the supply chain, followed by related criteria at the second level and the alternatives for supplier selection at the lowest level. The priority weight of each criterion at each level was determined.

In the FAHP, the decision-maker compares the criteria in the pairwise matrix via linguistic terms, which are represented by triangular numbers, as shown in Table 3. The same procedure was repeated for the sub-criteria.

In the hybrid AHP-PROMETHEE algorithms, a pairwise comparison matrix was constructed using the crisp numerical values based on Saaty's 9-point preference scale. The decision maker uses a preference scale to compare the criteria against each other, as shown in Table 4. A similar procedure was repeated for the sub-criteria. In both methods, if there is more than one decision maker, the preferences of all decision makers are averaged.

After completing the first step of the FAHP, the geometric mean of fuzzy comparison values of each criterion was calculated, as shown in Table 5. The total values and the reverse values are also presented. In the last row of Table 5, the fuzzy triangular numbers should be in increasing order; thus, the order of the numbers is changed.

In the next stage, the hybrid AHP-PROMETHEE generates the priority vectors for each pairwise comparison matrix in the hierarchy by a prioritization operator. The local weights of each comparison matrix were determined by the eigenvector corresponding to the largest eigenvalue of the cited matrix. Table 6 shows the calculated local weights for the main criteria.

In order to determine the final weight of each criterion for the FAHP, the relative fuzzy weights of each decision criterion were calculated, as shown in Table 7. Subsequently, the relative non-fuzzy weight of each criterion (M_i) was calculated by taking the average of fuzzy numbers for each criterion and non-fuzzy (Ni). The normalized weights of each criterion were calculated and tabulated in Table 8. After calculating the local weight of each criterion, the hybrid AHP-PROMETHEE can obtain the final weights of criteria. Table 9 shows the final weights of the main criteria.

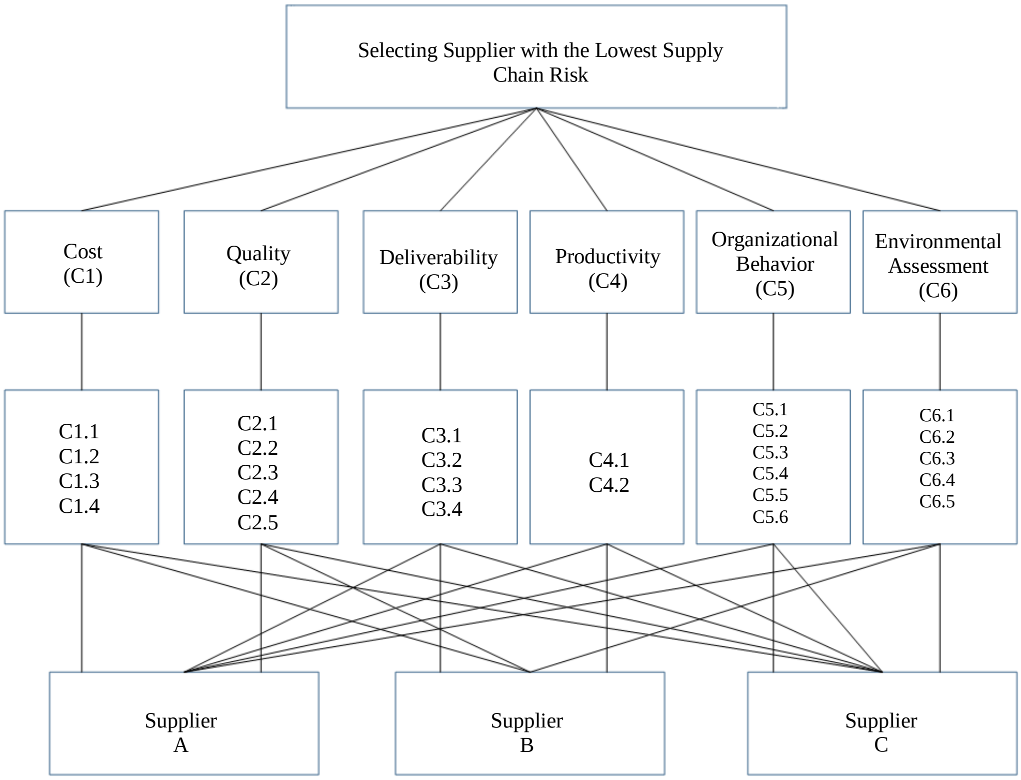

Fig. 1: The hierarchy of the criteria and the alternatives

Table 3: FAHP pairwise comparison matrix of the main criteria (Islam *et al*., 2016)

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
C_1	(1,1,1)	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(1,2,3)	(4,5,6)	(3,4,5)	(2,3,4)
C_2	(2,3,4)	(1,1,1)	(5,6,7)	(9,9,9)	(7,8,9)	(9,9,9)
C_3	$\left(\frac{1}{3},\frac{1}{2},1\right)$	$\left(\frac{1}{7},\frac{1}{6},\frac{1}{5}\right)$	(1,1,1)	(2,3,4)	(1,2,3)	(1,2,3)
C_4	$\left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right)$	$\left(\frac{1}{9},\frac{1}{9},\frac{1}{9}\right)$	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	(1,1,1)	(1,1,1)	$\left(\frac{1}{3},\frac{1}{2},1\right)$
C_5	$\left(\frac{1}{5},\frac{1}{4},\frac{1}{3}\right)$	$\left(\frac{1}{9},\frac{1}{8},\frac{1}{7}\right)$	$\left(\frac{1}{3},\frac{1}{2},1\right)$	(1,1,1)	(1,1,1)	$\left(\frac{1}{3},\frac{1}{2},1\right)$
C_6	$\left(\frac{1}{4},\frac{1}{3},\frac{1}{2}\right)$	$\left(\frac{1}{9},\frac{1}{9},\frac{1}{9}\right)$	$\left(\frac{1}{3},\frac{1}{2},1\right)$	(1,2,3)	(1,2,3)	(1,1,1)

Table 4: Pairwise comparison matrix of the main criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
C_1	1	1/3	2	5	4	3
C_2	3	1	6	9	8	9
C_3	1/2	1/6	1	3	2	2
C_4	1/5	1/9	1/3	1	1	1/2
C_5	1/4	1/8	1/2	1	1	1/2
C_6	1/3	1/9	1/2	2	2	1

Table 5: Geometric means of fuzzy comparison values (Islam *et al*., 2016)

Criteria	Geometric Mean		
Cost	1.348	1.849	2.376
Quality	4.223	4.762	5.228
Deliverability	0.676	1.000	1.390
Productivity	0.340	0.393	0.490
Organizational Behavior	0.368	0.445	0.602
Environmental Assessment	0.458	0.648	0.891
Total	7.412	9.098	10.977
Reverse (power of -1)	0.135	0.110	0.091
Increasing order	0.091	0.110	0.135

Table 6: AHP local weight

Criteria	C1 weight	C2 weight	C3 weight	C4 weight	C5 weight	C6 weight	Local weight
C1	0.19	0.18	0.19	0.24	0.22	0.19	1.21
C2	0.57	0.54	0.58	0.43	0.44	0.56	3.13
C3	0.09	0.09	0.10	0.14	0.11	0.13	0.66
C4	0.04	0.06	0.03	0.05	0.06	0.03	0.26
C5	0.05	0.07	0.05	0.05	0.06	0.03	0.30
C6	0.06	0.06	0.05	0.10	0.11	0.06	0.44

Table 7: Relative fuzzy weights of each decision criterion (Islam *et al*., 2016)

Criteria	Relative fuzzy weights		
Cost	0.123	0.203	0.321
Quality	0.385	0.523	0.705
Deliverability	0.062	0.110	0.187
Productivity	0.031	0.043	0.066
Organizational Behavior	0.033	0.049	0.081
Environmental Assessment	0.042	0.071	0.120

Table 8: Averaged and normalized relative weights of criteria (Islam *et al*., 2016)

Criteria	M_i	N_i
Cost	0.216	0.205
Quality	0.538	0.511
Deliverability	0.120	0.114
Productivity	0.047	0.044
Organizational Behavior	0.055	0.052
Environmental Assessment	0.078	0.074

In this case study, quality is one of the important characteristics for the company. Thus, quality has the highest weight of 0.52, followed by cost, with a relative weight of 0.20. Once the weights for the criteria were calculated, alternatives were ranked with respect to the criteria.

Determining Ranks of the Alternatives with Respect to Criteria

In the final step of the AHP calculation, a consistency check was performed to ensure that the pairwise comparison matrix judgments were neither random nor illogical. A consistency ratio (CR) of 0.10 or less is considered acceptable. A perfectly consistent ratio is zero; if CR is sufficiently small, the decision maker's comparisons are consistent to estimate the weights for the objective function. However, if CR > 0.1, serious inconsistencies may exist, and the AHP may not yield meaningful results. The CR obtained for the main criteria and each sub-criterion was consistent, with a CR < 0.1, as shown in Table 10. After achieving the normalized non-fuzzy relative weights for the criteria, the same methodology of the FAHP was applied to find the respective values for the alternatives. The alternatives were pair-wise compared with respect to each criterion. In this case study, the concept of weight-RPN was used to rank the best supplier. The weight-RPN was calculated by multiplying the RPN for each criterion by the relative weight of the decision criteria. The average weight-RPN for supplier A was 1.094, supplier B was 0.783 and supplier C was 1.111 (Table 11). Supplier B had the lowest weight-RPN, thus was chosen as the best supplier.

As compared to the FAHP method, this research implements the PROMETHEE method to rank the supply chain risks after obtaining the AHP global weight of criteria. The global weight was obtained by respective criterion. The PROMETHEE is initiated by constructing the decision matrix for all suppliers (A, B, C), as shown in Table 12. This matrix contains RPN values that were recorded based on the feedback from decision makers. The second step was to normalize the decision matrix. Table 13 shows the normalized decision matrix using the non-beneficial criteria, where the lower value of the performance measure is desirable. In our case, the objective was to select a supplier with the lowest supply chain risk, thus the non-beneficial criteria were considered for normalization.

In the third step, a paired comparison was conducted for all the supplier pairs using the normalized decision matrix and the preference function was calculated using the Athawale and Chakraborty (2010) formula, as shown in Table 14.

In the fourth step, the aggregated preference function for the suppliers was calculated. Table 15 shows the aggregated preference matrix, which takes into account the global weights.

In the final step, the values for the entering flow and leaving flow were calculated. Then the net outranking flow for each alternative was computed. The outranking flows for each supplier were based on attaining the lowest supply chain risk. In PROMOTHEE, the higher value of the net outranking corresponds to a preferred alternative. Supplier B had the highest net outranking and thus was selected as the supplier with the lowest supply chain risk. Table 16 shows the entering flow, leaving flow and net outranking flow values.

Table 9: Calculation of priority weights for the main criteria

Criteria	C1 weight	C2 weight	C3 weight	C4 weight	C5 weight	C6 weight	Total weight	Final weight
C1	0.19	0.18	0.19	0.24	0.22	0.19	1.21	0.202
C2	0.57	0.54	0.58	0.43	0.44	0.56	3.13	0.521
C3	0.09	0.09	0.10	0.14	0.11	0.13	0.66	0.110
C4	0.04	0.06	0.03	0.05	0.06	0.03	0.26	0.044
C5	0.05	0.07	0.05	0.05	0.06	0.03	0.30	0.050
C6	0.06	0.06	0.05	0.10	0.11	0.06	0.44	0.073

Table 10: Summary of CR results of the main criteria and sub-criteria

Pairwise comparison of	CR
Main criteria	0.015
Sub-criteria with respect to C1	0.004
Sub-criteria with respect to C2	0.065
Sub-criteria with respect to C3	0.049
Sub-criteria with respect to C4	0.000
Sub-criteria with respect to C5	0.009
Sub-criteria with respect to C6	0.000

Table 11: Ranking of alternatives

Supplier	Weight-RPN	Ranking
A	1.094	2
B	0.783	1
C	1.111	3

Table 12: Decision matrix for suppliers (A, B, C)

RPN of supplier	Criteria C1.1	C1.2	C1.3	C1.4	C2.1	C2.2	C2.3	C2.4	C2.5	C3.1	C3.2	C3.3	C3.4	C4.1	C4.2	C5.1	C5.2	C5.3	C5.4	C5.5	C5.6	C6.1	C6.2	C6.3	C6.4	C6.5
A	4	6	6	8	6	6	8	8	6	8	6	6	8	6	9	8	6	12	12	12	6	8	6	12	6	4
B	6	6	4	3	2	6	3	6	6	6	3	4	12	4	4	6	8	3	9	6	12	4	8	8	9	6
C	6	6	4	12	4	9	12	4	3	6	2	9	6	8	12	6	9	8	8	6	12	9	6	6	8	6

Table 13: Normalized decision matrix

RPN of supplier	Criteria C1.1	C1.2	C1.3	C1.4	C2.1	C2.2	C2.3	C2.4	C2.5	C3.1	C3.2	C3.3	C3.4	C4.1	C4.2	C5.1	C5.2	C5.3	C5.4	C5.5	C5.6	C6.1	C6.2	C6.3	C6.4	C6.5
A	1	0	0	0.44	0.00	1.00	0.44	0.00	0.00	0.00	0.00	0.60	0.67	0.50	0.38	0.00	1.00	0.00	0.00	0.00	1.00	0.20	1.00	0.00	1.00	1.00
B	0	0	1	1.00	1.00	1.00	1.00	0.50	0.00	1.00	0.75	1.00	0.00	1.00	1.00	1.00	0.33	1.00	0.75	1.00	0.00	1.00	0.00	0.67	0.00	0.00
C	0	0	1	0.00	0.50	0.00	0.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.44	1.00	1.00	0.00	0.00	1.00	1.00	0.33	0.00

Table 14: Preference functions for all supplier pairs

Suppliers comparison	Criteria C1.1	C1.2	C1.3	C1.4	C2.1	C2.2	C2.3	C2.4	C2.5	C3.1	C3.2	C3.3	C3.4	C4.1	C4.2	C5.1	C5.2	C5.3	C5.4	C5.5	C5.6	C6.1	C6.2	C6.3	C6.4	C6.5
(A,B)	1	0	0	0	0	0	0	0	0	0	0	0	0.67	0	0	0	0.67	0	0	0	1	0	1	0	1	1
(A,C)	1	0	0	0.44	0	1	0.44	0	0	0	0	0.6	0	0.5	0.38	0	1	0	0	0	1	0.2	0	0	0.67	1
(B,A)	0	0	1	0.56	1	0	0.56	0.5	0	1	0.75	0.4	0	0.5	0.63	1	0	1	0.75	1	0	0.8	0	0.67	0	0
(B,C)	0	0	0	1	0.5	1	1	0	0	0	0	1	0	1	1	0	0.33	0.56	0	0	0	1	0	0	0	0
(C.A)	0	0	1	0	0.5	0	0	1	1	1	1	0	0.33	0	0	1	0	0.44	1	1	0	0	0	1	0	0
(C,B)	0	0	0	0	0	0	0	0.5	1	0	0.25	0	1	0	0	0	0	0	0.25	0	0	0	1	0.33	0.33	0

Table 15: Aggregated preference function for suppliers

Supplier	A	B	C
A	Nil	0.171	0.345
B	0.478	Nil	0.445
C	0.351	0.148	Nil

Table 16: Outranking flows in PROMETHEE for suppliers

Supplier	Leaving flow	Entering flow	Net outranking
A	0.258	0.414	-0.156
B	0.464	0.159	0.305
C	0.249	0.398	-0.148

Discussion

The results of both the FAHP-based FMEA and hybrid AHP-PROMETHEE-based FMEA methods ranked supplier B as the best supplier from the perspective of lowest risk to the supply chain (Table 11 and 16). Suppliers A and C have approximately the same values and can be regarded as the second-best alternatives. Both methods produced approximately the same weights of criteria and attributed the highest weight to the quality criteria.

The use of the AHP scale results in absolute numerical values for all pairwise comparisons at each hierarchy level. However, when differences between alternatives are sufficiently small, the FAHP pairwise reciprocal comparison can lead to misleading results when fuzzy ratio scales are used to represent the linguistic scales. Thus, the proposed AHP-PROMETHEE algorithms- based FMEA is superior, as it can capture minor differences in alternatives based on clearly differentiated numerical values versus a confounding ratio scale using the FAHP method. Despite the contributions of fuzzy rules, in practice, the fuzzy-rule-based method for developing and testing a complete set of fuzzy rules is a tedious, time-consuming activity. It requires significant interaction with the decision makers, especially if one is working with a large number of criteria. Therefore, the hybrid AHP-PROMETHEE-based FMEA approach is an alternative to the FAHP-based FMEA. The hybrid AHP-PROMETHEE-based FMEA method provides a structured approach to compare the alternatives by using decision matrices. Furthermore, it provides decision makers a mathematically lucid method to incorporate risk factors in the decision-making process. Finally, the AHP-PROMETHEE-based FMEA is a suitable methodology, as it is capturing the decision intent with minimal overhead and is easy to implement for real-world scenarios of supplier selection.

Conclusion

In recent years, Additive Manufacturing (AM) supply chains have evolved due to the rapid proliferation of AM technologies. The highly customized nature of AM product offerings has resulted in disruption of the traditional multi-tier supply chain model. Thus, an effective tool is needed that can determine the risk associated with suppliers based on different criteria. This paper aims to integrate FMEA with hybrid AHP-PROMETHEE algorithms to evaluate suppliers in a risk-based environment. We compared our method with the FAHP approach for supplier selection. This research found that the new AHP-PROMETHEE algorithms based FMEA was able to capture the decision-maker's intent and had ease of implementation. Furthermore, the results were benchmarked with the FAHP-based FMEA method, showing consistent outcomes. This research establishes a foundation for the development of a multi-criteria decision-making algorithm for supplier selection in additive manufacturing supply chains.

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Author’s Contributions

Bandar Altubaishe: Contributed to the algorithm development and interpretation of data. He also participate in the writing and final review of the draft.

Jahlani Clarke: Contributed to the data analysis and interpretation of the data. He also contributed to background literature for the paper.

Christina McWilliams: Contributed to the formatting and checking of final review of the draft.

Salil Desai: Designed the overall theme of the research and contributed to the writing of the manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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