Technology Selection for Additive Manufacturing in Industry 4.0 Scenario Using Hybrid MCDM Approach

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1 Introduction

In the twenty-first century, knowledge resources increase at very high speed that do not permit conventional techniques to compete with existing manufacturing organizations. Design modifications play an important cost function, and this process begins very often and time again [1]. Additive Manufacturing (AM) refers to the technique of layer-by-layer connecting materials starting with a virtual model. A number of complicated and distinct procedures, differing for operation and materials employed, are additional manufacturing processes [2]. Additive production offers numerous significant benefits compared to traditional production processes, but probably most important is the capacity to create geometries that are highly demanding or often impossible to produce [3]. Through Smart Manufacturing (SM) technologies, the growth of digital innovation provides a new paradigm for production based on the interaction between human beings and machinery [2].

In order to strengthen AM process and enhance efficiency and quality, Industry 4.0 (I4.0) technologies have to be adopted in AM. The application of I4.0 technologies led to the industry being competitive in the global market and sustaining high performance. But industry practitioners cannot afford all technologies pertaining to I4.0 in order to implement in the industry due to high investment. For this, technologies need to be prioritized. Technology prioritization can assist industry practitioners in selecting the technologies under governing criteria pertaining to AM. Hence, this work is focused on identifying the list of I4.0 technologies that can assist and manage AM process. Then, the technologies are being prioritized using MCDM methods as a hybrid method named Fuzzy AHP-VIKOR.

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Significance of I4.0. Industry 4.0 fulfills the flexibility needed for design and production. I4.0 strives to accomplish all necessary desired functions as beneficial than that of the existing revolutions. I4.0 has a significant role in the competitiveness of the industrial economy. This revolution is excellent for automation with minimal material waste. I4.0 produces products through the latest technologies according to the customer's needs, which are the appropriate option for a personalized system on demand.

The goal of this study is to identify and rank technologies for AM in I4.0 scenario through a hybrid MCDM approach.

The remaining of this study is arranged as Sect. 2 presents the literature review, and case study is described in Sect. 3. Finally, Sect. 4 presents the conclusion of the study.

2 Literature Review

Baldassarre and Ricciardi [2] examined the usage of AM methods and demonstrated its advantages and limitations. The authors used the case study approach through which data was collected from the descriptive survey. Thus, it may be understood about the growth of I4.0, particularly the implementation of additive technology in our nation.

Chong et al. [1] explored the core information technologies through the examination of hybrid additive production. The findings showed that through the integration of digital technologies and production systems, the company could respond quickly to consumer demand, collect data, restructure information, and simulate and prototype function and design and eventually commit itself to produce the desired product.

Mehrpouya et al. [4] reviewed the latest developments and industrial applications to undertake a complete AM technology research. The authors explored AM applications in I4.0 challenges and limitations. Finally, the authors highlighted the emerging trends of AM in the fields of technology, applications, and materials that can produce new insights for future research on AM.

Butt [3] reviewed and presented the overview of interrelation among AM and I4.0. In addition, a hypothetical digital thread was presented which integrates AM and I4.0 technologies. The authors concluded that developing this digital thread for AM brings substantial benefits, enabling firms to react more efficiently to consumer needs and hasten the move to intelligent production.

Haleem et al. [5] examined the influence of AM on different fields of I4.0. The authors explored significant implications and future research guidelines for additive production. The authors concluded that AM contributes to a substantial reduction in the number of underutilized inventories in order to meet individual customer and market demands.

Wang et al. [6] examined the present Artificial Intelligence (AI) application research in AM, comprising product development, process design, manufacturing, and service operations. The authors proposed an intelligent AM framework in order to facilitate a more efficient and integrated environment for AI-enabled AM. The authors explored how AI technologies support AM products' creation and vision for the future of smart AM.

Ashima et al. [7] examined the need for SM technologies for AM operations and the benefits of IoT in AM. The authors also evaluated how integrated manufacturing technology of IoT will help industry and material suppliers. The authors concluded that IoT application of AM increased the efficiency of production, decreased waste, and satisfied the consumer criteria.

Majeed et al. [8] proposed "Big data-driven sustainable and smart additive manufacturing" framework. The framework designed by the authors was applied to selective laser melting approach of AM in a company to manufacture AlSi10Mg alloy components. The findings showed that energy usage and product quality are appropriately regulated and are beneficial for cleaner, smart sustainable manufacturing.

2.1 Research Gap

The relationship of AM with I4.0 had been explored [3]. Haleem et al. [5] explored the impact of AM in various areas of I4.0. Majeed et al. [8] developed the framework for AM in view of big data. It is noticed that the researchers focused on exploring the relationship between AM and I4.0 and on examining in concern to a specific selected technology. But the selection of technologies for AM has not been investigated. Hence, a research gap has been recognized in the identification and evaluation of I4.0 technologies for AM.

3 Case Study

The case study prioritizes I4.0 technologies to be implemented in AM using hybrid Fuzzy AHP–VIKOR approach. Fuzzy AHP and Fuzzy VIKOR approaches are multi-criteria decision-making techniques. An automobile component production company based in Tamil Nadu, India, manufactures additive automobile components suggested the integrated model used in case study. The integrated method has been utilized to determine the optimum selection of technologies. The weights of criteria have been computed using Fuzzy AHP depending on fuzzy interval arithmetic through triangular fuzzy numbers and confidence index using an interval mean method [9]. Fuzzy VIKOR is a decision-making technique for multiple considerations and a solution strategy in this work. VIKOR method was developed using various variables to get the compromise solution. The solution nearer to the ideal is called the compromise solution.

Step 1: I4.0 technologies pertaining to AM have been recognized from the literature. Identified technologies have been depicted in Table 1. In order to prioritize

Table 1 Identified list of I 4.0 technologies pertaining to AM

S. no	Technology	Research study
1	Internet of things (IoT) and Industrial IoT	Meng et al. [10]; Butt [3]; Haleem et al. [5]; Elhoone e al. [11]; Wang et al. [6]; Majeed et al. [8]; Zenisek et al. [12]
2	Big data analytics	Baldassarre and Ricciardi [2]; Meng et al. [10]; Mehrpouya et al. [4]; Butt [3]; Haleem et al. [5]; Majeed et al. [8]
3	Cyber physical systems (CPS)	Mehrpouya et al. [4]; Haleem et al. [5]; Wang et al. [6]; Majeed et al. [8]
4	Simulation (S)	Baldassarre and Ricciardi [2]; Chong et al. [1]; Mehrpouya et al. [4]; Butt [3], Zenisek et al. [12]
5	Cloud computing (CC)	Meng et al. [10]; Mehrpouya et al. [4]; Butt [3]; Elhoone e al. [11]; Majeed et al. [8]
6	Augmented and virtual reality (AR&VR)	Baldassarre and Ricciardi [2]; Butt [3]; Zenisek et al. [12]
7	Artificial intelligence (AI)	Wang et al. [6]; Majeed et al. [12]
8	Cyber-security (CS)	Baldassarre and Ricciardi [2]; Butt [3]
9	Horizontal and vertical integration (HVI)	Baldassarre and Ricciardi [2]; Butt [3]
10	Autonomous and Collaborative Robots (ACR)	Baldassarre and Ricciardi [2]; Mehrpouya et al. [4]; Butt [3]

technologies, the criteria that can govern these identified technologies have been recognized. The governing criteria are Interoperability (I), Scalability (SC), Security (SE), Networkability (N), Adaptability (AD), Compatibility (C), Flexibility (F), Accuracy (AC), Energy Competency (E), Complexity (CO), Energy consumption (EC), and Modularity (M).

3.1 Fuzzy AHP

The criteria weights computation using Fuzzy AHP is as follows [13].

Step 2: A pair-wise comparison matrix has been developed through the governing criteria for the selection of technology. A value is allocated to the components of the matrix depending on the relative significance of one criterion over other as per nine-point scale presented in Table 2 [14, 15].

The matrix inputs are derived from consensus views of experts with rich experience of more than 15 years in AM and I4.0. The consensus opinion of experts for criteria weights has been collected as per scale [14] and depicted in Table 3.

The linguistic inputs given by experts on a nine-point scale have been converted into fuzzy scales as presented in Table 2.

Table 2 Linguistic variables and scale of intensity using fuzzy numbers [15]

Importance in linguistic variables	Intensity of Importance (Nine-point Scale)	Triangular fuzzy numbers
Equally important	1	(1,1,1)
Intermediate	2	(1,2,3)
Moderately more	3	(2,3,4)
Intermediate	4	(3,4,5)
Strongly more	5	(4,5,6)
Intermediate	6	(5,6,7)
Very strongly more	7	(6,7,8)
Intermediate	8	(7,8,9)
Extremely more	9	(9,9,9)

Table 3 Consensus opinion of experts for criteria weights

	I	SC	SE	N	AD	C	F	AC	E	CO	EC	M
I	1	3	5	3	1	1	1	3	3	3	3	3
SC	1/3	1	1	1	1	1/3	1/3	1	1/3	3	3	1
SE	1/5	1	1	1/3	1/3	1	1/3	1/3	1/3	1/3	1/3	1/3
N	1/3	1	3	1	1	1	1/3	3	1	1	1	1
AD	1	1	3	1	1	1	1	5	3	1	3	1
C	1	3	1	1	1	1	1	3	3	3	3	1/3
F	1	3	3	3	1	1	1	5	3	3	1	3
AC	1/3	1	3	1/3	1/5	1/3	1/5	1	1/3	1/3	1/3	1/3
E	1/3	3	3	1	1/3	1/3	1/3	3	1	3	1	1
CO	1/3	1/3	3	1	1	1/3	1/3	3	1/3	1	1	1/3
EC	1/3	1/3	3	1	1/3	1/3	1	3	1	1	1	3
M	1/3	1	3	1	1	3	1/3	3	1	3	1/3	1

Step 3: The mean of the fuzzy numbers in the pair-wise matrix is calculated through the geometric mean approach [13].

$$\text{Geometric mean } r_i = (\hat{\text{C}}_{i1} \times \ldots\ldots \times \hat{\text{C}}_{ij} \ldots \hat{\text{C}}_{jn})^{(1/n)} \tag{1}$$

Step 4: Compute criteria fuzzy weight

$$w_i = (\text{lw}_i, \text{mw}_i, u\text{w}_i) = r_i \times (r_1 + r_2 + r_3 \cdots + r_n)^{-1} \tag{2}$$

where $\text{lw}_i, \text{mw}_i, u\text{w}_i$ are the lower, middle, and upper values of the fuzzy weights of ith criteria.

Table 4 Weights of the governing criteria

Criteria	Geometric mean	Fuzzy weights	De-fuzzified weight	Normalized weight
I	(1.682,2.171,2.606)	(0.116,0.178,0.261)	0.185	0.162
SC	(0.707,0.83,1)	(0.049,0.068,0.1)	0.072	0.063
SE	(0.341,0.418,0.561)	(0.024,0.034,0.056)	0.038	0.033
N	(0.891,0.998,1.122)	(0.061,0.082,0.112)	0.085	0.075
AD	(1.335,1.505,1.642)	(0.092,0.123,0.164)	0.126	0.111
C	(1.189,1.441,1.682)	(0.082,0.118,0.168)	0.123	0.108
F	(1.414,1.732,2)	(0.098,0.142,0.2)	0.147	0.129
AC	(0.348,0.439,0.595)	(0.024,0.036,0.06)	0.04	0.035
E	(0.794,0.997,1.26)	(0.055,0.082,0.126)	0.088	0.077
CO	(0.561,0.69,0.891)	(0.039,0.057,0.089)	0.062	0.054
EC	(0.749,0.909,1.122)	(0.052,0.075,0.112)	0.08	0.07
M	(0.891,1.093,1.335)	(0.061,0.09,0.134)	0.095	0.083

Step 5: De-fuzzifying the fuzzy weight into crisp value

$$W_i = ((lw_i + mw_i + uw_i)/3 \tag{3}$$

Step 6: Normalization of the weights

$$\hat{\mathrm{W}}_{ij} = W_i/\left(\sum_{i=1}^{n} W_i\right) \tag{4}$$

The weights have been computed using Eqs. (1–4) and are depicted in Table 4.

Table 4 represents the fuzzy geometric mean, fuzzy weights, de-fuzzified weights, and normalized weights of individual criteria using Eqs. 1–4. These weights will be used in further solution methodology.

3.2 Fuzzy VIKOR Approach

Application steps of Fuzzy VIKOR are as follows [16].

Inputs from the expert panel have been collected for technology ratings in linguistic terms as per the following scale. The linguistic scale represents the linguistic terms in trapezoidal fuzzy numbers and is depicted in Table 5.

Step 7: Aggregation and Normalization of technology ratings [17]

$$\text{Aggregation } T_{ij} = \{T_{ij1}, T_{ij2}, T_{ij3}, T_{ij4}\} \tag{5}$$

Table 5 Linguistic Scale for technology ratings [16]

Importance	Representation	Trapezoidal fuzzy numbers
Very low	VL	(0.0,0.0,0.1,0.2)
Low	L	(0.1,0.2,0.2, 0.3)
Medium low	ML	(0.2,0.3,0.4, 0.5)
Medium	M	(0.4,0.5,0.5, 0.6)
Medium high	MH	(0.5,0.6,0.7,0.8)
High	H	(0.7,0.8,0.8, 0.9)
Very High	VH	(0.8,0.9,1.0 1.0)

where $T_{ij1} = min_d\{T_{ijd1}\}$; $T_{ij2} = 1/d\sum_{d=1}^{D}\{T_{ijd2}\}$; $T_{ij3} = 1/d\sum_{d=1}^{D}\{T_{ijd3}\}$;

$$T_{ij4} = max_d\{T_{ijd4}\}$$

$$\text{Normalization}\,\mathfrak{U}_{ij} = \left\{\frac{T_{ij1}}{T^{+}_{ij4}}, \frac{T_{ij2}}{T^{+}_{ij4}}, \frac{T_{ij3}}{T^{+}_{ij4}}, \frac{T_{ij4}}{T^{+}_{ij4}}\right\} \tag{6}$$

where $T^{+}_{ij4} = max_i\{T_{ij4}\}$

The collected linguistic terms have been converted into fuzzy numbers and then aggregated and normalized using Eqs. 5 and 6.

Step 8: De-fuzzifying technology ratings in fuzzy numbers to crisp values [18]

$$\acute{P}_{ij} = \frac{1}{4}\left\{\frac{T_{ij1}}{T^{+}_{ij4}} + \frac{T_{ij2}}{T^{+}_{ij4}} + \frac{T_{ij3}}{T^{+}_{ij4}} + \frac{T_{ij4}}{T^{+}_{ij4}}\right\} \tag{7}$$

Stage 9: Evaluation of all best and worst criteria to evaluate total performance

$$\acute{P}^{*}_{i} = \max\left(\acute{P}_{ij}\right) \tag{8}$$

$$\acute{P}^{-}_{i} = \min\left(\acute{P}_{ij}\right) \tag{9}$$

The de-fuzzified crisp values of technology ratings from normalized fuzzy numbers using Eq. 7 and depicted in Table 6. The criteria have been evaluated for the best and worst cases in order to find the overall performance using Eqs. 8 and 9 and depicted in Table 6.

Stage 10: Evaluating the indices: utility ($\hat{S}_i$), regret $\left(\check{R}_i\right)$, and VIKOR ($\mathbb{Q}_i$) [19]

Table 6 De-fuzzified crisp values

Technology	I	SC	SE	N	AD	C	F	AC	E	CO	EC	M
IoT&IIoT	0.86	0.71	0.41	0.71	0.71	0.86	0.86	0.41	0.8	0.71	0.71	0.8
BDA	0.71	0.65	0.65	0.41	0.65	0.71	0.65	0.65	0.86	0.65	0.8	0.65
CPS	0.8	0.71	0.86	0.71	0.8	0.8	0.8	0.71	0.8	0.8	0.71	0.71
S	0.65	0.65	0.65	0.65	0.73	0.46	0.46	0.89	0.79	0.79	0.73	0.65
CC	0.86	0.71	0.59	0.71	0.71	0.65	0.65	0.71	0.8	0.8	0.71	0.8
AR&VR	0.8	0.65	0.71	0.8	0.8	0.71	0.8	0.8	0.86	0.8	0.71	0.71
AI	0.79	0.46	0.65	0.73	0.46	0.65	0.46	0.79	0.89	0.79	0.73	0.73
CS	0.71	0.71	0.93	0.5	0.41	0.59	0.5	0.65	0.71	0.8	0.41	0.59
HVI	0.8	0.59	0.71	0.8	0.8	0.8	0.8	0.8	0.8	0.86	0.8	0.8
ACR	0.8	0.65	0.41	0.65	0.71	0.71	0.71	0.71	0.86	0.8	0.41	0.71
Best	0.86	0.71	0.93	0.8	0.8	0.86	0.86	0.89	0.89	0.86	0.8	0.8
Worst	0.65	0.46	0.41	0.41	0.41	0.46	0.46	0.41	0.71	0.65	0.41	0.59

$$\hat{\mathrm{S}}_i = \sum_{j=1}^{n} \left\{ \left[\mathrm{W}_j \left(\mathrm{P}_i^* - \mathrm{P}_{ij} \right) \right] / \left[\mathrm{P}_i^* - \mathrm{P}_i^- \right] \right\} \tag{10}$$

$$\check{\mathrm{R}}_i = max_i \left(W \left(\mathrm{P}_i^* - \mathrm{P}_i^- \right) \right) / \left(\left(\mathrm{P}_i^* - \mathrm{P}_i^- \right) \right) \tag{11}$$

$$\mathbb{Q}_i = \left(v \left(\hat{\mathrm{S}}_i - \hat{\mathrm{S}}^* \right) \right) / \left(\hat{\mathrm{S}} - \hat{\mathrm{S}}^* \right) + \left((1 - v) \left(\check{\mathrm{R}}_i - \check{\mathrm{R}}^* \right) \right) / \left(\left(\check{\mathrm{R}}^- - \check{\mathrm{R}}^* \right) \right) \tag{12}$$

where $\hat{\mathrm{S}}^- = \max\left(\hat{\mathrm{S}}_i\right)$, $\hat{\mathrm{S}}^* = \min\left(\hat{\mathrm{S}}_i\right)$, $\check{\mathrm{R}}^- = \max\left(\check{\mathrm{R}}_i\right)$, $\check{\mathrm{R}}^- = \min\left(\check{\mathrm{R}}_i\right)$ and v is the maximum utility and $(1 - v)$ is the individual regret weight. The value of v is considered as 0.5.

Three indices have been computed using Eqs. 10–12 and depicted in Table 7.

Stage 11: Prioritizing the technologies depending on $\mathbb{Q}_i$ values. The technology with the smallest $\mathbb{Q}_i$ value is prioritized first. The derived priority order of technologies has been presented in Table 7.

3.3 Proposing Compromise Solution

In order to validate the compromise solution, the following two conditions must be fulfilled:

Condition 1: Adequate profit $\mathbb{Q}(\mathrm{R}_2) - \mathbb{Q}(\mathrm{R}_1) \geq \mathrm{DQ}$

where R_2 is the second place attained in the prioritization

Table 7 Indices of Regret ($\check{R}$), Utility ($\hat{S}$), and VIKOR index ($\mathbb{Q}$) and Prioritization of technologies based on indices

	$\hat{S}_i$	$\check{R}_i$	$\mathbb{Q}_i$	Prioritization	$\hat{S}_i$	$\check{R}_i$	$\mathbb{Q}_i$
IoT&IIoT	0.204	0.039	0.029	I	HVI	IoT&IIoT	IoT&IIoT
BDA	0.518	0.116	0.619	II	IoT&IIoT	CPS	HVI
CPS	0.222	0.046	0.077	III	CPS	AR&VR	AR&VR
S	0.613	0.162	0.891	IV	AR&VR	HVI	CPS
CC	0.272	0.068	0.207	V	CC	CC	CC
AR&VR	0.222	0.046	0.076	VI	ACR	ACR	ACR
AI	0.496	0.129	0.654	VII	AI	BDA	BDA
CS	0.736	0.116	0.814	VIII	BDA	CS	AI
HVI	0.171	0.046	0.031	IX	S	AI	CS
ACR	0.385	0.07	0.316	X	CS	S	S

$$\mathrm{DQ} = 1/(\text{Number of technologies} - 1)$$

Condition 2: Decision-making acceptable stability. Technology ranked first should also be ranked first by the utility and/or regret measures.

If two conditions got satisfied, then the technology with least index of VIKOR be the best technology; else more than one solution will be proposed as the best solution.

In this study, Internet of Things and Industrial Internet of Things (IoT&IIoT) are ranked first, and Horizontal and Vertical Integration (HVI) ranked second as per VIKOR index.

As per condition 1, the adequate profit is $\mathbb{Q}(\text{second}) - \mathbb{Q}(\text{first}) \geq \mathrm{DQ}$

where $\mathrm{DQ} = 1/(\text{Number of technologies} - 1) = \frac{1}{10-1} = \frac{1}{9} = 0.11$

Hence, $0.031 - 0.029 = 0.002 \geq 0.11$ (Not satisfied).

Here, the condition one is not satisfied. Hence, more than one solution is proposed as the best solution.

Hence, IoT&IIoT, HVI, and AR&VR are proposed as top prioritized technologies to be used in AM.

3.4 Implications

This study assists industry practitioners in selecting technologies and implementing them in existing AM industry with appropriate selection of suitable technologies. The management can attain the benefit of avoiding huge investment in all technologies to implement them in Industry. Through the enhancement in manufacturing process with technologies, organization that can produce customized products with low investment can provide a facility for the consumer to monitor manufacturing process from a remote location. Real-time monitoring can be facilitated through IoT and IIoT which can be fruitful to the consumer and industry practitioners. Through enhancement in technologies, industry can be more competitive in the global manufacturing era.

Limitations and Future Scope

This study identified and analyzed technologies for AM pertaining to the automotive manufacturing industry. The other technologies may be identified based on their specific application. In the future, a model will be developed among technologies in order to identify the interrelations among them using any modeling approach.

4 Conclusion

Implementation of Industry 4.0 technologies in AM is most advantageous to the organization. I4.0 technologies can overcome difficulties in AM process and make AM into a highly technological, accurate, and quick process. For the ease of implementation of technologies in AM process, technologies are prioritized using a hybrid decision-making method. In this study, governing criteria weight had been computed using Fuzzy AHP, and technologies had been prioritized using Fuzzy VIKOR. Three indices: Utility, Regret, and VIKOR index, have been identified using hybrid method. In this, more than one compromise solution is provided for technology selection. IoT and IIoT, Horizontal and Vertical Integration, Augmented Reality, and Vertical Reality are the priority technologies selected for the implementation in AM. This study can assist industry practitioners to enhance AM organization and make the industry competitive globally.

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