Quantification of the Strategic Fit Between Process Choice Criteria and Production Systems

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Abstract

Manufacturing systemsare the mode through which organizationscan achieve competitive advantage by producing products with the desired wants. Hence, selecting a manufacturing system is one of the critical decisionsin formulating a manufacturing strategy. Currently, there exist four traditional production systems (TPS) (i.e. job-shop, batch-shop, mass, and continuous) and additive manufacturing system (AMS), which appeared as the alternative for TPS during Industry 4.0 era. Different process choice criteria (PCC) need to be considered while determining a suitable system from five or a hybrid (AMS + TPS) configuration. This research has developed a framework comprising Delphi,voting analytical hierarchy process (VAHP), and machine learning (ML) based Bayesian network (BN) method techniques for selecting a suitable production system by quantifying the strategic fit between PCC and production systems. Initially, a pertinentbody of knowledge is researched to identify the critical PCC and further validated by industry experts through Delphi. This results in retaining thirty-six PCC. The relative importance of an individual criterion concerning a particular production system is computed using VAHP in the second stage to understand the alignment of PCC in different production systems for exhibiting the congruence between PCC and manufacturing systems (TPS and AMS). Total 22 cases falling under different production systems are evaluated for strategic fit computation to understand the benchmarked values of PCC in each of the production system environments (TPS and AMS).Finally, a suitable production system is selected for a special case of hydraulic and pneumatic valve manufacture using a Bayesian network method. The findings offer critical insights into the different PCC and their *level-of-fit* in TMS and AMS, which can assist researchers and practitioners in evaluating a suitable manufacturing system for an organization using identified PCC.

Keywords
Manufacturing Strategy, Production systems, Process Choice Criteria, Strategic Fit, Delphi, VAHP, Machine Learning and Bayesian Network.

1. Introduction
Over the past five decades, since the inception of the Manufacturing Strategy (MS) concept by Skinner (1969), MS has been studied, analyzed, and evaluated in depth through numerous academic studies highlighting its importance in creating competitive advantage. The role of manufacturing strategy in configuring the manufacturing decisions to achieve a long-range advantage by improving manufacturing performance is crucial (Choudhari et al. 2013; Demeter 2003; Dohaleet al. 2022b). PwC (2020) reported that organizations with strategized manufacturing function could be transformed easily and effectively to retain resilience and competitive advantage. This is why manufacturing strategy plays a significant role in achieving the overall goal of business strategy (Chatha et al. 2018; Chatha and Butt 2015). A well-formulated manufacturing strategy gives the manufacturer a competitive advantage to utilize the uniqueness of manufacturing functions, viz. “low-cost manufacturing, high-quality production, and manufacturing flexibility” (Swamidass 1986).

Production system is the core aspect of MS. In the literature, two terms – production system and process choice are used synonymously to represent the system configuration used in a manufacturing firm for producing tangible goods (Dohaleet al. 2021b; Hill and Hill 2009; Slack and Lewis 2011). Manufacturing is considered an essential function that helps firms achieve the desired competitiveness in the market through the products produced. The type of production system to retain such competence is crucial for a manufacturing company (Choudhari et al. 2012). Manufacturing consists of four different types of traditional production systems (also termed as process choices) based on the product volume and variety (PV) and plant layout, and material flow (LF). The four production systems or process choices are "Job shop (JSPS), Batch shop (BSPS), Mass/assembly line (M/ALPS), and Continuous flow (CFPS)" production systems (Hayes and Wheelwright 1979a). On the other hand, in the present Industry 4.0 context, the industrial additive manufacturing system (IAMS) has emerged as one of the significant manufacturing systems as an alternative to the traditional manufacturing environment (Eyers and Potter 2017; Khorram Niaki and Nonino 2018).

The manufacturing outputs in the form of competitive priorities, namely – cost, quality, delivery, and flexibility, are majorly driven by the type of production system or process choice employed at the firm (Hill and Hill 2018; Slack and Lewis 2018). For example, a wide range of product variety can be produced in a job shop production system using a highly skilled operator and general-purpose machines with higher flexibility. However, the product cost and delivery (lead time) will be more compared to other forms of production systems (i.e., batch, mass, or continuous). It is expected that AMS will outperform well to achieve these criteria at superior levels than the traditional production systems and can be a step toward mass customization (Minetola et al. 2020; Reeves et al. 2011).

Typically, any firm considers certain priorities at the order winning level as decided by the business strategy by which the firm performs exceptionally well compared with its competitors. While to sustain the market's requirement, some priorities are set at qualifier levels (Hill and Hill 2009; Miltenburg 2005). If appropriately chosen and configured, the production system retains the order winner priorities desired by business strategy and leads to improved manufacturing capability, thereby making the firm world-class (Chatha et al. 2018; Dohale et al. 2021b). A wrong selection of production system results in deviating from the firm's desired level, i.e., order winning level of manufacturing outputs resulting in losing market competence (Hill and Hill 2009; Rahman and Rahman 2020). Hence, selecting a production system or a strategic process choice is considered as one of the most critical steps in manufacturing strategy formulation (Hill and Hill 2018; Miltenburg 2005; Partovi2007; Slack and Lewis 2018).

2. Literature Review and Research Motivation

In the pioneering study, Hayes and Wheelwright (1979a) developed a graphical model to help practitioners select suitable traditional production systems (i.e. JSPS, BSPS, M/ALPS, and CFPS). The authors termed the graphical model as Product-Process Matrix. Apart from this model, Hill (1995) conceptualized a tool to decide process choice for a firm and termed it as a product profile. Although these frameworks are well-appreciated in the body of knowledge, both comprise significant lacunas. Firstly, these frameworks are limited in considering the different criteria for production systems selection and rely only on the traditional criteria, i.e. volume and variety, to decide the suitable production system for a firm. Secondly, market requirements are not effectively incorporated into these frameworks (Ahmad and Schroeder 2002; Artto and Turkulainen 2018; Bello-Pintado et al. 2019; McDermott et al. 1997; Partovi 2007). Thirdly, itwas observed that none of the frameworks has considered the characteristics of the novel AMS and thus lacks the ability to assess AMS. Considering these issues, researchers suggested formulating a quantitative framework that aids in production system decision-making (Ahmad and Schroeder 2002; Bello-Pintado et al. 2019).

The production system selection depends on different criteria. In literature, these criteria are referred as – process choice criteria/characteristics(PCC), which include – market needs, competitive priorities, and the monetary investment required for the production system (Dohaleet al. 2021b; Hill and Hill 2009; Hill 1986; Miltenburg 2005). It is essential to clearly understand these criteria and their alignment with the traditional production systems (TPS) and additive manufacturing systems (AMS) to effectively adopt the suitable one or hybrid configuration (TPS + AMS) for retaining the desired manufacturing outputs utilizing the strength of these systems. Thus, it is the need of the hour to rethink TPS and AMS with a manufacturing strategic lens to understand the level of PCC achievement through TPS and AMS adoption by determining the strategic fit of PCC with all five production systems.

The strategic fit assessment entails the congruence between the two phenomena. The strategic consistency between the different aspects can be effectively portrayed using the determination of strategic fit, which has emerged from the strategic consensus concept (Boyer and McDermott 1999). The strategic fit analysis aids practitioners in understanding how well two strategic functions match or fit each other in a predetermined standard pattern. A higher degree of congruence or strategic fit is associated positively with improved organizational performance (Mirzaei et al. 2016). The earlier research in the MS domain has highlighted the essentiality of bridging the strategic fit between different MS aspects (Chatha and Butt 2015; Choudhari et al. 2010, 2013; Dohale et al. 2021a; Mirzaei et al. 2016). Although it is crucial to demonstrate the strategic fit between different aspects, to the best of the author's knowledge, literature is scant in developing the quantitative model that helps evaluate the strategic fit (Dohale et al. 2021a).

Thus, this research tries to formulate a framework that can quantify the strategic fit between different aspects. Here the applicability of the proposed framework is demonstrated by exhibiting the strategic fit between process choice criteria and production systems. Further, an attempt is made to formulate a framework that can help manufacturing strategists in selecting the most suitable production system for their firm.

3. Research Objectives

This thesis attempts to address the following four research objectives (ROs) to accomplish the overall aim of the research, i.e. quantifying the strategic fit of process choice criteria and production systems –

RO 1. Determining the criteria considered for selecting a production system (process choice criteria)

RO 2. Formulating a framework to quantify the congruence between process choice criteria and the production systems

RO 3. Using the proposed framework (RO 2) and the multiple case study approach, evaluating the strategic fit index of process choice criteria and different production systems environments (TPSs and AMS) employed in manufacturing firms

RO 4. Developing a quantitative framework to determine the suitable production system for a particular firm considering the PCC

4. Research Methodology

Accomplishing the objectives of the research, a multi-method approach is utilized. Four different methods are deployed in this research, namely – Delphi, Voting Analytical Hierarchy Process (VAHP), Multiple case Study Method, and Bayesian Network (BN). The details of each the research objectives (ROs), research methodologies used for the specific RO, allied activities, and significant research outcomesare given next.

4.1 RO 1

RO 1 deals with the identification of critical PCC responsible for selecting a production system at a manufacturing firm. An extensive literature review was carried outthat resulted in the identification of 36 PCC, including group criteria, sub-criteria, and sub-sub-criteria levels. Further, a total of 100 industry experts, 20 from each of the 5 production systems environments, i.e. 4 TPS (JSPS, BSPS, MPS, CFPS) and AMS, are consultedto validate 36 PCC. A content validity ratio (CVR) method is used for consensus measurement. According to the CVR method, any criteria having CVR ≥ 0.29 are retained for the study (Dohale et al. 2022a; Emovon et al. 2018). In our analysis, all 36 PCC are retained as the received CVR ≥ 0.29. The list of PCC is given in Table 1.

4.2RO 2

In RO 2, a multi-criteria decision-making based voting analytical hierarchy process (VAHP) is used. VAHP utilizes a strong-ordering based mathematical formulation proposed by Noguchi et al. (2002) to evaluate the weights of all criteria using the linear programming (LP) based DEA formulation (Liu and Hai 2005) as given below in model (1). Here, θ_{rr} is the weighted sum of votes to the rth criteria, S represents the total number of ranking places $(where, S \leq R)$, R is the number of criteria, u_{rs} denotes the weight of the sth place with respect to the rth criteria, and x_{rs} are the total votes for the rth criteria at the sth place by$n$ voters. ε denotes the difference between the weights of criteria. In doing VAHP, initially, all the criteria under evaluation need to be arranged in a hierarchy as group criteria, sub-criteria, sub-sub-criteria, and alternatives (Table 1). Figure 1 illustrates the hierarchy of the PCC.

Table 1. Process Choice Criteria(Dohale et al. 2021a)

Group Criteria	Sub-Criteria	Sub-Sub-Criteria
Market Requirements (Hayes and Wheelwright 1979a; Hill	Product to be manufactured (Hayes and Wheelwright	Volume
		Variety

and Hill 2018; Miltenburg 2008)	1979b; Slack and Lewis 2018)	Cost of Product
Competitive Priority (Mirzaei et al. 2016; Safizadeh et al. 1996; Sansone et al. 2017; Ward et al. 1998)	Cost (Miltenburg 2008; Mirzaei et al. 2016; Ward et al. 1998)	Production Cost
		Productivity
		Capacity utilization
	Quality (Garvin 1984; Miltenburg 2008; Mirzaei et al. 2016; Sansone et al. 2017)	Performance
		Features
		Reliability
		Conformance
		Durability
		Serviceability
		Aesthetics
		Perceived Quality
	Flexibility (Gerwin 1993; Miltenburg 2008; Mirzaei et al. 2016; Sansone et al. 2017; Upton 1994)	Product Mix
		Volume Flexibility
		Changeover Flexibility
		Modification
		Rerouting
		Material and Sequencing
	Delivery (Miltenburg 2008; Mirzaei et al. 2016; Sansone et al. 2017)	On-time Delivery
		Delivery Speed
		Delivery Reliability
Monetary investment in resources (Hill and Hill 2018; Miltenburg 2005; Slack and Lewis 2018)	Machine Resource Investment	Equipment Cost
	Human Resource Investment	Labor Wages
		Training Cost

- **Model 1**

$$
\left.
\begin{aligned}
\theta_{rr} &= \max \sum_{s=1}^{S} u_{rs} x_{rs} \\
\theta_{rp} &= \sum_{s=1}^{S} u_{rs} x_{rp} \leq 1 \quad (p = 1, 2, \dots, R) \\
& u_{r1} \geq 2u_{r2} \geq 3u_{r3} \geq \cdots \geq S u_{rS} \\
& u_{rS} \geq \varepsilon \\
\varepsilon &= \frac{2}{\{n * S(S+1)\}}
\end{aligned}
\right\} \quad (1)
$$

The ranking of PCC based on their strengths and importance is done in this step. Let us assume; there are n voters (respondents). Every voter ranks each criterion at 1 to S, and S ≤ R, where S is the number of places, and R is the number of criteria. The votes for different places corresponding to different PCC at the individual level of the hierarchy are collected. Generally, the number of respondents (voters) ranges from 8 – 60 (Dohale et al. 2021b). Even having a sample size above 60 can be feasible (Ayyildiz and Taskin Gumus 2021). As the strength and importance of criteria vary with respect to the production system, 100 voters (experts), 20 from each production system (JSPS, BSPS, MPS, CFPS, and AMS) are deployed. These 100 voters are the same experts sampled for the Delphi method (as discussed in Section 3.2) to acquire consistent expertise. A sample ranking data for BSPS is given in Table 2. Further, using the formulation explained above in model 1, θ_{rr} i.e. weight of each process choice criterion is evaluated. The normalization of weights is done using an averaging method and used for further calculation. Table 3 provides a sample calculation of priority weights and global weight of PCC in BSPS.

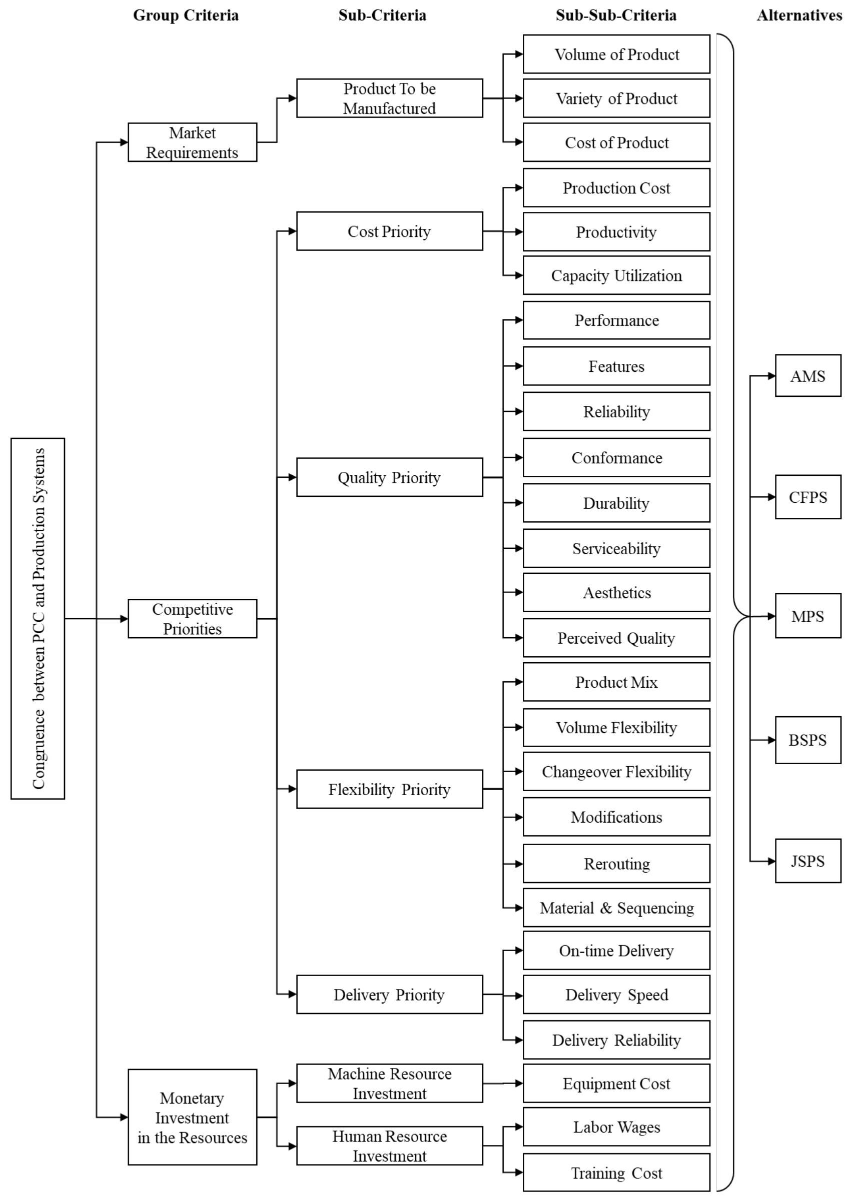

Figure 1. PCC hierarchy

4.3 RO 3

A multiple case study approach is utilized to determine the level of PCC achievement in real-life cases to determine how well these cases adhere to the PCC. For conducting a multiple case study research, a sample of 4 – 10 context-specific cases is considered adequate(Yin 2018). As our research comprises a total of five production systems (JSPS, BSPS, MPS, CFPS, and AMS) as context, this sample size is equally distributed over all the five production systems.In this manner, a total of 22 case studies, comprising 5 cases of JSPS, 4 cases of BSPS, 5 cases of MPS, 4 cases of CFPS, and 4 cases of AMS, are considered in this research work. The performance level of PCC preferred in different production systems is determined. The performance level of each PCC in these cases is critically assessed.This helps to determine which PCC are preferred the most and least in various production systems.

Table 2. Ranking Data – BSPS

PCC	Votes		
	1st	2nd	3rd
Market Need	14	6	0
Competitive Priority	13	6	1
Monetary Investment	12	5	3

PCC	Votes		
	1st	2nd	3rd
On-time delivery	14	4	2
Delivery Speed	8	3	9
Delivery reliability	11	9	0

PCC	Votes	
	1st	2nd
Labor Wages	14	6
Training Cost	11	9

PCC	Votes		
	1st	2nd	3rd
Volume	7	9	4
Variety	14	4	2
Cost of Product	7	8	5

PCC	Votes			
	1st	2nd	3rd	4th
Cost	4	8	5	3
Quality	12	5	2	1
Flexibility	13	6	1	0
Delivery	6	8	4	2

PCC	Votes							
	1st	2nd	3rd	4th	5th	6th	7th	8th
Performance	6	4	1	2	4	3	0	0
Features	5	4	2	3	2	1	2	1
Reliability	4	2	3	5	3	2	0	1
Conformance	7	3	5	2	1	1	0	1
Durability	3	6	2	5	1	1	0	2
Serviceability	3	2	1	7	4	1	1	1
Aesthetics	4	2	1	3	2	3	2	3
Perceived Quality	7	4	2	3	1	2	1	0

PCC	Votes					
	1st	2nd	3rd	4th	5th	6th
Product Mix	9	6	3	2	0	0
Volume flexibility	7	6	4	2	0	1
Changeover	8	2	5	3	1	1
Modification	5	4	5	3	2	1
Rerouting	2	6	0	5	3	4
Material and Sequencing	4	6	5	2	1	2

PCC	Votes		
	1st	2nd	3rd
Production Cost	9	6	5
Productivity	6	8	6
Capacity utilization	8	7	5

PCC	Votes	
	1st	2nd
Machine Resource Investment	4	16
Human Resource Investment	16	4

Table 3. Weight Calculation for BSPS

Group Criteria	**Priority weight of group criteria**	**Normalized weight of group criteria**	**Criteria**	**Priority weight of criteria**	**Normalized weight of criteria**	**Sub- Criteria**	**Priority weight of Sub-criteria**	**Normalized weight of Sub-criteria**	**Global Weight *(GW_i)***
Market Need	1.0000	0.3481	Product to be manufactured	1.000	1.000	Volume	0.770	0.304	0.106
						Variety	1.000	0.395	0.138
						Cost of Product	0.760	0.300	0.105
Competitive Priority	0.9608	0.3345	Cost	0.638	0.193	Production Cost	1.000	0.352	0.023
						Productivity	0.878	0.309	0.020
						Capacity utilization	0.963	0.339	0.022
			Quality	0.944	0.285	Performance	0.920	0.139	0.013
						Features	0.842	0.127	0.012
						Reliability	0.745	0.113	0.011
						Conformance	1.000	0.151	0.014
						Durability	0.765	0.116	0.011
						Serviceability	0.656	0.099	0.009
						Aesthetics	0.685	0.104	0.010
						Perceived Quality	1.000	0.151	0.014
			Flexibility	1.000	0.302	Product Mix	1.000	0.209	0.021
						Volume	0.889	0.186	0.019
						Changeover	0.886	0.185	0.019
						Modification	0.740	0.154	0.016
						Rerouting	0.557	0.116	0.012
						Material and Sequencing	0.719	0.150	0.015
			Delivery	0.724	0.219	On-time delivery	1.000	0.370	0.027
						Delivery Speed	0.750	0.278	0.020
						Delivery reliability	0.953	0.352	0.026
Monetary Investment in resources	0.9118	0.3174	Machine Resource Investment	0.667	0.400	Equipment Cost	1.000	1.000	0.127
			Human Resource Investment	1.000	0.600	Labor Wages	1.000	0.523	0.100
						Training Cost	0.912	0.477	0.091

For example, as the manual work content is more than the machine work content in BSPS to produce the variety of products as per the customers' specifications at lower volumes, more investment is needed in human resources than machine resource. Hence, the equipment cost is preferred the Least while the labor wages and training cost corresponding to human resources are preferred the Most. After determining the preferred performance levels, the performance choice on a five-point Likert scale for each criterion is captured for the respective case of each production system. The performance values are further assigned based on the choices as given by Liberator's scale. The five-point liker scale proposed by Liberator is provided in Table 4. Then the overall performance of the systems is quantified by adding the performance values of each PCC (Drake et al. 2013).

Table 4. Five Point Likert Scale (Liberatore 1987; Liberatore and Nydick 1997)

Criteria Preference (Performance Choice)		**Value**
Most Preferred	**Least Preferred**	
Very High (VH)	Very Low (VL)	0.51004
High (H)	Low (L)	0.26383
Medium (M)	Medium (M)	0.12957
Low (L)	High (H)	0.06364
Very Low (VL)	Very High (VH)	0.03292

Further, the benchmarked value of each PCC within the different production system environments is determined. The benchmarked performance value is given by the best performance (maximum value) from the respective group of cases under evaluation. The benchmarked case is the one that performs exceptionally well on every criterion and retains the *'best possible value'* for each criterion. Thereafter, the performance score (P_s) of each criterion is calculated by multiplying the global weight (GW_i) with the performance value of each criterion (P_i). The overall performance $OP_s$of the case is calculated by adding all the P_s values of the individual cases. Finally, the strategic fit index (SFI) is evaluated to measure the *level-of-fit* between the real-life cases under study and the identified benchmarked case within each production system environment. The SFI is evaluated using the following equation.

$$SFI_{(Case)} = \frac{OP_{s\,(Case)}}{OP_{s\,(Benchmarked\ Case)}} \times 100\ \%$$

The sample performance evaluation of the real-life cases and the benchmarked cases within the BSPS is provided in Table 5 and Table 6. The benchmarked values are determined by identifying the maximum value. For example, considering the 'reliability' criterion, as evident from Table 6, Cases B2, B3, and B4 received a maximum value, i.e. 0.0028, compared with Case B1 (0.0014). Thus, the benchmarked value for the 'reliability' criterion within BSPS cases is taken as 0.0028. Further, the strategic fit index evaluation is as explained. Take an example of Case B2. The overall performance score of Case B2 is computed as 0.2024, and the overall performance score of Benchmarked BSPS case is 0.2529 as highlighted in Table 7. The strategic fit index of Case B2 with Benchmarked BSPS case can be computed using the above equation as – $SFI_{(Case\ B2)} = \frac{0.2024}{0.2529} \times 100\ = \mathbf{80.03}\%$.

A similar approach is used to compute the strategic fit index of each case within different production system environments. The complete evaluation of the strategic fit index of all the cases falling under different production system environmentsis provided in Table 8.

4.4 RO 4

Finally, RO 4 is addressed using an integrated framework including Delphi, VAHP, and Bayesian Network (BN) model to determine the production system for a manufacturing firm. The applicability of the integrated Delphi-VAHP-BN framework is illustrated using the real-life case of a high-value manufacturing (HVM) firm producing hydraulic and pneumatic valves, i.e. the Focus Firm. Delphi is used for determining the most relevant PCC for the focus firm. The list of 36 PCC is provided to the 20 experts from the focus firm and asked them to select the most relevant one over which the production system selection can be evaluated. This resulted in the retention of 26 PCC. Further, the weights of these 26 PCC using the VAHP method are computed to know the criticality of each PCC for the focus firm. Finally, the weights of PCC are given as input into the Bayesian network (BN) model to determine the selection probability of the different production systems alternatives. As the focus firm operates in a traditional environment, only TPS, i.e. JSPS, BSPS, MPS, and CFPS are considered as the alternative system. The BN for MPS alternative evaluation is shown in Figure 2. Similarly, BNs for other alternatives are constructed.Further, the selection probability of each of the production system alternatives is evaluated using BN. It is observed that MPS receives the highest selection probability, i.e. 71.23%, than the other production system alternatives. Figure 3 provides the selection probabilities of each alternative. Thus, MPS is selected as the 'best-suited' production system for the focus firm.

Table 5. Performance Evaluation of PCC in Case B1

Group Criteria	Priority weight of group criteria	Sub-Criteria	Priority weight of Sub-criteria	Sub-Sub- Criteria	Priority weight of Sub-Sub-criteria	Global Weights (GW_i)	Performance Preferred	Case B1 Performance Choice	Case B1 Performance Value (P_i)	Case B1 Score (P_s) (GWi) × (Pi)
Market Requirement	0.3481	Product to be manufactured	1.0000	Volume	0.3043	0.1060	Least	L	0.2638	0.0280
				Variety	0.3953	0.1376	Most	H	0.2638	0.0363
				Cost of Product	0.3004	0.1046	Least	H	0.0636	0.0067
Competitive Priority	0.3345	Cost	0.1929	Production Cost	0.3519	0.0227	Least	H	0.0636	0.0014
				Productivity	0.3090	0.0199	Most	H	0.2638	0.0053
				Capacity utilization	0.3391	0.0219	Most	M	0.1296	0.0028
		Quality	0.2855	Performance	0.1391	0.0133	Most	VH	0.5100	0.0068
				Features	0.1273	0.0122	Most	M	0.1296	0.0016
				Reliability	0.1126	0.0108	Most	M	0.1296	0.0014
				Conformance	0.1512	0.0144	Most	VH	0.5100	0.0074
				Durability	0.1157	0.0110	Most	VH	0.5100	0.0056
				Serviceability	0.0992	0.0095	Most	H	0.2638	0.0025
				Aesthetics	0.1036	0.0099	Most	M	0.1296	0.0013
				Perceived Quality	0.1512	0.0144	Most	H	0.2638	0.0038
		Flexibility	0.3025	Product Mix	0.2088	0.0211	Most	H	0.2638	0.0056
				Volume Flexibility	0.1856	0.0188	Most	H	0.2638	0.0050
				Changeover Flexibility	0.1849	0.0187	Most	H	0.2638	0.0049
				Modifications	0.1544	0.0156	Most	H	0.2638	0.0041
				Rerouting	0.1163	0.0118	Most	H	0.2638	0.0031
				Material and Sequencing	0.1500	0.0152	Most	H	0.2638	0.0040
		Delivery	0.2191	On-Time Delivery	0.3700	0.0271	Most	H	0.2638	0.0072
				Delivery Speed	0.2775	0.0203	Most	H	0.2638	0.0054
				Delivery Reliability	0.3525	0.0258	Most	VH	0.5100	0.0132
Monetary Investment in resources	0.3174	Machine Resource Investment	0.4000	Equipment Cost	1.0000	0.1270	Least	H	0.0636	0.0081
		Human Resource Investment	0.6000	Labor Wages	0.5231	0.0996	Most	H	0.2638	0.0263
				Training Cost	0.4769	0.0908	Most	H	0.2638	0.0240
Overall Performance Score – Case B1										**0.2215**

Table 6. Performance Evaluation of PCC in Cases B2, B3, and B4

Group Criteria	**Sub-Criteria**	**Sub-Sub- Criteria**	**Global Weights (GW_i)**	**Performance Preferred**	**Case B2 Performance Choice**	**Case B2 Performance Value (P_i)**	**Case B2 Score (P_s) (GWi) × (Pi)**	**Case B3 Performance Choice**	**Case B3 Performance Value (P_i)**	**Case B3 Score (P_s) (GWi) × (Pi)**	**Case B4 Performance Choice**	**Case B4 Performance Value (P_i)**	**Case B4 Score (P_s) (GWi) × (Pi)**
Market Requirement	Product to be manufactured	Volume	0.1060	Least	L	0.2638	0.0280	L	0.2638	0.0280	L	0.2638	0.0280
		Variety	0.1376	Most	H	0.2638	0.0363	H	0.2638	0.0363	H	0.2638	0.0363
		Cost of Product	0.1046	Least	H	0.0636	0.0067	H	0.0636	0.0067	H	0.0636	0.0067
Competitive Priority	Cost	Production Cost	0.0227	Least	H	0.0636	0.0014	H	0.0636	0.0014	H	0.0636	0.0014
		Productivity	0.0199	Most	H	0.2638	0.0053	H	0.2638	0.0053	H	0.2638	0.0053
		Capacity utilization	0.0219	Most	M	0.1296	0.0028	M	0.1296	0.0028	M	0.1296	0.0028
	Quality	Performance	0.0133	Most	VH	0.5100	0.0068	VH	0.5100	0.0068	VH	0.5100	0.0068
		Features	0.0122	Most	M	0.1296	0.0016	M	0.1296	0.0016	M	0.1296	0.0016
		Reliability	0.0108	Most	M	0.1296	0.0014	M	0.1296	0.0014	M	0.1296	0.0014
		Conformance	0.0144	Most	VH	0.5100	0.0074	VH	0.5100	0.0074	VH	0.5100	0.0074
		Durability	0.0110	Most	VH	0.5100	0.0056	VH	0.5100	0.0056	VH	0.5100	0.0056
		Serviceability	0.0095	Most	H	0.2638	0.0025	H	0.2638	0.0025	H	0.2638	0.0025
		Aesthetics	0.0099	Most	M	0.1296	0.0013	M	0.1296	0.0013	M	0.1296	0.0013
		Perceived Quality	0.0144	Most	H	0.2638	0.0038	H	0.2638	0.0038	H	0.2638	0.0038
	Flexibility	Product Mix	0.0211	Most	H	0.2638	0.0056	H	0.2638	0.0056	H	0.2638	0.0056
		Volume Flexibility	0.0188	Most	H	0.2638	0.0050	H	0.2638	0.0050	H	0.2638	0.0050
		Changeover Flexibility	0.0187	Most	H	0.2638	0.0049	H	0.2638	0.0049	H	0.2638	0.0049
		Modifications	0.0156	Most	H	0.2638	0.0041	H	0.2638	0.0041	H	0.2638	0.0041
		Rerouting	0.0118	Most	H	0.2638	0.0031	H	0.2638	0.0031	H	0.2638	0.0031
		Material and Sequencing	0.0152	Most	H	0.2638	0.0040	H	0.2638	0.0040	H	0.2638	0.0040
	Delivery	On-Time Delivery	0.0271	Most	H	0.2638	0.0072	H	0.2638	0.0072	H	0.2638	0.0072
		Delivery Speed	0.0203	Most	H	0.2638	0.0054	H	0.2638	0.0054	H	0.2638	0.0054
		Delivery Reliability	0.0258	Most	VH	0.5100	0.0132	VH	0.5100	0.0132	VH	0.5100	0.0132
Monetary Investment in resources	Machine Resource Investment	Equipment Cost	0.1270	Least	H	0.0636	0.0081	H	0.0636	0.0081	H	0.0636	0.0081
	Human Resource Investment	Labor Wages	0.0996	Most	H	0.2638	0.0263	H	0.2638	0.0263	H	0.2638	0.0263
		Training Cost	0.0908	Most	H	0.2638	0.0240	H	0.2638	0.0240	H	0.2638	0.0240
Overall Performance Score							**0.2024**			**0.2475**			**0.2386**

Table 7. Strategic Fit Index Calculation – BSPS

Group Criteria	Sub-Criteria	Sub-Sub- Criteria	Performance Scores				
			Benchmarked BSPS Case	**Case B1**	**Case B2**	**Case B3**	**Case B4**
Market Requirement	Product to be manufactured	Volume	0.0280	0.0280	0.0280	0.0280	0.0280
		Variety	0.0363	0.0363	0.0178	0.0363	0.0363
		Cost of Product	0.0136	0.0067	0.0067	0.0136	0.0067
Competitive Priority	Cost	Production Cost	0.0029	0.0014	0.0014	0.0029	0.0014
		Productivity	0.0053	0.0053	0.0026	0.0053	0.0053
		Capacity utilization	0.0028	0.0028	0.0028	0.0028	0.0028
	Quality	Performance	0.0068	0.0068	0.0035	0.0035	0.0068
		Features	0.0032	0.0016	0.0032	0.0032	0.0032
		Reliability	0.0028	0.0014	0.0028	0.0028	0.0028
		Conformance	0.0074	0.0074	0.0038	0.0074	0.0074
		Durability	0.0056	0.0056	0.0056	0.0056	0.0056
		Serviceability	0.0025	0.0025	0.0025	0.0025	0.0025
		Aesthetics	0.0026	0.0013	0.0026	0.0026	0.0013
		Perceived Quality	0.0074	0.0038	0.0074	0.0074	0.0074
	Flexibility	Product Mix	0.0056	0.0056	0.0027	0.0056	0.0056
		Volume Flexibility	0.0050	0.0050	0.0024	0.0050	0.0050
		Changeover Flexibility	0.0049	0.0049	0.0049	0.0049	0.0024
		Modifications	0.0041	0.0041	0.0020	0.0020	0.0020
		Rerouting	0.0031	0.0031	0.0031	0.0031	0.0031
		Material and Sequencing	0.0040	0.0040	0.0040	0.0040	0.0040
	Delivery	On-Time Delivery	0.0138	0.0072	0.0072	0.0138	0.0138
		Delivery Speed	0.0054	0.0054	0.0054	0.0054	0.0054
		Delivery Reliability	0.0132	0.0132	0.0132	0.0132	0.0132
Monetary Investment in Resources	Machine Resource Investment	Equipment Cost	0.0165	0.0081	0.0165	0.0165	0.0165
	Human Resource Investment	Labor Wages	0.0263	0.0263	0.0263	0.0263	0.0263
		Training Cost	0.0240	0.0240	0.0240	0.0240	0.0240
Overall Performance Score (OP_s)			0.2529	0.2215	0.2024	0.2475	0.2386
Strategic Fit index (SFI)				**87.58%**	**80.03%**	**97.88%**	**94.33%**

Table 8. Evaluation of the cases within different production system environment

	Criteria	**Market Needs**			**Competitive Priority**																			**Monetary Investment**			**Overall Performance Score (OPs)**	**Strategic Fit index (SFI)**
	Sub-Criteria	**Product to be manufactured**			**Cost**			**Quality**								**Flexibility**						**Delivery**			**Machine Resource**	**Human Resource**			
	Sub-Sub-Criteria	**Volume**	**Variety**	**Cost of Product**	**Production Cost**	**Productivity**	**Capacity utilization**	**Performance**	**Features**	**Reliability**	**Conformance**	**Durability**	**Serviceability**	**Aesthetics**	**Percieved Quality**	**Product Mix**	**Volume Flexibility**	**Changeover Flexibility**	**Modifications**	**Rerouting**	**Material and Sequencing**	**On-Time Delivery**	**Delivery Speed**	**Delivery Reliability**	**Equipment Cost**	**Labour Wages**	**Training Cost**		
AMS	Case A1	0.0312	0.0331	0.0070	0.0018	0.0070	0.0068	0.0063	0.0037	0.0057	0.0074	0.0025	0.0009	0.0020	0.0038	0.0051	0.0062	0.0095	0.0038	0.0028	0.0027	0.0077	0.0068	0.0041	0.0405	0.0350	0.0360	0.2792	82.92%
	Case A2	0.0153	0.0331	0.0142	0.0036	0.0070	0.0068	0.0063	0.0037	0.0029	0.0074	0.0025	0.0019	0.0020	0.0074	0.0051	0.0121	0.0095	0.0038	0.0028	0.0013	0.0149	0.0068	0.0041	0.0405	0.0350	0.0360	0.2858	84.88%
	Case A3	0.0153	0.0640	0.0070	0.0018	0.0070	0.0068	0.0032	0.0037	0.0029	0.0074	0.0025	0.0019	0.0010	0.0074	0.0051	0.0062	0.0095	0.0038	0.0028	0.0013	0.0149	0.0068	0.0041	0.0405	0.0350	0.0360	0.2978	88.43%
	Case A4	0.0312	0.0640	0.0142	0.0018	0.0070	0.0068	0.0063	0.0037	0.0057	0.0074	0.0025	0.0019	0.0010	0.0074	0.0051	0.0121	0.0095	0.0038	0.0028	0.0013	0.0149	0.0068	0.0041	0.0405	0.0350	0.0360	0.3325	98.74%
	Benchmarked AMS Case	0.0312	0.0640	0.0142	0.0036	0.0070	0.0068	0.0063	0.0037	0.0057	0.0074	0.0025	0.0019	0.0020	0.0074	0.0051	0.0121	0.0095	0.0038	0.0028	0.0027	0.0149	0.0068	0.0041	0.0405	0.0350	0.0360	0.3368	
JSPS	Case J1	0.0436	0.0872	0.0420	0.0109	0.0039	0.0004	0.0035	0.0077	0.0052	0.0077	0.0020	0.0041	0.0052	0.0078	0.0149	0.0122	0.0118	0.0090	0.0030	0.0031	0.0056	0.0011	0.0102	0.0162	0.0301	0.0521	0.4004	97.39%
	Case J2	0.0436	0.0872	0.0420	0.0109	0.0019	0.0008	0.0067	0.0077	0.0027	0.0040	0.0020	0.0041	0.0027	0.0078	0.0149	0.0122	0.0061	0.0046	0.0030	0.0031	0.0108	0.0011	0.0053	0.0080	0.0301	0.0521	0.3754	91.29%
	Case J3	0.0436	0.0872	0.0420	0.0109	0.0039	0.0004	0.0035	0.0040	0.0052	0.0040	0.0020	0.0021	0.0027	0.0078	0.0077	0.0063	0.0118	0.0090	0.0015	0.0031	0.0056	0.0006	0.0053	0.0080	0.0301	0.0521	0.3601	87.59%
	Case J4	0.0436	0.0872	0.0420	0.0109	0.0019	0.0004	0.0035	0.0077	0.0052	0.0077	0.0020	0.0041	0.0052	0.0078	0.0077	0.0122	0.0118	0.0046	0.0030	0.0031	0.0056	0.0011	0.0102	0.0162	0.0301	0.0521	0.3869	94.11%
	Case J5	0.0436	0.0872	0.0420	0.0109	0.0039	0.0008	0.0067	0.0077	0.0052	0.0077	0.0039	0.0021	0.0052	0.0078	0.0077	0.0122	0.0118	0.0023	0.0015	0.0031	0.0108	0.0011	0.0102	0.0162	0.0301	0.0521	0.3938	95.77%
	Benchmarked JSPS Case	0.0436	0.0872	0.0420	0.0109	0.0039	0.0008	0.0067	0.0077	0.0052	0.0077	0.0039	0.0041	0.0052	0.0078	0.0149	0.0122	0.0118	0.0090	0.0030	0.0031	0.0108	0.0011	0.0102	0.0162	0.0301	0.0521	0.4112	
M/ALPS	Case M1	0.0351	0.0541	0.0330	0.0073	0.0073	0.0077	0.0025	0.0043	0.0030	0.0061	0.0025	0.0046	0.0006	0.0068	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0157	0.0129	0.0144	0.0449	0.0200	0.0207	0.3194	87.00%
	Case M2	0.0172	0.0280	0.0638	0.0073	0.0073	0.0149	0.0049	0.0043	0.0030	0.0061	0.0025	0.0046	0.0011	0.0035	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0157	0.0129	0.0144	0.0221	0.0200	0.0207	0.2902	79.04%
	Case M3	0.0351	0.0541	0.0330	0.0036	0.0073	0.0077	0.0025	0.0043	0.0030	0.0031	0.0025	0.0046	0.0006	0.0068	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0157	0.0129	0.0144	0.0449	0.0200	0.0207	0.3128	85.19%
	Case M4	0.0351	0.0541	0.0330	0.0073	0.0073	0.0077	0.0025	0.0043	0.0030	0.0031	0.0025	0.0024	0.0006	0.0068	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0081	0.0066	0.0075	0.0449	0.0200	0.0207	0.2935	79.95%
	Case M5	0.0351	0.0541	0.0638	0.0073	0.0142	0.0149	0.0049	0.0043	0.0030	0.0061	0.0025	0.0046	0.0006	0.0068	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0081	0.0129	0.0144	0.0449	0.0098	0.0102	0.3383	92.14%
	Benchmarked MPS Case	0.0351	0.0541	0.0638	0.0073	0.0142	0.0149	0.0049	0.0043	0.0030	0.0061	0.0025	0.0046	0.0011	0.0068	0.0036	0.0028	0.0026	0.0026	0.0022	0.0023	0.0157	0.0129	0.0144	0.0449	0.0200	0.0207	0.3672	
CFPS	Case C1	0.0716	0.0325	0.0577	0.0168	0.0082	0.0094	0.0063	0.0018	0.0029	0.0061	0.0025	0.0029	0.0022	0.0018	0.0043	0.0042	0.0035	0.0043	0.0030	0.0038	0.0165	0.0171	0.0157	0.0571	0.0195	0.0175	0.3891	95.51%
	Case C2	0.0716	0.0325	0.0577	0.0087	0.0082	0.0182	0.0033	0.0018	0.0029	0.0061	0.0025	0.0007	0.0022	0.0036	0.0043	0.0042	0.0035	0.0043	0.0030	0.0038	0.0165	0.0171	0.0157	0.0571	0.0195	0.0175	0.3863	94.83%
	Case C3	0.0716	0.0325	0.0577	0.0168	0.0159	0.0182	0.0033	0.0018	0.0029	0.0061	0.0025	0.0029	0.0022	0.0036	0.0043	0.0042	0.0035	0.0043	0.0030	0.0038	0.0165	0.0171	0.0157	0.0571	0.0195	0.0175	0.4043	99.25%
	Case C4	0.0716	0.0325	0.0577	0.0087	0.0159	0.0182	0.0033	0.0018	0.0029	0.0061	0.0025	0.0029	0.0022	0.0036	0.0043	0.0042	0.0035	0.0043	0.0030	0.0038	0.0165	0.0171	0.0157	0.0571	0.0195	0.0175	0.3962	97.26%
	Benchmarked CFPS Case	0.0716	0.0325	0.0577	0.0168	0.0159	0.0182	0.0063	0.0018	0.0029	0.0061	0.0025	0.0029	0.0022	0.0036	0.0043	0.0042	0.0035	0.0043	0.0030	0.0038	0.0165	0.0171	0.0157	0.0571	0.0195	0.0175	0.4074	

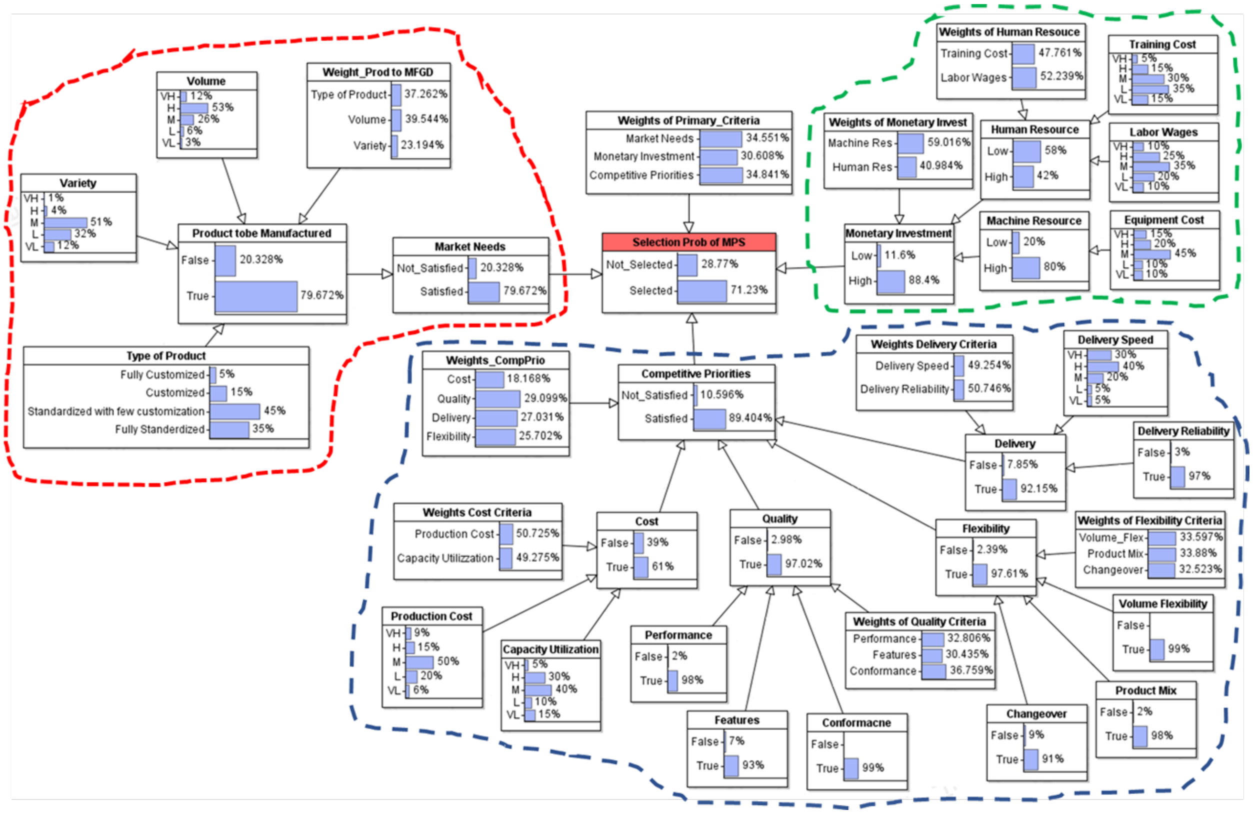

Figure 2. Bayesian Network model for MPS

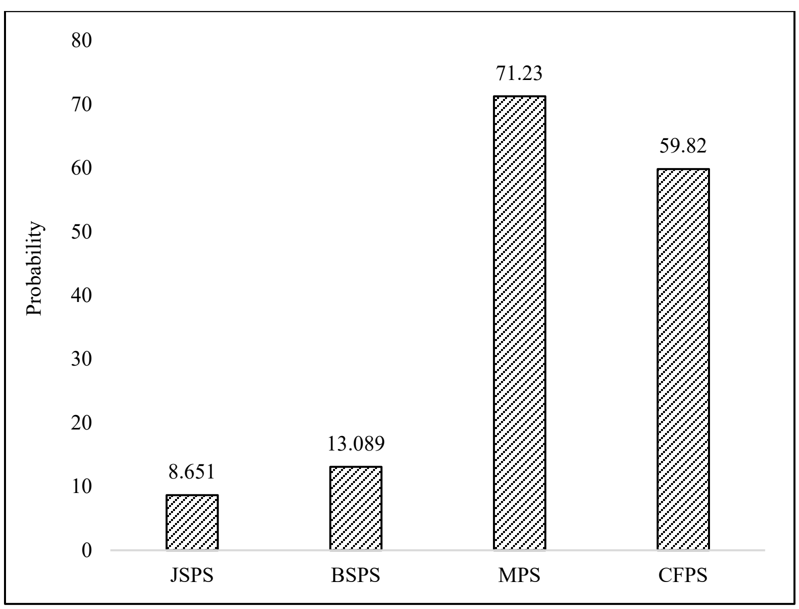

Figure 3. Selection probability for production systems

5. Results and Analysis

For the multiple case studies, within-case and cross-case analyses are conducted to determine the resemblance and divergence in PCC performance levels of the real-life cases and the benchmarked cases. The impact of the number of mismatches between the PCC levels of real-life cases and the benchmarked cases over the SFI isanalyzed.

Further, PCC that contributes the most to the overall performance of benchmarked cases are identified to determine the critical ones. The analyses depict that the real-life cases that comprise the maximum mismatches with the benchmarked cases in terms of critical PCC receive the least overall performance and SFI.

From the cross-case analyses, It can be concluded that the more the real-life firms make a perfect match with the benchmarked case in terms of critical PCC, the more the SFI it will gain and, in turn, provide production competence to the firm (Dohale et al. 2021). Higher SFI of real-life cases indicates a better alignment of these cases with the benchmarked case. So, the approach should be to have perfect congruence with the benchmarked case for gaining strategic competence.

6. Conclusion and Research Implications

The present research has utilized VAHP methodology to establish the congruence of PCC and production systems using the 22 realistic case studies of different production system environments (TPS and AMS). Further, in this thesis work, the implication of the proposed three-stage Delphi-MCDM-BN methodology is illustrated in a real-life case of a hydraulic and pneumatic valve manufacturing firm. This reflects that the present research promises significant implications to the body of knowledge and for practitioners and manufacturing strategists.

- This research work is the primitive study that has developed the quantifiable framework based on the VAHP method to evaluate strategic fit or congruence between different aspects, which was missing in the existing body of knowledge.
- The role of machine learning (ML) algorithms in solving strategic decision-making problems in the productions and operations management domain is crucial (Kang et al. 2020). However, in recent review articles, it is observed that the utilization of ML techniques in the MS domain is still nascent (Dohale et al. 2021a; Dohale et al. 2022b). The present research made an initial attempt to overcome this gap by utilizing the ML-based Bayesian network (BN) method to solve a decision-making problem in the MS domain.
- The application of the proposed methodology helps in determining the most suitable production system for a manufacturing firm. The identified PCC can be utilized by manufacturing strategists and practitioners for strategic decision-making of the production system. Thus, the present research work can be utilized by manufacturing strategists for –
  - *Evaluation of Existing Production System*

  The proposed VAHP framework can aid practitioners and manufacturing strategists in computing the strategic fit index of the production system deployed at their firm. This helps them strategically audit the existing production system at their manufacturing firm to assess the strategic fit between PCC and the production systems. This can guide practitioners in understanding whether the existing production system is properly in sync with the benchmarked production system or not? And if not, over which criteria do they need to work to enhance the strategic fit index.
  - *Deciding Production System*

  The practitioners and manufacturing strategists are advised to utilize the integrated three-stage Delphi-MCDM-BN framework for selecting suitable production systems for their new manufacturing plant or while introducing new products.

7. Publications fromthe Thesis Work

Dohale, V., Verma, P., Gunasekaran, A., & Akarte, M. (2022). Manufacturing strategy 4.0: a framework to usher towards industry 4.0 implementation for digital transformation. Industrial Management & Data Systems. https://doi.org/10.1108/IMDS-12-2021-0790

Dohale, V., Akarte, M., Gunasekaran, A. and Verma, P. (2022), "Exploring the role of artificial intelligence in building production resilience: learnings from the COVID-19 pandemic", International Journal of Production Research, https://doi.org/10.1080/00207543.2022.2127961

Dohale, V., Gunasekaran, A., Akarte, M.M. and Verma, P. (2022), "52 Years of manufacturing strategy: an evolutionary review of literature (1969–2021)", International Journal of Production Research, Vol. 60 No. 2, pp. 569–594.https://doi.org/10.1080/00207543.2021.1971788

Ghuge, S., **Dohale, V.** and Akarte, M. (2022), "Spare part segmentation for additive manufacturing – A framework", Computers & Industrial Engineering, Vol. 169, p. 108277.https://doi.org/10.1016/j.cie.2022.108277

Dohale, V., Gunasekaran, A., Akarte, M. and Verma, P. (2021), "An integrated Delphi-MCDM-Bayesian Network framework for production system selection", International Journal of Production Economics, Vol. 242, p.

108296.https://doi.org/10.1016/j.ijpe.2021.108296

Dohale, V., Akarte, M.M. and Verma, P. (2021), "Systematic review of manufacturing strategy studies focusing on congruence aspect", Benchmarking: An International Journal, available at:https://doi.org/10.1108/BIJ-02-2021-0103.https://doi.org/10.1108/BIJ-02-2021-0103

Dohale, V., Gunasekaran, A., Akarte, M.M. and Verma, P. (2020), "Twenty-five years' contribution of 'Benchmarking: an International Journal' to manufacturing strategy: a scientometric review", Benchmarking: An International Journal, Vol. 27 No. 10, pp. 2887–2908.https://doi.org/10.1108/BIJ-06-2020-0316

References

Ahmad, S. and Schroeder, R.G., "Refining the product-process matrix", *International Journal of Operations and Production Management*, Vol. 22 No. 1, pp. 103–124, 2002.

Artto, K. and Turkulainen, V., "It takes two to tango: Product-organization interdependence in managing major projects", *International Journal of Operations and Production Management*, Vol. 38 No. 6, pp. 1312–1339, 2018.

Ayyildiz, E. and Taskin Gumus, A., "A novel distance learning ergonomics checklist and risk evaluation methodology: A case of Covid-19 pandemic", *Human Factors and Ergonomics in Manufacturing & Service Industries*, Vol. 31 No. 4, pp. 397–411, 2021.

Bello-Pintado, A., García Marco, T. and Zouaghi, F., "Product/process definition, technology adoption and workforce qualification: impact on performance", *International Journal of Production Research*, Taylor & Francis, Vol. 57 No. 1, pp. 200–215, 2019.

Boyer, K.K.K. and McDermott, C., "Strategic consensus in operations strategy", *Journal of Operations Management*, Vol. 17 No. 3, pp. 289–305, 1999.

Chatha, K.A. and Butt, I. , "Themes of study in manufacturing strategy literature", *International Journal of Operations and Production Management*, Vol. 35 No. 4, pp. 604–698, 2015.

Chatha, K.A., Butt, I., Jajja, M.S.S. and Arshad, M., "Theoretical developments in empirical quantitative manufacturing strategy literature", *International Journal of Operations and Production Management*, Vol. 38 No. 1, pp. 183–210, 2018.

Choudhari, S.C., Adil, G.K. and Ananthakumar, U., "Congruence of manufacturing decision areas in a production system: A research framework", *International Journal of Production Research*, Vol. 48 No. 20, pp. 5963–5983, 2010.

Choudhari, S.C., Adil, G.K. and Ananthakumar, U., "Exploratory case studies on manufacturing decision areas in the job production system", *International Journal of Operations and Production Management*, Vol. 32 No. 11, pp. 1337–1361, 2012.

Choudhari, S.C., Adil, G.K. and Ananthakumar, U., "Configuration of manufacturing strategy decision areas in line production system: Five case studies", *International Journal of Advanced Manufacturing Technology*, Vol. 64 No. 1–4, pp. 459–474, 2013.

Demeter, K., "Manufacturing strategy and competitiveness", *International Journal of Production Economics*, Vol. 81–82, pp. 205–213, 2003.

Dohale, V., Akarte, M.M. and Verma, P., "Systematic review of manufacturing strategy studies focusing on congruence aspect", *Benchmarking: An International Journal*, available at:https://doi.org/10.1108/BIJ-02-2021-0103, 2021a.

Dohale, V., Ambilkar, P., Gunasekaran, A. and Bilolikar, V., "Examining the barriers to operationalization of humanitarian supply chains: lessons learned from COVID-19 crisis", *Annals of Operations Research*, available at:https://doi.org/10.1007/s10479-022-04752-x., 2022a

Dohale, V., Gunasekaran, A., Akarte, M. and Verma, P., "An integrated Delphi-MCDM-Bayesian Network framework for production system selection", *International Journal of Production Economics*, Vol. 242, p. 108296, 2021b.

Dohale, V., Gunasekaran, A., Akarte, M.M. and Verma, P., "52 Years of manufacturing strategy: an evolutionary review of literature (1969–2021)", *International Journal of Production Research*, Vol. 60 No. 2, pp. 569–594, 2022b.

Drake, P.R., Lee, M.D. and Hussain, M., "The lean and agile purchasing portfolio model", *Supply Chain Management: An International Journal*, Vol. 18 No. 1, pp. 3–20, 2013.

Emovon, I., Norman, R.A. and Murphy, A.J., "Hybrid MCDM based methodology for selecting the optimum maintenance strategy for ship machinery systems", *Journal of Intelligent Manufacturing*, Springer US, Vol. 29 No. 3, pp. 519–531, 2018.

Eyers, D.R. and Potter, A.T., "Industrial Additive Manufacturing: A manufacturing systems perspective", *Computers in Industry*, Elsevier B.V., Vol. 92, pp. 208–218, 2017.

Garvin, D.A., "What Does 'Product Quality' Really Mean?", *MIT Sloan Management Review*, Vol. 26 No. 1, pp. 25–43, 1984.

Gerwin, D., "Manufacturing Flexibility: A Strategic Perspective", *Management Science*, Vol. 39 No. 4, pp. 395–410, 1993.

Hayes, R.H. and Wheelwright, S.C., "Link Manufacturing Process and Product life cycle", *Harvard Business Review*, Vol. 57 No. 1, pp. 133–140, 1979a.

Hayes, R.H. and Wheelwright, S.C., "The Dynamics of Process- Product Life Cycles", *Harvard Business Review*, Vol. 57 No. 2, pp. 127–136, 1979b.

Hill, A. and Hill, T., *Manufacturing Operations Strategy*, Palgrave:Macmillan, UK, 2009.

Hill, A. and Hill, T., *Operations Strategy: Design, Implementation and Delivery*, Palgrave Macmillan, UK, 2018.

Hill, T., *Manufacturing Strategy: Text and Cases*, 1st Edn., MACMILLAN PRESS LTD, London, 1995.

Hill, T.J., "Teaching Manufacturing Strategy", *International Journal of Operations and Production Management*, Vol. 6 No. 3, pp. 10–20, 1986.

Kang, Z., Catal, C. and Tekinerdogan, B., "Machine learning applications in production lines: A systematic literature review", *Computers & Industrial Engineering*, Elsevier Ltd, Vol. 149, p. 106773, 2020.

Khorram Niaki, M. and Nonino, F., *The Management of Additive Manufacturing*, Springer International Publishing, Cham, 2018.

Liberatore, M.J., "An extension of the analytic hierarchy process for industrial R&D project selection and resource allocation", *IEEE Transactions on Engineering Management*, IEEE, Vol. EM-34 No. 1, pp. 12–18, 1987.

Liberatore, M.J. and Nydick, R.L., "Group decision making in higher education using the analytical hierarchy process", *Research in Higher Education*, Vol. 38 No. 5, pp. 593–614, 1997.

Liu, F.-H.F. and Hai, H.L., "The voting analytic hierarchy process method for selecting supplier", *International Journal of Production Economics*, Vol. 97 No. 3, pp. 308–317, 2005.

McDermott, C.M., Greis, N.P. and Fischer, W.A., "The diminishing utility of the product/process matrix: A study of the US power tool industry", *International Journal of Operations and Production Management*, Vol. 17 No. 1, pp. 65–84, 1997.

Miltenburg, J., *Manufacturing Strategy: How to Formulate and Implement a Winning Plan*, 2nd Edn., Productivity Press, New York, 2005.

Miltenburg, J., "Setting manufacturing strategy for a factory-within-a-factory", *International Journal of Production Economics*, Vol. 113 No. 1, pp. 307–323, 2008.

Minetola, P., Priarone, P.C. and Ingarao, G., "Sustainability for 3DP Operations", *Managing 3D Printing*, Springer International Publishing, Cham, pp. 97–126, 2020.

Mirzaei, N.E., Fredriksson, A. and Winroth, M., "Strategic consensus on manufacturing strategy content Including the operators' perceptions", *International Journal of Operations & Production Management*, Vol. 36 No. 4, pp. 429–466, 2016.

Noguchi, H., Ogawa, M. and Ishii, H., "The appropriate total ranking method using DEA for multiple categorized purposes", *Journal of Computational and Applied Mathematics*, Vol. 146 No. 1, pp. 155–166, 2002.

Partovi, F.Y., "An analytical model of process choice in the chemical industry", *International Journal of Production Economics*, Vol. 105 No. 1, pp. 213–227, 2007.

PwC, *An Operations Strategy Life Cycle for the Current Crisis*, available at: https://www.pwc.com/us/en/library/covid-19/pdf/pwc-manufacturing-operations-strategy-lifecycle-crisis.pdf, 2020.

Rahman, M.H. and Rahman, A., "Strategic fit strategy formulation: keys to enhancing competitiveness and improving capabilities of a manufacturing unit", *Production & Manufacturing Research*, Taylor & Francis, Vol. 8 No. 1, pp. 59–79, 2020.

Reeves, P., Tuck, C. and Hague, R., "Additive Manufacturing for Mass Customization", *Mass Customization: Engineering and Managing Global Operations*, Springer-Verlag London, pp. 275–289, 2011.

Safizadeh, M.H., Ritzman, L.P., Sharma, D. and Wood, C., "An Empirical Analysis of the Product-Process Matrix", *Management Science*, Vol. 42 No. 11, pp. 1576–1591, 1996.

Sansone, C., Hilletofth, P. and Eriksson, D., "Critical operations capabilities for competitive manufacturing: a systematic review", *Industrial Management & Data Systems*, Vol. 117 No. 5, pp. 801–837, 2017.

Skinner, W., "Manufacturing - Missing Link in Corporate Strategy", *Harvard Business Review*, Vol. 47 No. 3, pp. 136–145, 1969.

Slack, N. and Lewis, M., *Operations Strategy*, 3rd Edn., Pearson education Limited, England, 2011.

Slack, N. and Lewis, M., *Operations Strategy*, 5th Edn., Pearson Education Limited, Harlow, England, 2018.

Swamidass, P.M., "Manufacturing Strategy: Its Assessment and Practice", *Journal of Operations Management*, Vol. 6 No. 4, pp. 471–484, 1986.

Upton, D.M., "The Management of Manufacturing Flexibility", *California Management Review*, Vol. 36 No. 2, pp. 72–89, 1994.

Ward, P.T., McCreery, J.K., Ritzman, L.P. and Sharma, D., "Competitive Priorities in Operations Management", *Decision Sciences*, Vol. 29 No. 4, pp. 1035–1046, 1998.

Yin, R.K., *Case Study Research and Applications : Design and Methods*, Sixth Edn., Sage Publications Inc., California, 2018.

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