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Evaluating the Ranking of Performance Variables in Flexible Manufacturing System through the Best-Worst Method

Anthony Bagherian [1,*], Gulshan Chauhan [2], Arun Lal Srivastav [3] and Rajiv Kumar Sharma [4]

[1] International School of Management, 17, Boulevard Raspail, 75007 Paris, France
[2] Geeta University, Panipat 132145, India; pvc@geetauniversity.edu.in
[3] Chitkara University School of Engineering and Technology, Chitkara University Himachal Pradesh, Chandigarh 175103, India; arun.srivastav@chitkarauniversity.edu.in
[4] National Institute of Technology, Hamirpur 177005, India; rksfme@nith.ac.in
* Correspondence: anthony6@gmx.de

Abstract: Flexible Manufacturing Systems (FMSs) provide a competitive edge in the ever-evolving manufacturing landscape, offering the agility to swiftly adapt to changing customer demands and product lifecycles. Nevertheless, the complex and interconnected nature of FMSs presents a distinct challenge: the evaluation and prioritization of performance variables. This study clarifies a conspicuous research gap by introducing a pioneering approach to evaluating and ranking FMS performance variables. The Best-Worst Method (BWM), a multicriteria decision-making (MCDM) approach, is employed to tackle this challenge. Notably, the BWM excels at resolving intricate issues with limited pairwise comparisons, making it an innovative tool in this context. To implement the BWM, a comprehensive survey of FMS experts from the German manufacturing industry was conducted. The survey, which contained 34 key performance variables identified through an exhaustive literature review and bibliometric analysis, invited experts to assess the variables by comparing the best and worst in terms of their significance to overall FMS performance. The outcomes of the BWM analysis not only offer insights into the factors affecting FMS performance but, more importantly, convey a nuanced ranking of these factors. The findings reveal a distinct hierarchy: the "Quality (Q)" factor emerges as the most critical, followed by "Productivity (P)" and "Flexibility (F)". In terms of contributions, this study pioneers a novel and comprehensive approach to evaluating and ranking FMS performance variables. It bridges an evident research gap and contributes to the existing literature by offering practical insights that can guide manufacturing companies in identifying and prioritizing the most crucial performance variables for enhancing their FMS competitiveness. Our research acknowledges the potential introduction of biases through expert opinion, delineating the need for further exploration and comparative analyses in diverse industrial contexts. The outcomes of this study bear the potential for cross-industry applicability, laying the groundwork for future investigations in the domain of performance evaluation in manufacturing systems.

Keywords: Flexible Manufacturing System; FMS; performance variables; quality; productivity; flexibility; BWM

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1. Introduction

Flexible Manufacturing Systems (FMSs) have recently emerged as a focal point in the manufacturing domain, primarily due to their exceptional adaptability to dynamic production demands and their capacity to boost efficiency and productivity levels significantly. FMSs seamlessly amalgamate an array of machinery, equipment, and computer-controlled systems to automate manufacturing processes, enabling swift reconfiguration for producing diverse product ranges. The ultimate significance of assessing the efficacy of FMSs is emphasized by the potential they hold for optimizing system efficiency, pinpointing areas for refinement, and guiding well-informed decisions concerning system design and operation.

Research in this domain, as noted in [1], defines the flexibility of a manufacturing system as its "capacity to efficiently and effectively adapt to changes in the product mix, volume, or timing of activities" [2]. Furthermore, ref. [3] characterizes FMSs as a manufacturing approach that "employs programmed machines, computer systems, and/or robotics for processing and assembling raw parts" [4]. In the context of modern digital manufacturing, FMSs assume an imperative role, vividly portrayed in Figure 1, by bolstering productivity, elevating quality standards, and boosting responsiveness to changes while simultaneously curbing time, effort, and operational costs, even in the face of proliferating product variations. It is essential to recognize that, as emphasized by [5], the quest to achieve flexibility in conjunction with productivity and quality stands as a substantial challenge confronting numerous manufacturers [6]. However, it is noteworthy that the flexibility of an FMS hinges on a multitude of factors, including its components, capabilities, interconnections, and mode of operation and control [2].

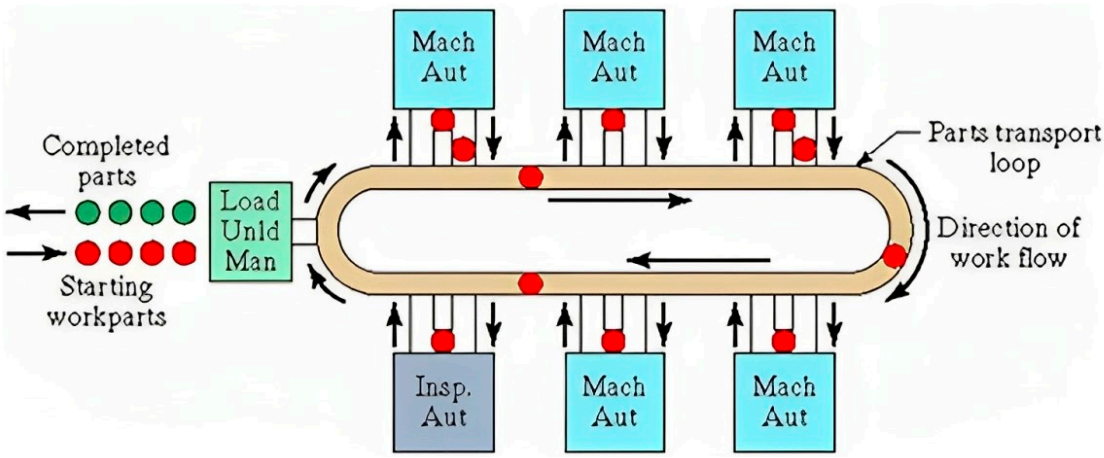

Figure 1. FMS loop layout [7].

In recent years, there has been a surge in studies aimed at investigating the performance variables within FMSs and formulating suitable methodologies for evaluating their effectiveness. Researchers have attempted to adopt diverse methodologies, ranging from mathematical modeling and simulation to statistical assessment, to gauge the efficiency of FMSs through key performance indicators (KPIs) such as productivity, throughput, flexibility, quality, and cost-effectiveness. A recent study by [6] has identified three paramount parameters closely associated with FMS performance: productivity, flexibility, and quality. These performance factors within FMSs are delineated in Figure 2.

Researchers have employed a variety of methodologies to evaluate FMS performance, including conventional approaches like the Analytical Hierarchy Process (AHP) [8] or fuzzy logic [9], as well as contemporary methodologies such as data envelopment analysis [10] and machine learning algorithms [11]. In this study, our goal is to make a significant contribution to the current body of knowledge related to FMS performance evaluation by introducing an innovative approach based on the Best-Worst Method (BWM). The BWM, which has gained popularity in recent years, excels at systematically and intuitively capturing the comparative ranking of various criteria used in decision-making processes.

Through the implementation of the BWM, we aim to provide a comprehensive and reliable assessment of performance variables in FMS, enabling a deeper understanding and optimization of FMS performance in modern manufacturing environments. Furthermore, our approach incorporates insights gained from an extensive literature review and consultation with industry professionals and experts. As a result, we have identified a total of 34 variables that significantly influence FMS performance.

The subsequent sections of this article are organized as follows: Section 2 offers a comprehensive overview of the literature related to FMS performance evaluation, including a discussion of relevant studies that have employed various methodologies to assess FMS performance variables. Section 3 outlines the methodology and provides the specifics of the proposed BWM-based approach for evaluating FMS performance. Section 4 presents the outcomes and analyzes the performance evaluation using our proposed approach. Finally, in Section 5, we draw conclusions from the implications of the results and outline future research directions in the field of FMS performance evaluation.

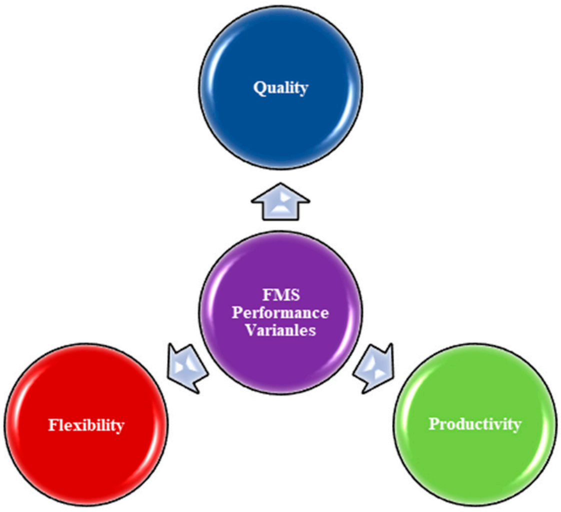

Figure 2. FMS performance variables.

2. Review of Literature

This literature review introduces an overview of relevant research conducted on the performance variables that influence the outcomes of FMSs. The authors conducted a comprehensive investigation of the literature, reviewing a total of 272 scientific publications. While the 'Dimensions' database spanning the years 2013 to 2023 conveys a comprehensive selection of recent research, it is essential to note that a substantial portion of the literature review incorporates seminal works published before 2000. It is imperative to include older publications in comprehending the essential concepts and theoretical development in the domain of FMSs. It allows us to trace the historical evolution of FMS research and recognize the enduring principles that continue to shape current investigations. The scrutinizing of the literature comprises three primary sections. The first part summarizes prior research on the factors that affect FMS performance. The second section discusses the research approach of MCDM in relation to FMSs. Finally, the third part identifies gaps in the current literature related to FMS performance.

By acknowledging the historical development of FMS research, we gain valuable insights into the origins and evolution of the field, conveying a comprehensive perspective that combines both essential principles and contemporary findings. This holistic approach enriches our interpretation of the complexity of FMS performance.

2.1. Literature Review on FMS Performance, Accompanied by a Bibliometric Overview

The literature offers various definitions of flexibility in the context of manufacturing. Ref. [12] presents flexibility principles, while [13] proposes additional types, including material handling flexibility, program flexibility, and industry flexibility. Ref. [14] identified four additional dimensions of flexibility: automation flexibility, labor flexibility, modern design flexibility, and distribution flexibility. Numerous studies have explored diverse performance indicators and research methods to determine the most influential factors in FMSs. According to [15], earlier research on FMSs focused solely on investigating the systems' performance from a single perspective. For example, certain research has focused on the productivity dimension; nevertheless, other studies have investigated time flow as a single metric or dimension.

Ref. [4] classified 15 performance variables into three groups—quality, productivity, and flexibility—in order to analyze FMSs. Ref. [1] defined FMS capacity as the ability to accommodate changes in product mix, volume, or timing of activities. Ref. [2] further emphasizes that FMS adaptability is contingent on its components, capabilities, interconnections, and mode of operation and control. Additionally, ref. [5] emphasizes the significant challenge manufacturers face in achieving flexibility alongside productivity and quality.

Researchers have utilized FMS in conjunction with various frameworks and methods to model productivity variables and evaluate FMSs. Ref. [15] employed Data Envelope Analysis (DEA) for FMS evaluation. Ref. [16] quantified the advantages of FMS implementation by employing the Multiple Attribute Decision Making (MADM) framework, specifically the Analytic Hierarchy Process (AHP). Ref. [17] utilized the AHP strategy to assess advanced technologies. Ref. [18] employed MADM frameworks such as MOORA (Multi-Objective Optimization by Ratio Analysis) and PSI (Preferential Similarity Index) to rank FMS performance variables. Refs. [19,20] applied FMSs to assess machine workload balance. Ref. [18] utilized FMSs for modeling parameters influencing flexibility. Ref. [14] applied FMSs as a case study for evaluating performance parameters in a printed circuit board manufacturing plant. Ref. [19] utilized FMSs to assess loading and routing influences. Refs. [20–23] disclose formulations and methods for resolving system-loading issues through the FMS framework.

Ref. [24] conducted an evaluation and prioritization of the Industry 4.0 challenges pertaining to Indian automotive industry utilizing the BWM approach.

The literature also identifies common and uncommon indicators affecting FMS quality, flexibility, and productivity. Common variables include production lead time, scrap percentage, automation, unit labor cost, and setup time. On the other hand, uncommon variables, such as training, tool inventory, customer satisfaction, and rejection reduction, are statistically insignificant to FMS performance variables. Additionally, bibliometric analysis quantitatively evaluates the interconnections among published papers based on FMS performance variables. By reviewing a wide array of literature from the Dimensions database from 2014–2023, about 50 articles were identified in the context of FMSs in their titles, abstracts, and keywords (see Figure 3). Utilizing VOSViewer software, the interactions among parameters in the publications are visually represented in a diagram (refer to Figure 4).

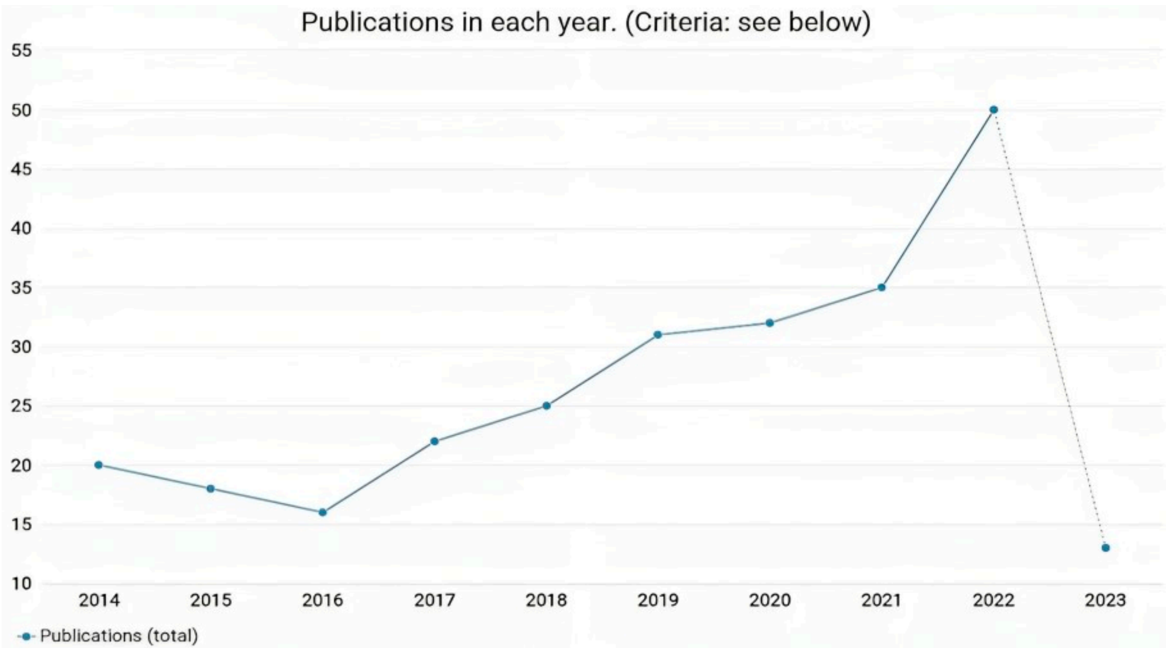

Figure 3. The number of scientific articles published in academic journals. Source: extractions were conducted by the authors with VOSViewer based on the data extracted in the Dimensions Database [Dimensions Database, www.dimensions.ai, accessed on 20 September 2023].

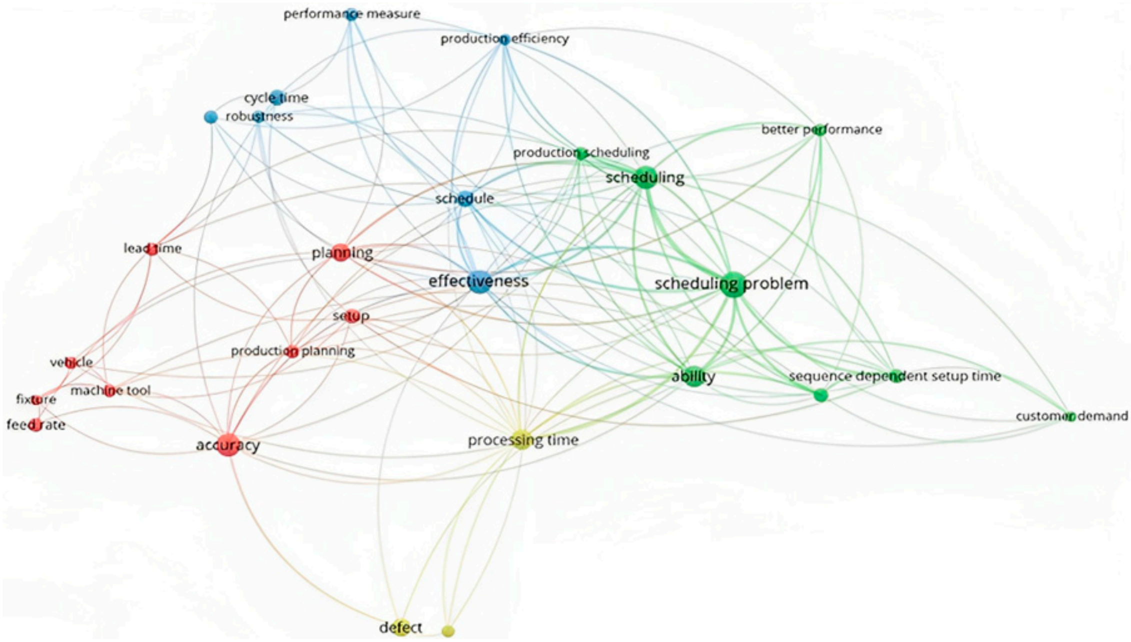

Figure 4. A graphical representation of connections among academic studies related to FMS performance variables. Source: extractions were conducted by the authors with VOSViewer based on the data extracted in the Dimensions Database [Dimensions Database, www.dimensions.ai, accessed on 20 September 2023].

Furthermore, multiple studies deployed a variety of performance variables and research methods to spot the most effective FMS factors. The contributions of previous authors are depicted in Table 1.

Table 1. Contributions of previous authors.

No	Author	Publication	Methodology	Performance Variable
1	[2]	2011	Simulation modelling, Fuzzy logic	1. Routing variety; 2. Routing efficiency; 3. Routing versatility.
2	[4]	2018	Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Absolute Fit Indices, Incremental Fit Indices	1. Automation; 2. Capacity to handle new product; 3. Flexible fixturing; 4. Automation; 5. Increase machine utilization; 6. Flexibility in the design of the production system; 7. Use of automated material handling devices; 8. Ability to manufacture a variety of products; 9. Manufacturing lead time and setup time reduction; 10. Quality consciousness; 11. Speed of response; 12. Combination of operation; 13. Reduced WIP inventories; 14. Reduction in material flow; 15. Reduction in scrap; 16. Use of a reconfigurable machine tool.

Table 1. *Cont.*

No	Author	Publication	Methodology	Performance Variable
3	[6]	2014	ISM, SEM, GTMA	1. Effect of tool life; 2. Training; 3. Financial incentive; 4. Unit labor cost; 5. Customer satisfaction; 6. Reduction in scrap percentage; 7. Reduction of rejection; 8. Reduction in rework percentage; 9. Equipment utilization; 10. Trained worker; 11. Manufacturing lead time and setup time; 12. Unit manufacturing cost; 13. Setup cost; 14. Throughput time; 15. Automation; 16. Use of automated material handling devices; 17. Reduction in material flow; 18. Reduced work in process inventory; 19. Ability to manufacture a variety of products; 20. Capacity to handle new product.
4	[25]	2016	Effectiveness Index, ISM	1. Machine flexibility; 2. Setup or changeover time; 3. Tool magazine or tool current capacity; 4. Availability of technical know-how; 5. Skills and versatility of workers in the system; 6. Type of machine; 7. Max. No. of tools available; 8. Variety of parts to be handled by the machine; 9. Space availability; 10. Max. no. of operations available; 11. Number of machines available in the system; 12. Common tooling available; 13. Similarities of parts in the system; 14. Tool changing time of the machine; 15. Design changes required in the product; 16. Flexibility of material handling system; 17. Similarity of workstations; 18. Variety of products; 19. No of existing part families matching the new product design; 20. Type of operations to be performed on the machine; 21. Maximum number of routes available; 22. Offline part programming preparation facility.

Table 1. *Cont.*

No	Author	Publication	Methodology	Performance Variable
5	[19]	2018	Interpretive Structural Modelling (ISM), Structural Equation Modelling (SEM), Graph Theory, Matrix Approach (GTMA)	1. Effect of tool life; 2. Unit manufacturing cost; 3. Unit labor cost; 4. Manufacturing lead time; 5. Throughput time; 6. Setup cost; 7. Scrap percentage; 8. Rework percentage;; 9. Automation; 10. Use of automated material handling devices; 11. Equipment utilization; 12. Ability to manufacture a variety of product; 13. Capacity to handle new product; 14. Setup time; 15. Reduced work in process inventory.
6	[26]	2016	Total Interpretive Structural Modelling (TISM)	1. Capacity to handle new products; 2. Ability to manufacture a variety of product; 3. Flexibility to design production system; 4. Combination of operation; 5. Automation; 6. Flexible fixturing; 7. Use of automated material handling devices; 8. Increased machine utilization; 9. Use of reconfigurable machine tool; 10. Speed of response; 11. Reduced work in progress; 12. Manufacturing lead time and setup time reduction; 13. Quality consciousness; 14. Reduction in material flow; 15. Reduction in scrap.
7	[21]	1991	Identification of flexibilities, Fishbone diagram	1. Minimize machine to machine movements; 2. Balance workload per machine for equal size machine; 3. Unbalance workload per machine for unequal size machine; 4. Balance machine processing time; 5. Maximize the number of operation assignments; 6. Operation processing time variation; 7. Tool inventory.

Table 1. *Cont.*

No	Author	Publication	Methodology	Performance Variable
8	[27]	2018	MOORA Approach, Ratio System Approach	1. Increased machine utilization; 2. Automation; 3. Use of automated material handling devices; 4. Manufacturing lead time and setup time; 5. Flexible fixturing; 6. Scrap percentage.
9	[19]	2018	MOORA Approach, Ratio System Approach	1. Effect of tool life; 2. Unit manufacturing cost; 3. Unit labor cost; 4. Manufacturing lead time; 5. Setup cost; 6. Scrap percentage; 7. Throughput time; 8. Rework percentage; 9. Setup time; 10. Equipment utilization; 11. Automation; 12. Ability to manufacture variety of products; 13. Use of automated material handling devices; 14. Reduced work in process inventory; 15. Training; 16. Capacity to handle new product; 17. Financial incentive; 18. Customer satisfaction; 19. Reduction of rejection; 20. Reduction in material flow; 21. Trained worker; 22. Flexibility in the design of production system 23. Flexible fixturing; 24. Use of reconfigurable/machine tool; 25. Speed of response; 26. Quality consciousness; 27. Combination of operation.

Table 1. *Cont.*

No	Author	Publication	Methodology	Performance Variable
10	[28]	2019	TISM, Fuzzy logic	1. Unit manufacturing cost; 2. Unit labor cost; 3. Manufacturing lead time; 4. Effect of tool life; 5. Throughput time; 6. Setup cost; 7. Scrap percentage; 8. Setup time; 9. Rework percentage; 10. Equipment utilization; 11. Automation; 12. Ability to manufacture a variety of product; 13. Use of automated material handling devices; 14. Capacity to handle new product; 15. Reduced work in process inventory.
11	[29]	2012	COPRAS approach	1. Increased machine utilization; 2. Automation; 3. Use of automated material handling devices; 4. Flexible fixturing; 5. Scrap percentage; 6. Manufacturing lead time and set up time.

2.2. Review of Multi-Criteria-Decision-Making (MCDM) Approaches

The multicriteria decision-making (MCDM) approach is commonly used to address complex problems [30]. There are four main MCDM pathways for constructing structural networks: Decision Making Trial and Evaluation Laboratory (DEMATEL), Fuzzy Cognition Map (FCM), and Interpretative Structural Modeling (ISM) [31]. Based on a systematic literature review of MCDM approaches, it was found that the DEMATEL and FCM approaches have limitations compared to ISM [32]. Particularly, the DEMATEL approach lacks consideration of all criteria and the aggregation of relative weights from experts for group decisions [33]. On the other hand, FCM requires rigorous optimization and convergence of membership functions, which can be cumbersome [34]. In contrast, ISM overcomes these limitations by effectively identifying interrelationships among factors and is considered a reliable approach for developing hierarchical structural models [31]. Combining ISM with MICMAC yields favorable results for decision makers and researchers [34]. Additionally, integrating SEM (Structural Equation Modeling) enables the estimation and testing of interactions among both measured and latent factors in the developed structural network [30], and it allows for the validation of the proposed network fitness based on expert responses [31]. Notably, BWM outperforms AHP in terms of consistency, minimal violation, total deviation, and conformity, as demonstrated in studies by [35–37]. Thus, the BWM framework is known for producing consistent results and has been extensively utilized in various domains, including manufacturing, supplier selection, risk assessment, biology, automotive, air freight transportation, R&D performance evaluation, banking services, communication technologies, and logistics. These approaches provide a systematic and quantitative means to evaluate the relative importance and impact of different factors on FMS performance, aiding decision makers in making informed decisions.

2.3. Gap Analysis

Drawing from the extensive literature assessment discussed in the preceding section, subsequent gaps have been pinpointed:

1. **Lack of Consistent Labeling**: While numerous researchers have defined the weights of performance variables in various studies pertaining to Flexible Manufacturing Systems (FMSs), only a few have classified them into dimensions based on "Quality (Q)", "Productivity (P)", and "Flexibility (F)", which would encompass the manufacturing system and technological methods [30]. This research introduces a novel classification system based on these dimensions, conveying a structured framework to assess FMS performance.
2. **Limited Deployment of a Novel MCDM Approach**: Although FMS performance variables have been considered in studies using various approaches, such as ISM, SEM, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and others, no single study has employed a novel Multi-Criteria Decision Making (MCDM) approach comparable to BWM for assessing the significance (weight) of these variables. BWM offers enhanced consistency, minimal violation, total deviation, and conformity.
3. **Inclusion of More Variables** [14]: This research has incorporated 34 key performance variables and three factors extracted from the manufacturing industry, encompassing a larger number of variables compared to other studies, indicating a more comprehensive approach.
4. **Empirical Validation**: There is a need for more empirical studies that validate the findings from conceptual frameworks and propose practical solutions for enhancing FMS performance [2]. This study bridges this gap by presenting a comprehensive empirical analysis based on a broad literature review, consultations with industry experts, and the BWM approach.
5. **Exploring Technological Advancements**: Additionally, there is limited research on the implication of technological advancements, such as Industry 4.0, on FMS performance, indicating a potential research gap in this area [4,30]. This study acknowledges this gap and, through the BWM methodology, explores the implications of these advancements on FMS performance.
6. **Scarcity of Case Studies in Europe and the USA Context**: There is a lack of case studies on FMS implementation not only in India [37] but also in German manufacturing firms, which hinders a precise understanding of the outcomes and implications of performance variables in the German context. This research draws attention to this gap and, by providing a case study, offers valuable insights into FMS performance in distinct geographical contexts.

2.4. Contributions of the Study

This study makes numerous significant contributions to the field of FMS performance evaluation. The key contributions are summarized below in Table 2:

Table 2. Key contributions of this study to FMS performance evaluation.

1.	Introduction of an innovative approach based on BWM for evaluating FMS performance.
2.	Incorporation of insights gained from an extensive literature review and consultation with industry professionals.
3.	Comprehensive overview and analysis of 272 scientific publications.
4.	Identification of research gaps in the literature.
5.	Development of a novel classification for FMS performance variables based on "(Q)", "(P)", and "(F)" dimensions.
6.	Enhancement of consistency, minimal violation, total deviation, and conformity compared to other existing approaches such as AHP.
7.	Identification of the need for further empirical studies.

Table 2. *Cont.*

8.	Highlighting the limited research on the implications of technological advancements, such as Industry 4.0, on FMS performance.
9.	Integration with other smart production system components.
10.	Consideration of sustainability.
11.	Generalizability to other industries.

3. Research Methodology

The BWM is a favored MCDM approach employed through research to evaluate and rank alternatives based on their relative strengths and weaknesses. The research process for applying the BWM method encompasses several key steps, including defining the research problem, identifying criteria and alternatives, developing the BWM survey, collecting and analyzing data, interpreting the results, validating the findings, and presenting the outcomes in a comprehensive and systematic manner. A visual representation of the research method is depicted in Figure 5, illustrating the flowchart of the further steps involved.

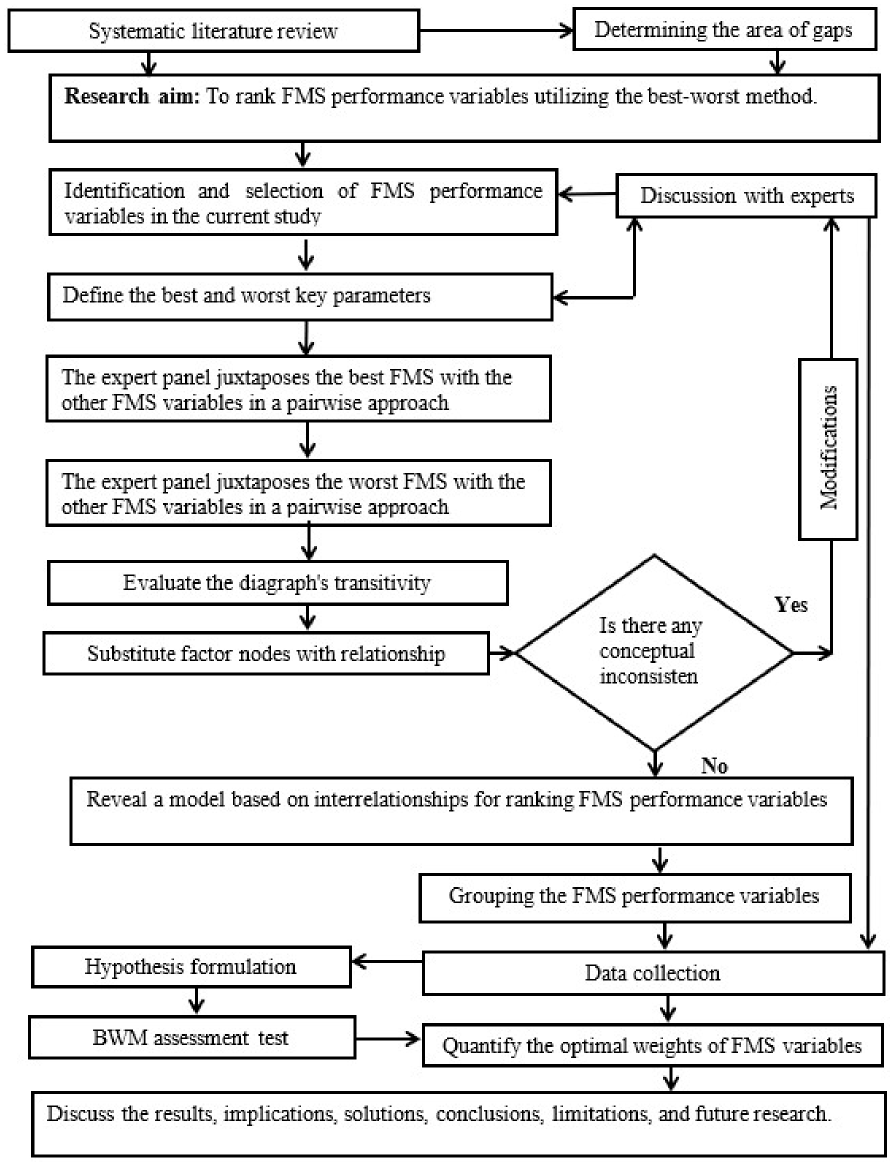

Figure 5. Research methodology flowchart.

In this investigation, a panel comprising thirteen experts was convened to determine the FMS variables that would be included in the analysis (see Table 3).

Table 3. List of decision panel experts.

Expert	Designation	Education	Exp. (in Years)
Expert 1	Academician	Ph.D. Supply Chain Management	13
Expert 2	Production Manager	M. Tech Production Engineering	9
Expert 3	Production Manager	M. Tech Industrial Engineering	13
Expert 4	Manufacturing Manager	B. E. Mechanical	9
Expert 5	Plant Manager	M. Industrial Management	14
Expert 6	Operations Manager	M. Tech Mechanical	13
Expert 7	Operation Management	Ph.D. Operational Management	4
Expert 8	Manufacturing Manager	Ph.D. Operational Management	10
Expert 9	Production Engineer	M. Industrial Management	7
Expert 10	Quality Engineer	M. Industrial Management	8
Expert 11	Production Management	M. Operational Management	10
Expert 12	Operation Management	Ph.D. Operational Management	9
Expert 13	Manufacturing Manager	Ph.D. Operational Management	13

The authors conducted in-person visits to the case organization and held brainstorming sessions with the organization's experts to present the study's framework and procedures. A concise survey was designed to collect input from the participants, and the experts were asked to complete it. Throughout the data study, the authors personally engaged with the experts to gather their viewpoints and inputs at each stage.

Based on a comprehensive literature review and expert analysis, Table 4 presents details about the chosen FMS elements. These selected FMS variables were then classified into three primary criteria: quality (Q), productivity (P), and flexibility (F).

Table 4. FMS performance variables.

Major Factor	Sub-Factor	References
Quality (Q)	Defect rate (Q1)	[37]
	Automation (Q2) *	[37,38]
	Scrap rate (Q3)	[4,38,39]
	Process capability (Q4)	[37,40,41]
	Conformance to specification (Q5)	[42]
	Effect of tool life (Q6)	[43]
	Rework percentage (Q7)	[4,43]
	First-pass yield (FPY) (Q8)	[44]
	Customer satisfaction (Q9)	[26,45]
	Rejection percentage (Q10)	[4,46]
	Takt time (Q11)	[47]

Table 4. *Cont.*

Major Factor	Sub-Factor	References
Productivity (P)	Machine utilization (P1)	[48]
	Unit labor cost (P2)	[4,49,50]
	Unit manufacturing cost (P3)	[4,43]
	Production rate (P4)	[45]
	Manufacturing lead time (P5)	[43,51]
	Work-in-progress (WIP) inventory (P6)	[4]
	Setup time (P7)	[45,48]
	OEE (Overall Equipment Effectiveness) (P8)	[52,53]
	Throughput time (P9)	[4,43]
	Labor productivity (P10)	[54]
	Setup cost (P11)	[4,48]
	Cycle time (P12)	[55]
Flexibility (F)	Changeover time (F1)	[56]
	Equipment utilization (F2)	[4,57]
	Volume flexibility (F3)	[28]
	Routing flexibility (F4)	[48]
	Product mix (F5)	[4]
	Use of automated material handling device (F6)	[25,58]
	Reduced work in process inventory (F7)	[4,43]
	Redundancy (F8)	[58]
	Use of reconfigurable machine tool (F9)	[38]
	Flexible fixturing (F10)	[59–61]
	Machine reconfiguration time (F11)	[53]

Automation (Q2) * in this study refers to the level of automation in the manufacturing process itself, not the automation of quality inspection.

3.1. Overview of BWM Approach

"Rezaei introduced the Best-Worst Method (BWM) in 2015 as a pairwise evaluation methodology used for multicriterion decision-making (MCDM) issues [36]". Its goal is to achieve consistent comparison outcomes while minimizing the number of pairwise comparisons required. BWM replaces the complete pairwise matrix with two vectors, which enables analysts to make decisions with less data. Furthermore, BWM employs a single integer scale ranging from 1 to 9 for ease of contemplation. Due to its ability to obtain quality outcomes with fewer pairwise comparisons, BWM is well suited for assessing the ranking of 34 FMS (Flexible Manufacturing System) indicators in this study.

In BWM, multiple variables are evaluated and consolidated into a single standard variable, which is then used to calculate the values of other items based on the preferences of the most effective element and the most severe element. The most effective or best parameter is compared to all other chosen elements, while the most severe or worst parameter is compared to all other parameters. BWM follows a step-by-step approach that involves five stages of implementation. In this article, to determine the pairwise comparison of the components throughout the BWM process, the Excel Solver program was employed.

3.1.1. Phases of the BWM Process

To convey a clearer understanding of how BWM works, it is essential to outline the specific phases of the methodology:

Phase 1: Determine the performance variables of the FMS.

The first step in the BWM process involves identifying the performance metrics of the FMS. An expert panel comprising manufacturing experts, denoted as {C1, C2, . . ., Cn}, is engaged to finalize the chosen FMS criteria. These criteria play an essential role in clarifying the industry's specific requirements and maximizing its capabilities. After extensive consultation with manufacturing experts, an array of 34 FMS components was validated for ranking and assessment.

Phase 2: Determining the Best and Worst FMS Components.

In this phase, the most favorable and least favorable components of the FMS are identified with input from manufacturing experts. The best criterion is considered the most imperative, preferable, or indispensable, while the worst criterion is recognized as the weakest, least essential, least preferred, or of lesser value.

Phase 3: Expert Panels' Pairwise Comparison.

In this phase, the expert panel employs a pairwise approach to compare the best parameter with the remaining elements. The panel assigns values ranging from one to nine to convey the preference for the best variable over each of the other variables. The preference of the superior variable *B* over variable j, as assessed by the expert panel, is denoted as

$$AB = (aB1, aB2, \ldots, aBn) \tag{1}$$

Here, aBj signifies the preference of the superior variable *B* over variable j, as assessed by the expert panel.

Phase 4: Expert Panels' Pairwise Comparison of the Worst Parameter.

During this phase, the expert panels utilize a pairwise approach to compare the worst parameter with the remaining variables. The panels assign values ranging from one to nine to express the preference of other variables over the suboptimal variable. The worst performance of variable *W* over variable j is denoted as:

$$AW = (a1w, a2w, \ldots, anw)T \tag{2}$$

where ajw reveals the favor of parameter j over the suboptimal variable *W*, which was determined by the expert panel.

The value of aww = 1 is constant, signifying an equal preference between the worst variable and itself.

Phase 5: Estimation of Weights for the Optimal FMS Components.

In this critical step, the previously described issue is mathematically transformed into a linear programming framework. This framework presents a structured approach to optimizing the assigned weights while considering various constraints. The primary objective is to minimize the maximum value among the expressions {$|WB/Wj - aBj| \leq \xi$, for every 'j' and $|Wj/Ww - ajW| \leq \xi$, for every 'j'. Here is a detailed explanation of this essential step:

- Minimizing Maximum Discrepancies: The core objective is to minimize the maximum absolute discrepancy between two expressions for each variable 'j'. The first expression is $|WB/Wj - aBj|$, which measures the extent to which the assigned weight WB deviates from the normalized weight aBj. The second expression is $|Wj/Ww - ajW|$, assessing the extent to which Wj differs from the variable's weight relative to the normalized.
- Balancing Variables: The linear programming framework aims to balance these variables and minimize their discrepancies. The objective is to find an optimal solution where the differences between the assigned weights (Wj) and the benchmark-based weights (aBj and ajW) are as small as possible.

- Accounting for Constraints: The framework considers specific constraints to ensure a feasible solution. These constraints include:
    - Non-negativity constraints: ensuring that all weights (Wj) are non-negative ($Wj \geq 0$ for every 'j').
    - Weight sum condition: maintaining the sum of all weights equal to 1, indicating that the weights encompass all evaluated components ($\sum j$ Wj = 1).

This linear programming approach has a single unique solution and offers a systematic method for balancing the weights while considering the constraints and normalized weight:

$$\mid WB/Wj - aBj \mid \leq \xi \text{ for all j, } \mid Wj/Ww - ajW \mid \leq \xi \text{ for every j, } \sum j\, Wj = 1, Wj \geq 0 \text{ for all j} = 1 \quad (3)$$

The outcome of this optimization process provides not only the optimal weights (W1*, W2*, W3*, . . ., Wn*) for each variable but also the optimal value of ξ, denoted as ξ*. This value reflects the degree of balance achieved in assigning weights to the FMS performance variables, with a lower ξ* indicating a more balanced and consistent allocation of weights based on the chosen normalized weight. This comprehensive approach ensures that the relative significance of these components is carefully and consistently evaluated in the FMS assessment process.

3.1.2. Consistency Ratio and Interpretation

An important aspect of the BWM methodology is assessing consistency. To evaluate how reliable the rankings are, we calculate a consistency ratio employing the consistency index.

The consistency ratio can be calculated using Equation (4):

$$\text{Consistency Ratio} = \xi^*/(\text{Consistency Index}) \quad (4)$$

The closer the ratio is to 0, the more consistent the outcome. A consistency ratio closer to 1 would imply a less reliable ranking.

3.2. Case Explanation

3.2.1. Introduction to the Subject Company

Our case study focuses on a long-standing manufacturing firm specializing in automotive component production. With nearly 40 years of experience in the automobile industry, a workforce of 1300 employees, and prestigious certifications in TS 16949 and ISO 14001, this company has maintained its position but aspired to achieve market leadership.

3.2.2. Motivation for BWM Implementation

Despite their significant achievements, the organization faces increasing competition and a need to boost manufacturing performance. To respond more effectively to customer demands for product diversity, demand, and quality in real time, the leadership decided to implement a comprehensive strategy.

After careful consideration, they selected BWM as the ideal approach to evaluate and prioritize essential performance variables for successful FMS implementation. The stakeholders and management teams were convinced by the method's analytical robustness and its systematic approach to measuring the weights of FMS variables. This adoption reflects a commitment to data-driven decision making and strategic manufacturing improvements.

3.3. Analysis of Weight Ranking

3.3.1. The Expert Panel

In an earlier phase, a panel of thirteen experts representing diverse organizations was responsible for evaluating FMS performance variables. Their task was to identify the most effective-to-others (Table 5) and other-to-most severe (Table 6) relationships for each major element. The experts' evaluations were based on their collective industry knowledge and experience. These evaluations led to the creation of best-to-others and other-to-most severe vectors, which were essential data for the subsequent analysis.

Table 5. Best compared to other variables.

Expert	Best	Q	P	F
Expert 1	Q	1	3	5
Expert 2	Q	1	8	6
Expert 3	P	2	1	3
Expert 4	Q	1	8	7
Expert 5	Q	1	2	3
Expert 6	Q	1	3	2
Expert 7	F	7	8	1
Expert 8	F	4	3	1
Expert 9	Q	1	6	4
Expert 10	P	2	1	7
Expert 11	Q	1	4	7
Expert 12	Q	1	4	7
Expert 13	Q	1	7	6

Table 6. Others compared to the worst variables.

Expert	Worst	Q	P	F
Expert 1	P	8	1	4
Expert 2	F	4	6	1
Expert 3	F	8	9	1
Expert 4	P	9	1	7
Expert 5	F	8	7	1
Expert 6	F	3	5	1
Expert 7	P	3	1	2
Expert 8	P	5	1	6
Expert 9	F	2	4	1
Expert 10	Q	1	3	4
Expert 11	F	7	4	1
Expert 12	F	7	4	1
Expert 13	P	9	1	6

3.3.2. Calculating Average Weights

After the expert panel's assessment, the individual weights assigned by each expert for Quality (Q), Productivity (P), Flexibility (F), and the Ksi* index were combined to generate average weights (see Table 7). These average weights represent a consensus of expert opinions.

Table 7. Weightage of major factors.

Expert	Q	P	F	Ksi*
Expert 1	0.6790	0.1234	0.1975	0.3086
Expert 2	0.7636	0.1454	0.0909	0.4000
Expert 3	0.3958	0.5208	0.0833	0.2708
Expert 4	0.8000	0.0555	0.1444	0.3555
Expert 5	0.5750	0.3000	0.1250	0.3250
Expert 6	0.5278	0.3611	0.1111	0.1944
Expert 7	0.6786	0.1786	0.1429	0.3929
Expert 8	0.1667	0.6852	0.1481	0.3519
Expert 9	0.7083	0.2083	0.0833	0.1250
Expert 10	0.1750	0.1000	0.7250	0.3250
Expert 11	0.7589	0.0714	0.1696	0.2589
Expert 12	0.6607	0.2143	0.1250	0.4107
Expert 13	0.7083	0.2083	0.0833	0.1250
Final weight	0.5844	0.2240	0.1715	0.2956

The formula to calculate the Ksi* (consistency index) in the Best-Worst Method (BWM) is as follows: Ksi* = $(\sum(\omega i - w\bar{\imath})2)/(n(n-1))$; Where: Ksi* is the consistency index; ωi is the BWOR (Best-to-Worst Ratio) for performance variable I; w$\bar{\imath}$ is the average BWOR ratio across all performance variables; n is the number of performance variables.

3.3.3. Ensuring Consistency

The AHP methodology was employed for this analysis, and it was imperative to assess the consistency of expert responses. The median consistency ratio weight, shown in Table 7, was calculated and found to be 0.2956. This value, close to zero, indicates a high level of consistency in expert comparisons, reinforcing the reliability of the outcomes.

3.3.4. Determining Global Weights

The major weights for each group of FMS performance variables (Quality, Productivity, and Flexibility) were calculated using their average weights. While detailed calculations are beyond the scope of this section, these weights are derived from the expert assessments in Table 8. The final rankings in Table 8 represent the global weighting for each performance variable, determined by multiplying the major weights and local weights and ranking them based on their relative importance. The local weights were assessed using Formula (3).

Table 8. Final ranking of FMS performance variables.

Major Factor	Major Weight	Sub-Factor Element	Local Weighting	Global Weighting	Ultimate Rank
Quality (Q)	0.5544	Q1	0.0942	0.0522	4
		Q2	0.0969	0.0537	3
		Q3	0.0815	0.0452	10
		Q4	0.0724	0.0401	11
		Q5	0.0933	0.0517	5
		Q6	0.0889	0.0493	7
		Q7	0.0933	0.0517	5
		Q8	0.0981	0.0544	2
		Q9	0.0863	0.0478	8
		Q10	0.1093	0.0606	1
		Q11	0.0858	0.0476	9

Table 8. *Cont.*

Major Factor	Major Weight	Sub-Factor Element	Local Weighting	Global Weighting	Ultimate Rank
Productivity (P)	0.2240	P1	0.0792	0.0177	20
		P2	0.0902	0.0202	15
		P3	0.0844	0.0189	18
		P4	0.0889	0.0199	16
		P5	0.0728	0.0163	27
		P6	0.0658	0.0147	31
		P7	0.0959	0.0215	12
		P8	0.0764	0.0171	22
		P9	0.0922	0.0207	14
		P10	0.0759	0.0170	24
		P11	0.0857	0.0192	17
		P12	0.0926	0.0207	13
Flexibility (F)	0.1715	F1	0.0790	0.0135	32
		F2	0.0912	0.0156	29
		F3	0.0975	0.0167	25
		F4	0.1069	0.0183	19
		F5	0.0892	0.0153	30
		F6	0.0924	0.0158	28
		F7	0.0750	0.0129	33
		F8	0.1005	0.0172	21
		F9	0.0958	0.0164	26
		F10	0.0733	0.0126	34
		F11	0.0992	0.0170	23

3.3.5. Final Ranking of FMS Performance Variables

In this phase of our research, the BWM analysis resulted in the assignment of weights to each major FMS factor and its subfactors. These weights indicate the relative significance of each element in the overall evaluation of FMS performance. The outcomes are presented in Table 7 for major factors and Table 8 for the final ranking of FMS performance variables based on their global weights.

To ensure the credibility of our results, we calculated the outgoing median consistency ratio, which was found to be 0.2956, a value close to zero. This proximity indicates a high level of consistency in our comparisons, reinforcing the reliability of our findings.

Table 8 provides a concise summary of the weights assigned to the major FMS factors. These factors are pivotal in evaluating FMS performance, and their weights were determined through expert evaluation and the robust BWM methodology.

Table 8 presents the global weightings of various FMS performance variables. These variables underwent a rigorous evaluation process following the BWM methodology. Due to space limitations, we provide a concise overview of the results in this section. The table includes the final rankings, scores, and relative influence of each extracted FMS performance variable.

To highlight the significance of these outcomes, let us focus on the three primary performance variables:

- Quality (Q): This factor carries a weight of 0.5544, indicating its paramount role in the FMS performance assessment.
- Productivity (P): With a weight of 0.1715, productivity is a notable, although secondary, factor in the assessment.

- Flexibility (F): Flexibility is assigned a weight of 0.2208, signifying its essential yet less influential role in the assessment process.

3.4. Findings and Discussion

The primary objective of this study was to investigate and prioritize the critical performance variables and qualitative attributes, along with their respective weightings, within German manufacturing companies utilizing the BWM method. In this study, the chief factors of FMSs that influence their performance were taken into account, i.e., quality, productivity, and flexibility, and 34 attributes that affect these parameters were also considered. To enhance the level of flexibility in manufacturing systems, organizations must therefore prioritize these performance variables based on their importance or weight. The case study's findings disclosed that among the essential parameters, the quality performance variable had the highest weight (0.5542), followed by productivity (0.2247) and flexibility (0.2208).

Quality (Q): This factor, bestowed with a weight of 0.5544, is paramount in the FMS performance hierarchy. Its high weightage signifies its vital role in the overall assessment. The highest weighted variable in terms of quality is the rejection percentage (Q10), with a weight of 0.0606. Ref. [47] argue that rejection might be caused by malfunctioning equipment and tools, workers' low levels of skill, or errors in technical working instruction and control. Nonetheless, rejected parts could be recycled; however, the effects of part rejection might also be varied and are generally grouped into two classifications: "ROI losses and operational disruptions" [43].

Nevertheless, rejection might be resolved by the following strategies: process improvement, training and skill development, feedback loops, supplier evaluation, and continuous improvement. The First-pass yield was ranked second as a quality factor, with a global weight of 0.0544. First-pass yield and rejection percentage have comparable sources of defects. Ref. [61] suggests that First-pass yield could be maintained through robust design and optimization, preventive maintenance, and supplier qualification.

Automation (Q2) came in third place in the rankings, embracing a global weight of 0.0537. According to [37,62], automation and technological improvements reduce annual labor costs while increasing productivity and flexibility in the manufacturing system. Furthermore, "a higher level of automation increases this flexibility, partly as a result of both lower machine setup costs and lower variable costs" [62].

Defect Rate (Q1) resulted in the fourth position with a global weight of 0.0522. The sources of defect rate are design, manufacturing defects, or inspection errors, which lead to increased costs, lost sales, and customer dissatisfaction. According to the study by [36], the defect in manufacturing could vary significantly depending on the industry, the product being manufactured, and the manufacturing process employed. Ref. [37] assert that the defect rate in manufacturing has been declining over time due to numerous factors, including the adoption of novel technologies, the implementation of quality improvement initiatives, and an enhanced awareness of the importance of quality. Process capability (Q4) had a global weight of 0.0401 and was the lowest ranking among the Quality (Q) segments as performance variables. Process capability is a statistical measure that quantifies the ability of a process to consistently produce output within specified limits or tolerances of customer requirements [41]. Process capability is typically evaluated by a process capability index of Cp or Cpk.

Flexibility (F): In the dimension of flexibility, F4 (routing flexibility), F8 (redundancy), F11 (machine reconfiguration time), F3 (volume flexibility), and F9 (use of reconfigurable machine tools) have the most global weight and thus have the greatest influence on FMSs [49]. The F4 (routing flexibility) had the highest global weight of 0.0236. Routing flexibility is a vital element that enables manufacturers to produce a wide range of products with varying specifications and requirements. It enhances production agility, reduces lead time, and increases overall efficiency in the manufacturing process. F8 (redundancy) is in the second position with a global weight of 0.0222. Ref. [63] define it as the presence of duplicate equipment within the FMS that can be used to take over for a machine that has failed or is undergoing maintenance. Higher redundancy can increase the FMS's flexibility [53].

Productivity (P): Among the Productivity (P) factors, Setup time (P7), Cycle time (P12), Throughput time (P9), and Unit labor cost (P2) have the highest performing effects on FMS. Setup time (P7) has a global weight of 0.0215 and refers to the time required to prepare the machines, equipment, tools, and materials for a specific production run [60]. Furthermore, Cycle time (P12) has a final weight of 0.0208, and this is the time required to finish a part from beginning to completion [55].

In summary, this study investigated a total of 34 parameters, emphasizing the importance of effective management of these flexibilities by decision makers. Ultimately, the analysis highlights that the following elements—Rejection percentage (Q10), First-pass yield (Q8), Automation (Q2), and Defect Rate (Q1)—stand out as the key factors exerting a substantial implication on FMS performance.

4. The Implications of this Study

The Experts and researchers in the manufacturing industry can derive practical value from the study's findings:

- Strategic Prioritization: Manufacturing professionals can employ the insights to strategically prioritize FMS elements. By recognizing the essential role of quality, they can focus on enhancing quality management practices and minimizing rejection rates.
- Operational Improvements: The findings on productivity and automation suggest opportunities for operational enhancement. Implementing automation and optimizing cycle times could lead to cost reductions and increased efficiency.
- Flexibility Enhancements: Manufacturing experts can leverage the interpretation of flexibility dynamics to boost their production agility in real time. Strategies such as routing flexibility and redundancy can improve overall efficiency and responsiveness in the context of Industry 4.0.
- Research and Innovation: Researchers in the field could build on this study's findings to explore related topics further. Future research might delve into specific strategies for implementing prioritized factors in real manufacturing settings.

In conclusion, this study's implications are intended to motivate practitioners and academics to develop diverse strategies for prioritizing and managing FMS variables in their respective domains of work and drive improvements within their manufacturing processes.

4.1. Theoretical Contributions

This study breaks new ground in the realm of Flexible Manufacturing Systems (FMSs) research. While several prominent manufacturing firms, such as Toyota and General Motors, have delved into the examination of FMS performance variables, none have approached the task with the comprehensive and structured methodology employed. Our research develops a novel theoretical framework that harmonizes queuing theory with decision theory [57], creating a model that unravels the intricate dynamics of FMS performance variables within the stochastic production environment. Queuing theory, a discipline rooted in mathematics, opens a gateway to understanding and analyzing an array of systems, from manufacturing to transportation and communication [64]. It allows for an in-depth exploration of how different factors, such as arrival rates, service rates, and queueing disciplines, influence these systems' performance. By merging queuing theory with decision theory, we introduce an innovative theoretical framework that affords the ability to weigh the trade-offs between distinct performance objectives like productivity, flexibility, and quality. This empowers us to pinpoint optimal strategies for operating FMSs within diverse production contexts.

Additionally, our study identifies and validates a number of significant performance variables, including operator skill level, system flexibility, and organizational culture, as the primary determinants of FMS effectiveness within real-world manufacturing environments.

According to [43], an FMS pertains to a combined computer-controlled system of digitally controlled machinery and automated material handling parts and tools that are capable of processing medium-sized volumes of various part kinds sequentially. These insights offer essential guidance to managers, enabling them to prioritize these factors when implementing and managing FMS.

Furthermore, our research serves as an empirical validation for the resource-based view (RBV) theory, emphasizing its relevance in elucidating the competitive advantage of firms that have embraced FMSs. This quantitative analysis, conducted across multiple firms, supports the applicability of the RBV concept in the context of FMSs, enriching the field of strategic management theory.

Moreover, we conveyed a lucid and comprehensive definition of FMSs, accompanied by a classification framework that classifies FMSs into diverse types based on their operational characteristics. This lucidity ensures consistency and clarity within the existing body of knowledge regarding FMS the concept and classification of FMS.

The contributions of this research extend beyond the academic realm, shedding light on the roles that require fortification and anticipating prospective enhancements. The unparalleled application of the BWM approach to assess the potential weights of FMS performance parameters, particularly within the context of 34 variables, sets this research apart in the FMS domain. Prior studies have primarily examined a smaller array of performance variables, making this comprehensive analysis a noteworthy addition to the study of FMS in the manufacturing industry.

4.2. Practical Implications

The research on FMS performance variables utilizing the BWM method offers two distinct advantages. Firstly, it requires smaller pairwise relations compared to other MCDM strategies, simplifying weight assessment for experts. Additionally, due to the reduced number of pairwise comparisons, the BWM approach generates more consistent outcomes. These reliable results and the efficiency of the BWM strategy encourage professionals and decision makers to adopt FMSs, facilitating the transformation of traditional operations into sustainable business practices.

By employing the BWM approach to analyze an array of 34 qualitative performance variables, which have not previously been explored in the field of FMSs, this study becomes a valuable tool for clarifying complex problems involving the selection of significant factors from a large array of variables.

While the study was conducted at a manufacturing firm, its findings could serve as a catalyst for further exploration and application of the BWM strategy in diverse manufacturing industries, such as steel and iron, aviation, and others. Given the growing concerns in the manufacturing industry about diminishing environmental implications, this research could be essential for companies and researchers seeking to boost sustainable frameworks within manufacturing firms. Identifying the most significant performance variables through the BWM strategy can enable companies facing limitations in personnel or resources. By prioritizing and focusing on key performance variables, companies can indirectly clarify other variables; solutions for significant variables might positively affect related ones. This approach allows for a more efficient allocation of resources and efforts to the most influential performance variables.

Furthermore, the outcomes of this investigation open up novel research avenues for academics. Future studies could expand the scope of performance variables by grouping them based on other conceptual dimensions, such as the three major dimensions of business (human, economic, and environmental). This broader application of the BWM methodology to investigate other aspects within the domain of FMS can lead to a deeper interpretation and analysis of performance variables in various contexts and perspectives.

The comprehensive approach of the FMS model, encompassing challenges in applicability and efficiency in batch system planning and design, while incorporating the job-shop layout, ensures that key system parameters and design considerations, such as work center and lot dimensions, storage management, and planning processes, are considered. This approach leads to an enhanced applicability and efficiency in batch system planning and design, particularly in the context of job-shop layouts.

5. Discussion and Conclusions

In this study, the BWM was effectively harnessed to manage the assessment of FMS performance metrics, taking into account qualitative characteristics. This method distinctly captures the qualitative characteristics of pairwise comparisons using the BWM framework, thus empowering researchers to pinpoint variables with the highest loading values. The selection of key FMS parameters was a complex process, initiated with an extensive literature review to ensure comprehensive FMS variable prioritization. Subsequently, the identified performance metrics for the study were thoughtfully curated with the invaluable input of experts from both academic and industrial backgrounds.

Through consultation with these experts, the identified FMS parameters were thoughtfully classified into three major categories: Quality, Productivity, and Flexibility. Leveraging the BWM methodology, this research assessed and assigned appropriate weightings to these finalized parameters. As a result, the study not only enables professionals to have essential interpretations of FMSs but also equips them with the tools to analyze the individual implications of each variable. This, in turn, enables deeper explorations of the most vital parameters, fostering the development of systematic strategies for their optimization.

A distinctive facet of this research is its utilization of BWM for ranking and rating, a choice that yields notably more consistent results compared to other MCDM methods. These findings will prove instrumental for professionals seeking to grasp the nuanced dynamics within their organizations, as each FMS performance variable considered in this study mirrors the influence of one of the key stakeholders—employees, suppliers, and clients. Consequently, this investigation transcends the limitations of singular, one-dimensional analyses and delves into the multifaceted aspects of FMS.

Additionally, by spotting underperforming functions within an organization, this research enables companies to proactively devise strategies for enhancing their performance by focusing on the selected key variables. The insights gathered throughout this study suggest that the performance variables it identifies, along with their respective influence powers, will serve as invaluable tools for professionals looking to discern and address the most pivotal elements for effective FMS deployment.

In addition to these merits, it is essential to note that this research makes a significant contribution in comparison to existing studies in the field. Unlike numerous prior works that concentrate on the singular dimensions of FMS, this study casts a wider net by comprehensively exploring distinct dimensions of FMS performance. Its robust methodology and inclusion of qualitative characteristics for pairwise comparisons ensure a more holistic comprehension of the subject. This not only boosts its value for experts and researchers but also solidifies its position as a significant reference point for future explorations in the realm of FMS performance assessment.

6. Limitations and Future Research

Although the current study classified 34 performance variables into three groups, it is imperative to acknowledge that other parameters might continue to influence the adoption of FMSs. These additional parameters could be further organized into logically coherent groups for more in-depth analysis.

Furthermore, the outcomes of the study heavily rely on the opinions and perspectives of experts, making a thorough evaluation of expert input essential.

It is also important to note that the current investigation focuses on the manufacturing industry in Germany, and the findings might not be directly applicable to other sectors such as aviation, construction, services, etc. Nonetheless, they could still hold value for manufacturing industries in other emerging economies such as France, the UK, Italy, and others. Conducting a large-scale survey in the manufacturing sector and comparing and verifying the findings with other research results could provide more accurate insights.

Additionally, the results of this study are specific to the case analyzed and cannot be generalized to the entire manufacturing industry in all domains. Further analysis could investigate the interrelationships between FMS performance variables using fuzzy BWM with a different set of performance variables. The findings could also be compared with other fuzzy MCDM strategies such as fuzzy PROMETHEE, fuzzy TOPSIS, fuzzy VIKOR, and fuzzy ELECTRE.

Finally, investigating the implications of external factors, such as regulatory changes, technological advancements, and market dynamics, on FMS adoption could reveal a more comprehensive interpretation of the topic.

In conclusion, the authors believe that this study makes a significant contribution to the adoption of FMSs by prioritizing performance variables. Nonetheless, additional research and analysis are needed to validate and generalize the findings to different contexts and explore other fuzzy MCDM approaches for a more comprehensive understanding of FMS adoption.

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