Research Article

Identification of Decision Support and Control Criteria in Production Systems with an Emphasis on Productivity, Reliability, Quality, and Consumption

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ABSTRACT

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Abstract:

This study aimed to identify decision support and control criteria in production systems, considering the impact of productivity, reliability, quality, and energy consumption factors at Behran Oil Company. Initially, 56 preliminary criteria were extracted based on theoretical foundations, categorized into 10 domains: production, organization, marketing and sales, finance, human resources, reliability, quality, productivity, environment, and political–governance factors. Using the fuzzy Delphi method, 10 criteria were removed, 6 were merged, and 4 new criteria were added, resulting in 41 criteria for the final evaluation. These criteria were ranked through pairwise comparison using Expert Choice software. The results indicated that production (0.183), environment (0.140), reliability (0.118), marketing and sales (0.113), and finance (0.105) held the highest importance, whereas human resources (0.038) and productivity (0.037) were considered least important. Among the indicators, the adoption of innovative methods and technologies in production was deemed most significant, while improving the viscous product quality in accordance with international standards was least significant. The findings suggest that Behran Oil Company’s success depends on simultaneous attention to sustainable production, environmental requirements, and process reliability. Although human factors and productivity were evaluated as less critical, investing in human resource development alongside advanced technologies remains essential. Accordingly, achieving optimal decision-making and organizational sustainability requires a balance between technological approaches and effective human resource management.

Keywords:

Decision Support, Production System Control, Fuzzy Delphi, Behran Oil Company

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1. Introduction

Decision-making is an inseparable component of management and plays a fundamental role in all managerial tasks, from setting policies and defining objectives to production design and performance evaluation (Tang et al., 2017). The significance of decision-making in production management is such that some researchers have defined the production process as a network of decisions and management as an act of decision-making (Miguel et al., 2021). Decision-making forms the core of production planning, and without it, planning in production systems is meaningless (Zhang et al., 2020).

Managers of production units encounter diverse situations and conditions in performing their duties, making appropriate decision-making concerning different production areas essential. Consequently, decision-making is considered one of their fundamental responsibilities in the production process (Saz et al., 2019). Moreover, managers' decision-making styles evolve throughout their professional lives, reflecting their personal approaches to understanding and responding to decision-making tasks (Skadi et al., 2015).

Continuous planning in production units requires the adoption of diverse measures and solutions so that managers can direct, lead, and control their organizations (Liu et al., 2018). Decision-making in the control of production systems represents a major managerial challenge, as managers face a variety of structural issues and situations throughout organizational operations that demand precise decision-making (Miguel et al., 2021). The decisions made not only affect organizational performance but also influence employees' quality of life and work performance (Shan & Gong, 2021). Therefore, managers must be familiar with their areas of responsibility and provide a logical rationale for each action and decision to ensure the reliability of decisions (Saz et al., 2019).

Factors affecting the quality of decision-making include production quality and energy consumption. Identifying and prioritizing these factors can enhance the production decision-making process (Zhang et al., 2020). Given the critical role of production units in the national economy, the quality of decision-making in these units has increasing importance (Tang et al., 2017) and is influenced by managerial styles and the reliability of decisions (Liu et al., 2018). Any shortcomings in planning related to quality and productivity may lead to poor decisions and adverse social consequences (Miguel et al., 2021).

In today's competitive world, productivity, as both a philosophy and a strategy for improvement, is the primary objective of production units and can, like a chain, influence the activities of various sectors of society (Dewi de J. & Dick, 2020). Productivity reflects an organization's success in utilizing resources and production factors to achieve goals, with energy consumption serving as a coordinating factor for other elements (Zhou et al., 2016; Saz et al., 2019).

With the rapid changes in markets and the need to deliver high-quality products and services, the adoption of modern management practices and quality management has become essential (Miguel et al., 2021). However, implementing productivity and quality enhancement systems in production units can sometimes lead to excessive bureaucracy and reduced performance (Liu et al., 2018; Zhang et al., 2020). Therefore, evaluating the effectiveness of these systems is necessary. In the era of knowledge-based organizations, identifying and managing the factors affecting productivity is a prerequisite for the growth and development of production units (Tang et al., 2017). Productivity is closely linked to organizational survival and competitive capability, making its understanding a key managerial priority (Saz et al., 2019). Knowledge management related to decision-making and total quality management are critical tools for enhancing productivity, quality, and human resource capabilities (Zhang et al., 2020; Liu et al., 2018). The goal of modern quality management is to achieve customer satisfaction by providing better-quality products at reasonable costs

(Miguel et al., 2021; Long, 2019). Total quality management ensures the participation of all employees and managers in the continuous improvement of quality and the maintenance of the organization's competitive advantage (Liu et al., 2018; Zhang et al., 2020).

Considering the importance of decision-making and production system control, as well as the impact of productivity, reliability, quality, and energy consumption factors, the main research question is: What are the criteria for supporting decision-making and controlling production systems while accounting for the influence of these factors?

2. Theoretical Foundations

Decision Support Systems and Production Simulation Models

Recent studies have highlighted the importance of Decision Support Systems (DSS) in improving the performance of production systems. Miguel et al. (2021), in their study titled "A Modeling Framework for Supporting Decision-Making and Control in Production Systems," demonstrated that productivity, reliability, quality, and energy consumption factors have a direct and positive impact on the effectiveness of DSS frameworks. Similarly, Pierce et al. (2023) showed that trust-based DSSs, utilizing reinforcement learning and digital twins, can enhance the accuracy of recommendations in industrial environments. Wang and Choi (2022) proposed the CEPC framework, illustrating that human augmentation in the decision-making process and providing workflow flexibility can create an efficient human-centered production system.

Within Iran, Sifi Sariqieh (2017) designed a model-driven DSS to integrate performance evaluation and risk management in construction investment projects, demonstrating increased decision-making accuracy and effectiveness in both planning and execution phases. Shirazi et al. (2018) examined the current state of production control in an industry and proposed a production control system using various modeling tools, showing that simulation and process flowcharts can address existing weaknesses. Additionally, Bateni et al. (2018) developed a comprehensive simulation model for multi-product workshop systems with customized demand, offering an optimized production system approach for decision-making and resource allocation management.

Productivity, Quality, and Reliability in Production Systems

The relationship between productivity, quality, and reliability with the performance of production systems has been examined in various studies. Witt (2019), using an organizational climate questionnaire, demonstrated that organizational climate has a positive relationship with productivity. Komatsu (2015) showed that human, structural, and physical capital -components of reliability-significantly affect company profitability and productivity. In the area of quality and performance, Carmeli (2021) found that management and decision-making skills can rapidly enhance organizational performance. Bakil et al. (2020) also demonstrated that managers' political capabilities and adaptability to the environment are significantly associated with job performance. García Lara et al. (2017) emphasized the role of decision-making algorithms and prudence in improving company investment and profitability. Kheirkhah et al. (2024) also identified and analyzed the importance–performance matrix of effective indices in lean product manufacturing with an emphasis on the circular economy approach based on the requirements of Industry 4.0.

Multi-Criteria and Fuzzy Decision-Making Methods in Management and Production

The use of multi-criteria and fuzzy decision-making methods in project management and production has facilitated the identification and prioritization of key criteria. Domestic studies indicate that these approaches are highly applicable to the oil and gas industries as well as industrial manufacturing. For instance, Reyhaninia et al. (2023) employed multi-criteria decision-making to identify 20 main criteria for prioritizing upstream oil investment projects. Moniri et al. (2022) evaluated the risks of major maintenance projects in upstream process industries using a combined fuzzy SWARA and EDAS method. Additionally, Aghdasi et al. (2019) and Ghodrati Abbasi et al. (2019) analyzed the impact of changes in production control parameters on system performance through simulation and sensitivity analysis. In the context of supplier selection and environmental decision-making, Haji Yakhchali et al. (2017) combined fuzzy methods with AHP to identify key criteria for selecting green suppliers. Moreover, Amoushahi et al. (2015) examined outranking methods, PROMETHEE and ELECTRE, for ranking options in environmental decision-making.

A review of domestic and international studies reveals that the integration of productivity, quality, reliability, and energy consumption within DSS frameworks and multi-criteria decision-making models has not yet been comprehensively examined in a systematic framework. Most studies focus either on simulation and DSS or on multi-criteria and fuzzy decision-making, but few have analyzed the interrelated effects of these factors in real production processes. Therefore, the present study aims to identify criteria for supporting decision-making and controlling production systems, considering the influence of productivity, reliability, quality, and energy consumption, thereby filling an existing gap and providing a practical framework for industrial managers.

3. Material and methods

This study is applied in nature and aims to identify and prioritize criteria for supporting decision-making and controlling production systems, considering productivity, reliability, quality, and energy consumption factors at Behran Oil Company. The research adopts a mixed-methods approach. In the qualitative phase, the relevant criteria were identified through literature review and expert interviews. In the quantitative phase, these criteria were prioritized using a pairwise comparison questionnaire.

The statistical population consisted of experts and specialists with relevant positions, at least five years of work experience, and related educational backgrounds at Behran Oil Company (Tehran Province). Participants were selected through non-random judgmental sampling, and ultimately 12 accessible and willing experts were chosen as the sample. Data collection tools included semi-structured interviews in the qualitative phase and pairwise comparison questionnaires in the quantitative phase.

Data analysis for the criteria identification phase was conducted using the fuzzy Delphi method (based on the standard steps of Chang, Hsu, & Chang, 2011), while prioritization was performed using the pairwise comparison method. According to the researcher’s judgment, the Delphi stopping criteria in this study were defined as follows:

All indicators or questions are recognized as important;

No new indicators are proposed by the experts.

4. Results

Definition of Linguistic Variables

To reduce the subjective effects of different experts in interpreting qualitative variables, triangular fuzzy numbers were defined for the linguistic variables: Very Low, Low, Medium, High, and Very High (Table 1 and Figure 1). The crisp (defuzzified) values of the fuzzy numbers were calculated using the Minkowski formula as follows (Chang & Lin, 2002).

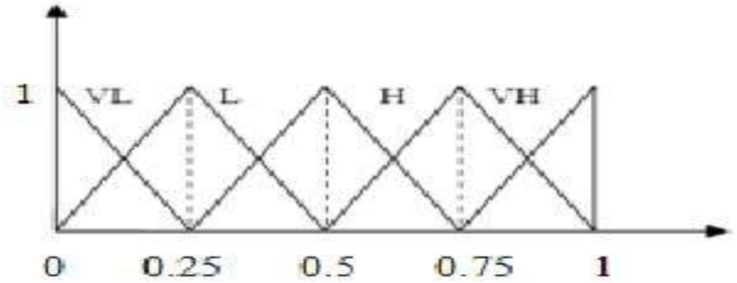

Figure 1. Definition of Linguistic Variables

Table 1. Triangular Fuzzy Numbers and Linguistic Variables

Linguistic Terms	Triangular Fuzzy Numbers	Defuzzified Fuzzy Number
Very Low	(0, 0, 0.25)	0.0625
Low	(0, 0.25, 0.5)	0.0625
Medium	(0.25, 0.5, 0.75)	0.3125
High	(0.5, 0.75, 1)	0.5625
Very High	(0.75, 1, 1)	0.75

$$X = m + \frac{\beta - \alpha}{4}$$

Equation (1)

In the above equation, X represents the defuzzified value of the fuzzy number, while m denotes the lower limit, β the upper limit, and α the middle value of the triangular fuzzy number.

First-Stage Survey

In this stage, 56 criteria were initially identified based on the research literature (Table 2). The selected components were then sent to the expert group, and their level of agreement with each component was collected. Suggested and corrective comments were also compiled. Based on the proposed options and the linguistic variables defined in the questionnaire, the results of the review and responses are presented in Table 2. The fuzzy average of each component was calculated using the following equations (Cheng & Lin, 2002):

$$A_1 = (a_1^{(i)}, a_2^{(i)}, a_3^{(i)}), i = 1,2,3,..n$$

Equation (2)

$$A_{ave} = (m_1, m_2, m_3) = (\frac{1}{n}\sum_{i=1}^{n} a_1^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a_2^{(i)}, \frac{1}{n}\sum_{i=1}^{n} a_3^{(i)})$$

In Equation (2), Ai represents the opinion of the i-th expert, and A_{ave} denotes the average of the experts' opinions. a1, a2, and a3 correspond to the triangular fuzzy numbers.

The results of the first-stage calculations indicated that some factors with a fuzzy mean less than 0.3 were considered of low importance and were removed from further calculations. These include:

- Improvement and development of transportation and logistics systems
- Inspection and control of instrumentation, mechanical, and electrical equipment
- Accurate identification and definition of activities

- Participation of organizational units
- Understanding and reducing employee resistance regarding adopted decisions
- Reduction of operational staff in production planning and workshop sections
- System reconfiguration
- Physical conditions of the work environment
- Occupational health and safety
- Transfer of human intelligence to production

After reviewing the first-stage survey forms and collecting expert feedback from both the forms and open-ended questions, the following changes were made to the factors:

- The factors (Responsiveness to changes, Rapid response to market changes, Quick response to changing customer needs, and Production planning to align with customer requirements) were conceptually similar and merged under the title Rapid Responsiveness to Unplanned Changes.
- The factors (Performance evaluation and feedback) and (Information on time spent and costs related to performance) were merged under Performance Evaluation Information.
- The factors (Standardization of operations and documentation of production procedures) and (Standardization and implementation according to global standards) were merged and retained as Standardization and Implementation According to Global Standards.
- The factors (System integration and development/implementation of integrated control systems, Automation and Robotics) were combined under System Integration.
- The factors (Making the production system flexible and centralized, Just-in-Time production system) were merged as Flexible and Just-in-Time Production System.
- The factors (Supplier relationships and Supply Chain Management) were merged and examined under Supply Chain Management.

Additionally, the following factors were added to the model:

- Reduction of production cycle time
- Product variety according to current customer needs
- Information on budget allocation
- Detailed information on the timing and sequencing of operations for each part of the final product and for the final product as a whole

Second-Stage Survey

In this stage, after applying the necessary modifications to the criteria for supporting decision-making and controlling production systems, considering the influence of productivity, reliability, quality, and energy consumption, a second questionnaire was prepared. This was sent to the expert group along with each expert's previous responses and the degree of deviation from the average of other experts' opinions. The threshold was calculated using the following equation:

Equation (4)

$$s(A_{m2} \times A_{m1}) = \left| \frac{1}{3}[(a_{m21} + a_{m22} + a_{m23}) - (a_{m11} + a_{m12} + a_{m13})] \right|$$

In Equation (4), (am_{21},am_{22},am_{23}) represents the expert's opinion in the second stage, and (am_{11},am_{12},am_{13}) denotes the expert's opinion in the first stage. The difference between the two stages is shown as $S(A_{m2},A_{m1})$. The results of the second-stage survey responses are presented in Table 2.

Table 2. Second-Stage Survey Results and Experts' Average Opinions

No.	Criterion Name	Importance Level					Triangular Fuzzy Mean			Defuzzified Mean
		Very Low	Low	Medium	High	Very High	B=Upper bound	α =Middle	M= Lower bound	
1	Ability to respond quickly to unplanned changes	0	3	3	4	2	0.8125	0.6042	0.3542	0.4063
2	Providing a basis for participation in decision-making	0	2	4	4	2	0.8333	0.6250	0.3750	0.4271
3	Process reliability	1	1	2	4	4	0.8542	0.6875	0.4583	0.5000
4	System integration	1	2	3	4	2	0.7917	0.5833	0.3542	0.4063
5	Information related to performance evaluation	1	2	4	3	2	0.7708	0.5625	0.3333	0.3854
6	Supply security (ensuring products are sold) and customer stability	0	1	3	5	3	0.8958	0.7083	0.4583	0.5052
7	Quality control during the process and use of advanced laboratory tests for product quality control	0	2	3	4	3	0.8542	0.6667	0.4167	0.4635
8	Competition in production and product sales	0	1	4	5	2	0.8750	0.6667	0.4167	0.4688
9	Accurate information about machinery and equipment along with complete data listed by power, speed, and feeds of all devices	0	2	5	3	2	0.8125	0.6042	0.3542	0.4063
10	Product design and production automation	1	2	4	3	2	0.7708	0.5625	0.3333	0.3854
11	Utilization of modern methods and technologies in production	0	2	2	4	4	0.8750	0.7083	0.4583	0.5000
12	Reduction of production cycle time	0	2	4	4	2	0.8333	0.6250	0.3750	0.4271
13	Information about the workforce in the organization and monitoring their efficiency and production capacities	1	2	4	4	1	0.7708	0.5417	0.3125	0.3698
14	Productivity growth through the use of skilled personnel	0	1	5	4	2	0.8542	0.6458	0.3958	0.4479
15	Capital and operational costs	1	1	4	4	2	0.8125	0.6042	0.3750	0.4271
16	Comprehensive environmental quality management	1	2	2	5	2	0.8125	0.6042	0.3750	0.4271
17	Increasing energy consumption efficiency	0	0	3	4	5	0.9375	0.7917	0.5417	0.5781
18	Research and development and new product development	1	2	3	4	2	0.7917	0.5833	0.3542	0.4063
19	Comprehensive maintenance and repair	1	1	3	4	3	0.8333	0.6458	0.4167	0.4635
20	Product diversity according to current customer needs	1	1	5	3	2	0.7917	0.5833	0.3542	0.4063
21	Improving the viscosity quality index of products according to global standards	1	1	5	4	1	0.7917	0.5625	0.3333	0.3906
22	Training and motivating employees to understand the requirements of the production control system	1	2	4	4	1	0.7708	0.5417	0.3125	0.3698

No.	Criterion Name	Importance Level					Triangular Fuzzy Mean			Defuzzified Mean
		Very Low	Low	Medium	High	Very High	B=Upper bound	α =Middle	M= Lower bound	
23	Management of raw materials consumption and inventory control to minimize production costs	0	1	4	4	3	0.8750	0.6875	0.4375	0.4844
24	Providing additional services and support to customers	1	2	4	4	1	0.7708	0.5417	0.3125	0.3698
25	Appropriate hardware and software infrastructure	1	2	5	2	2	0.7500	0.5417	0.3125	0.3646
26	Information regarding budget allocation	0	1	4	5	2	0.8750	0.6667	0.4167	0.4688
27	Application of knowledge management in the organization	1	2	4	4	1	0.7708	0.5417	0.3125	0.3698
28	Supply chain management	0	1	4	5	2	0.8750	0.6667	0.4167	0.4688
29	Benchmarking	1	2	5	3	1	0.7500	0.5208	0.2917	0.3490
30	Overhaul operations for repairing and refurbishing worn-out equipment	1	1	5	3	2	0.7917	0.5833	0.3542	0.4063
31	Accurate information about the timing and sequence of operations for each part of the final product and the overall final product	0	2	6	2	2	0.7917	0.5833	0.3333	0.3854
32	Pollution control (recycling of waste inside and outside the organization) and reducing harmful environmental impacts	1	1	3	4	3	0.8333	0.6458	0.4167	0.4635
33	Countering sanctions	0	1	5	4	2	0.8542	0.6458	0.3958	0.4479
34	Political and regional developments	0	2	5	3	2	0.8125	0.6042	0.3542	0.4063
35	Export management	1	1	4	3	3	0.8125	0.6250	0.3958	0.4427
36	Information about production orders and demand management	0	2	4	4	2	0.8333	0.6250	0.3750	0.4270
37	Material requirements planning (accurate and up-to-date information about total raw material needs, available materials, and the time required to receive them)	0	2	4	4	2	0.8333	0.6250	0.3750	0.4271
38	Support from senior management and all influential individuals in the organization or those affecting organizational decision outcomes	1	2	4	3	2	0.7708	0.5625	0.3333	0.3854
39	Database for scheduling, planning, and production control	0	3	4	3	2	0.7917	0.5833	0.3333	0.3854
40	Standardization and implementation of standards according to global levels	0	1	5	4	2	0.8542	0.6458	0.3958	0.4479
41	Increase and continuity of current production levels	0	0	4	5	3	0.9167	0.7292	0.4792	0.5260

In the first survey round, the experts' opinions regarding the importance of the criteria showed considerable divergence. By repeating the Delphi process and providing feedback from the first round, the level of disagreement decreased in the second round, and consensus among members increased. The difference between the first and second rounds was calculated using Equation 4. Since this difference was lower than the very low threshold (0.1), the survey process was terminated. This trend indicates an increased agreement and the reliability of the criteria assessment, confirming that the use of the fuzzy Delphi method was able to systematically integrate the diverse viewpoints of the experts.

Based on the results obtained from the previous round of the fuzzy Delphi method (refining the criteria for supporting decision-making and controlling production systems while considering the influence of productivity, reliability, quality, and energy consumption), the final research model, which includes the criteria refined by the experts, is presented in Table 3.

Table 3. Criteria and sub-criteria for supporting decision-making and controlling production systems

Main Criterion	Sub-Criteria	Status	Code
Production	Management of raw materials and inventory control for production at minimum cost	Approved	P1
	Detailed information on the timing and sequence of operations for each part of the final product and for the final product as a whole	Approved	P2
	Research and development and new product development	Approved	P3
	Utilization of modern methods and technology in production	Approved	P4
	Supply chain management	Approved	P5
	Product design and production automation	Approved	P6
	Increase and continuity of current production levels	Approved	P7
	Material requirements planning (accurate and up-to-date information on all material needs, available materials, and time required for procurement)	Approved	P8
	Database for production scheduling, planning, and control	Approved	P9
	Information on production orders and demand management	Approved	P10
	Reduction of production cycle time	Approved	P11
	Detailed information about machinery and equipment along with complete data listed by power, speed, and feed of all machines	Approved	P12
Organization	System integration	Approved	O1
	Availability of participation in decision-making	Approved	O2
	Adequate hardware and software infrastructure	Approved	O3
	Application of knowledge management in the organization	Approved	O4
	Benchmarking	Approved	O5
	Rapid responsiveness to unplanned changes	Approved	O6
	Performance evaluation-related information	Approved	O7
	Standardization and implementation of standards according to global level	Approved	O8
	Support from top management and all influential individuals in the organization or those affecting organizational decision outcomes	Approved	O9
Marketing & Sales	Competition in production and sales	Approved	M1

Main Criterion	Sub-Criteria	Status	Code
	Supply security (assurance of product sales) and customer stability	Approved	M2
	Providing additional services and customer support	Approved	M3
	Export management	Approved	M4
	Product variety according to daily customer needs	Approved	M5
Finance	Capital and operational costs	Approved	F1
	Information related to budget allocation	Approved	F2
Human Resources	Training and motivating employees to understand the requirements of the production control system	Approved	H1
	Information on workforce, productivity, and control of employees and production capacities	Approved	H2
Reliability	Process reliability	Approved	R1
	Overhaul operations for repairing and refurbishing worn-out equipment	Approved	R2
	Comprehensive maintenance	Approved	R3
Quality	In-process quality control and use of advanced laboratory modifications for product quality control	Approved	Q1
	Improvement of product viscosity index quality according to global standards	Approved	Q2
Productivity	Productivity growth using skilled personnel	Approved	E1
	Increasing energy consumption efficiency	Approved	E2
Environment	Pollution control (recycling of waste inside and outside the organization) and reducing harmful environmental impacts	Approved	En1
	Comprehensive environmental quality management	Approved	En2
Political & Governance Factors	Political and regional developments	Approved	P1
	Countering sanctions	Approved	P2

Prioritization of Model Criteria and Sub-Criteria Using the Pairwise Comparison Technique

To prioritize the components obtained from the previous fuzzy Delphi technique, the pairwise comparison technique was applied within each of the ten dimensions of the research model (Production, Organization, Finance, Marketing & Sales, Human Resources, Reliability, Quality, Productivity, Environment, Political & Governance). Accordingly, a pairwise comparison questionnaire was designed, and the research experts were asked to express their opinions regarding the importance of the indicators that had been identified through interviews and confirmed in the fuzzy Delphi stage.

Based on Table 3, the decision hierarchy tree for prioritizing the criteria of decision support and control systems in Behran Oil Company was drawn, as shown in Figure 2.

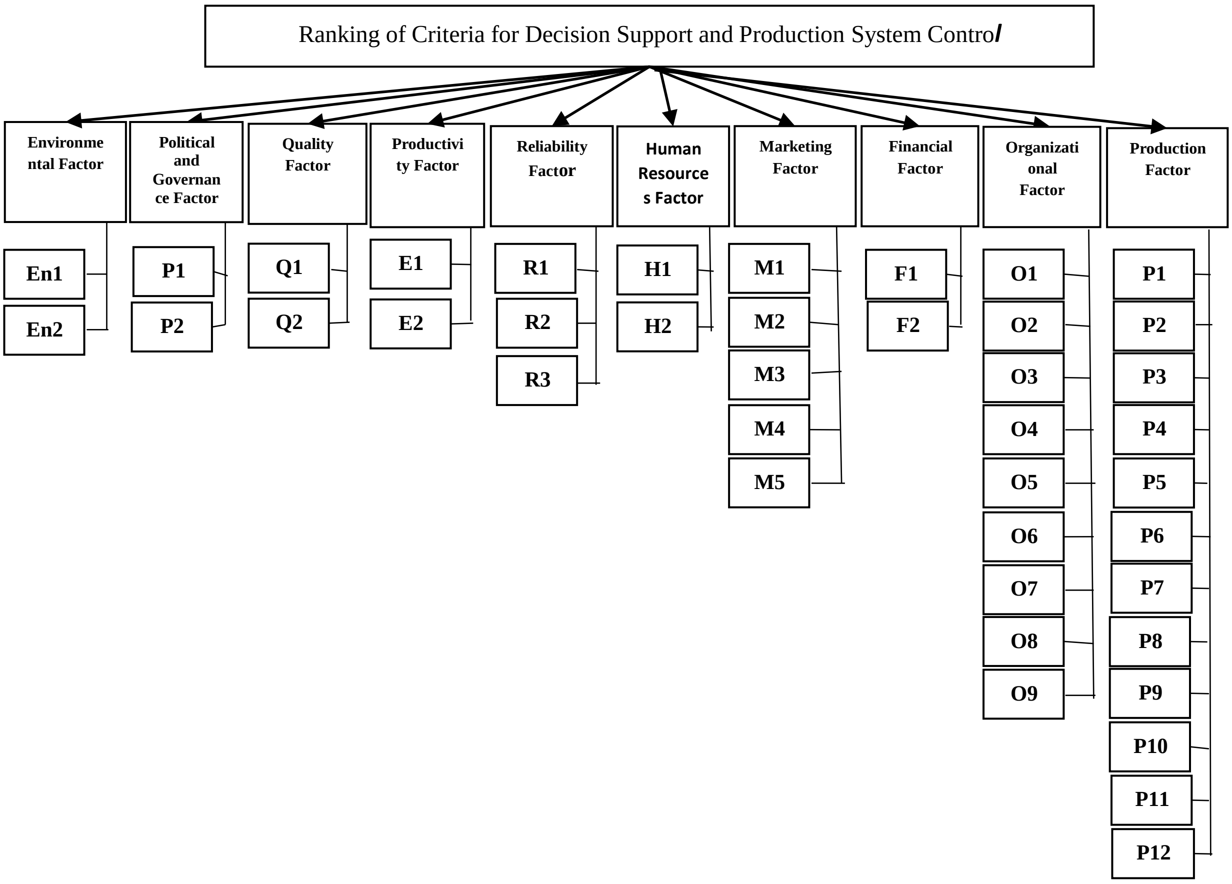

Figure 2. Hierarchical Tree of Criteria for Decision Support and Control Systems in Behran Oil Company

After preparing the pairwise comparison questionnaire and distributing it among the experts of Behran Oil Company, the geometric mean of their opinions was entered into Expert Choice software, and the results of the group analysis of decision-makers' views were presented. To this end, the pairwise comparison questionnaire was first distributed among the experts, and after collecting their responses, the opinions were aggregated using the geometric mean and used for the subsequent stages of analysis.

According to the experts' opinions and the software output, the prioritization of the criteria for decision support and control systems in Behran Oil Company is presented in Figure 3. Considering that the inconsistency ratio extracted from the software is 0.08, the results are acceptable.

Figure 3. Prioritization Results of Decision Support and Control System Criteria in Behran Oil Company

The calculation of the weights of the sub-criteria for decision support and control systems in Behran Oil Company, based on the experts' opinions and software output, is presented in Figure 4. Since the inconsistency ratio obtained from the software is 0.08, the results are considered acceptable.

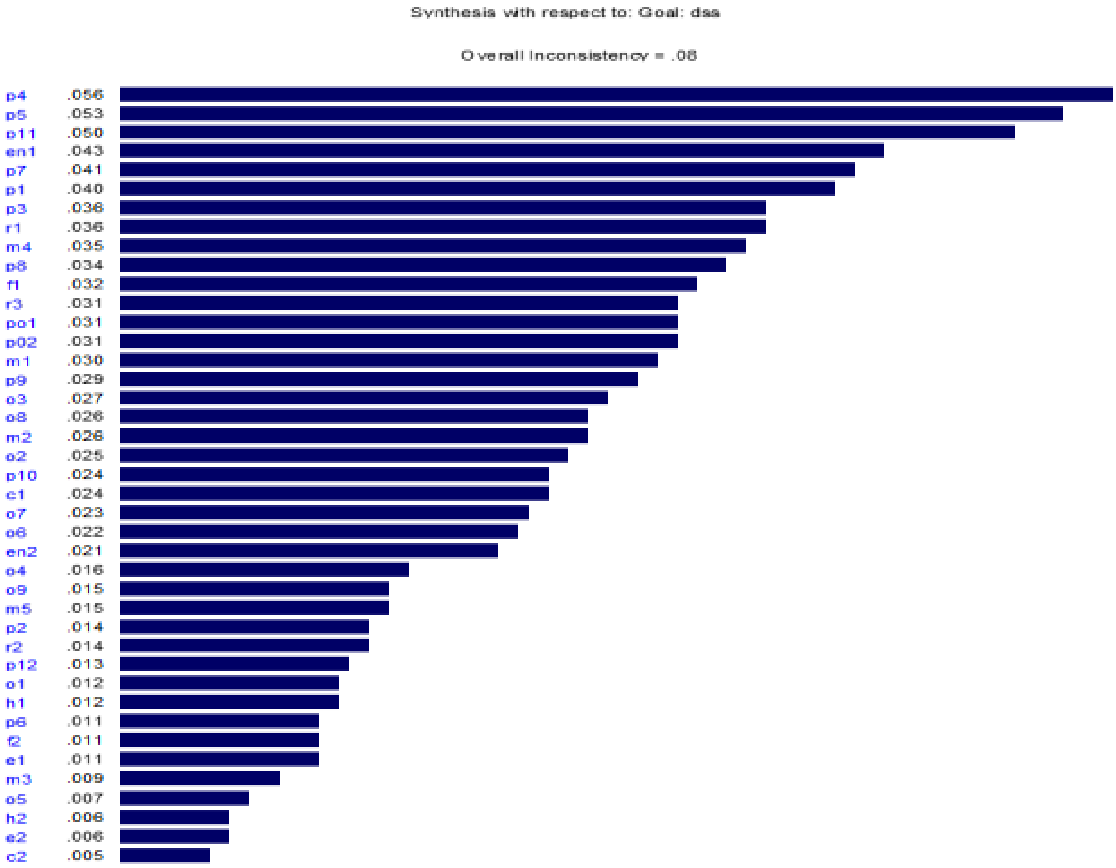

Figure 4. Ranking of Sub-Criteria for Decision Support and Control Systems in Behran Oil Company

5. Discussion and Conclusion

This study aimed to identify and prioritize the criteria for decision support and control of production systems, with an emphasis on productivity, reliability, quality, and energy consumption in Behran Oil Company. Based on the theoretical foundations, the criteria were identified across ten main dimensions: production, organization, marketing and sales, finance, human resources, reliability, quality, productivity, environment, and political-governance factors. Then, using the fuzzy Delphi method, 10 criteria were removed, 6 criteria were merged, and 4 new criteria were added, resulting in a final set of 41 criteria for evaluation.

The results of this study showed that the production dimension holds the highest importance among the identified criteria. This finding is expected, as in the oil industry, production continuity and sustainability are considered critical for organizational survival and competitiveness. The presence of complex equipment, high sensitivity of processes, and the substantial costs associated with production downtime lead managers to focus primarily on this area. This finding aligns with the research of Zeng et al. (2020), which identified production and reliability as two fundamental elements for improving productivity.

The second-ranked dimension was environment, reflecting the growing importance of environmental issues in energy industries. Currently, legal pressures and social expectations require companies to comply with environmental standards and reduce pollutants. This finding is consistent with recent studies in the Iranian oil sector, which emphasize the necessity of adhering to environmental requirements and corporate social responsibility.

Reliability was identified as the third most important factor. Given the high capital costs of oil equipment and processes, any failure or operational interruption can result in significant losses. Therefore, attention to system reliability is essential to reduce risk and enhance safety. This result is reinforced by Liu et al. (2018), who highlighted that quality management systems are effective only when implemented alongside technical reliability measures.

Conversely, human resources and productivity were rated as the least important. This result may reflect the specific conditions of Behran Oil Company, where production processes are heavily dependent on technology and equipment, and the direct role of human resources in decision-making is less pronounced. However, this could be considered a weakness, as previous studies (e.g., Migal et al., 2021) have shown that a well-trained human capital plays a key role in supporting advanced production technologies. Therefore, the low importance of human resources in this study can serve as a warning for managers to focus more on employee training and empowerment.

Among individual criteria, “utilization of modern technology in production” received the highest priority. This indicates that for competing in international markets and improving product quality, the organization primarily needs technological innovation. In contrast, “improving the viscosity quality index of products according to global standards” was ranked lowest, suggesting that managers perceive current minimum quality requirements as already met, and further improvements provide limited added value.

Overall, the findings of this study indicate that the success of production systems in Behran Oil Company depends on simultaneously focusing on sustainable production, compliance with environmental standards, and enhancing process reliability. While criteria such as human resources and productivity were assigned lower importance, this does not imply they are unimportant; rather, it reflects the technology-oriented perspective dominating organizational decision-making. Comparison with previous studies shows that these results align with global trends in the energy sector, with the difference that human factors are still less emphasized at Behran Oil Company. Accordingly, achieving optimal decision-making and organizational sustainability requires managers not only to invest in modern technologies and improve equipment reliability but also to pay greater attention to human resource development and organizational culture.

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The author has no conflicts of interest to declare that are relevant to the content of this article.

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