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Uncovering Critical Drivers and Structuring a Hierarchical Criterion Framework for Maintenance Integration in Open-Shop Manufacturing Systems: A Hybrid DEMATEL–ROV Decision Model

[1]Samira Karimi Sefiddashti, [2]Majid Vaziri Sarashk, [3]Gholamreza Esmailian

[1]Department of Industrial Engineering, Na.C., Islamic Azad University, Najafabad, Iran.

[2]Department of Industrial Engineering, Na.C., Islamic Azad University, Najafabad, Iran.

Email: ma.vs1360@iau.ac.ir

[3]Department of Industrial Engineering, Payame Noor University, Tehran, Iran.

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ABSTRACT

Production planning and scheduling play a critical role in enhancing operational efficiency within manufacturing facilities. In practical applications, such as scheduling net activities, cleaning operations, production in various industries, and associated auxiliary processes, any delay in task execution inevitably leads to increased resource expenditure. This phenomenon, widely recognized in the literature, is often described as the time-dependent degradation effect. Consequently, integrating maintenance and repair strategies into production planning, particularly within open-shop manufacturing systems, is of paramount importance. Motivated by the lack of research systematically identifying factors affecting the integration of maintenance and production activities, the present study investigates this issue within an open-shop production context. A hybrid multi-criteria decision-making approach, combining the DEMATEL method with a novel Ordered Priority Approach (OPA), is employed. DEMATEL is utilized to screen the collected criteria and uncover causal relationships among them, while OPA is applied for systematic ranking. The results indicate that, after DEMATEL-based screening, ten critical criteria are identified. According to the OPA analysis, availability of tools, materials, spare parts, and equipment, production operating costs, and maintenance and repair expenses are ranked as the top three factors in terms of significance.

Keywords: Maintenance and repair, open-shop production system, DEMATEL, Ordered Priority Approach

1. Introduction

Adaptability to demand fluctuations and efficient product design under limited time and cost constraints is widely regarded as a key success factor in manufacturing industries (Zhao & Zhou, 2022). Traditional production systems, such as job-shop and flow production, often fail to respond swiftly to such variations, leading to inefficiencies and increased operational costs. In contrast, modern production paradigms, including cellular manufacturing and open-shop systems, offer enhanced flexibility and are well-suited to address these challenges. Specifically, open-shop manufacturing systems provide a structured approach to implementing advanced production technologies (Wang et al., 2022), enabling better utilization of process similarities across product lines to improve overall productivity.

An open-shop system can be viewed as a hybrid approach, combining elements of both job-shop and flow production, and is particularly effective for producing medium-volume, multi-product batches (Goli et al., 2021). Over recent decades, considerable attention has been given to integrating different operational domains, including production planning, quality control, maintenance, and material supply (Ertogral & Ozturk, 2019). Each of these domains functions as a core component of the manufacturing system, with interdependencies that make isolated analysis inadequate. Therefore, a holistic integration strategy is essential to capture all relevant factors affecting operational performance.

Significant efforts have been made to integrate production planning with maintenance activities, especially preventive maintenance (PM), to ensure machines operate efficiently over time. The interdependence between production schedules and maintenance planning is particularly critical in high-volume manufacturing, where machinery depreciation and system wear directly influence operational efficiency (Liu et al., 2009; Kim & Gershwin, 2008; Bouslah et al., 2016). Preventive maintenance mitigates equipment degradation, reduces unexpected downtime, and enhances machine longevity (Souza et al., 2022).

Moreover, production outputs inherently include historical waste data, with finished products transferred to quality control centers for inspection. Defective items are discarded, while approved products proceed to customers. This highlights the importance of integrating production planning, preventive maintenance, and quality management to minimize losses, optimize resource allocation, and ensure consistent product quality.

This study contributes to the literature by simultaneously addressing production, maintenance, and quality dimensions within an open-shop manufacturing context. Unlike previous studies that often focus on isolated aspects, the proposed framework leverages a hybrid DEMATEL-OPA approach, offering both causal insights and prioritized decision-making for critical operational factors. This approach enhances managerial decision-making, providing actionable guidance for optimizing maintenance-production integration in dynamic manufacturing environments.

2. Literature Review

Maintenance decision-making and production scheduling have been widely investigated across various manufacturing contexts, yet their integration—especially within Open Shop environments—remains comparatively underexplored. Recent studies highlight diverse methodological approaches aimed at improving maintenance strategy selection, machine reliability, and production efficiency through multi-criteria and optimization techniques.

Farwaha et al. (2025) developed a comprehensive case-based MCDM framework incorporating SAW, TOPSIS, and VIKOR to determine optimal maintenance strategies for a placer boom system, demonstrating that combining cost, reliability, implementation time, and operational feasibility yields superior maintenance decisions. In a complementary direction, Dos Santos et al. (2024) integrated process mining, MCDM, and data fusion techniques to evaluate risk and crisis scenarios for prioritizing industrial machinery, showing that maintenance-related indicators significantly influence equipment ranking accuracy.

Mahmud et al. (2024) employed the Analytic Hierarchy Process (AHP) to select appropriate maintenance tactics for a cement manufacturing plant, identifying a mixed strategy dominated by preventive maintenance. Their findings reinforce the critical role of multi-dimensional performance factors—such as failure likelihood, downtime, and cost—in maintenance planning. Other optimization-centered studies such as Zhang et al. (2023) proposed advanced multi-phase particle swarm algorithms to resolve dynamic job-shop scheduling problems, highlighting the computational complexity and uncertainty inherent in NP-hard production systems.

Research also emphasizes the growing importance of integrating maintenance policies into scheduling environments. Suza et al. (2022), for example, proposed a mathematical model to coordinate job-shop

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Research Article

scheduling under deterministic and stochastic machine unavailability due to preventive and corrective maintenance. Their hybrid simulation–genetic approach demonstrated the necessity of incorporating machine breakdown risks into robust scheduling policies. In earlier work, Fitouhi and Nourelfath (2014) investigated joint tactical production planning and non-cyclic preventive maintenance in multi-state systems, emphasizing the interdependence between production targets and equipment health.

Several scholars have focused on improving scheduling efficiency by linking setup times, machine readiness, and deterioration effects. Loh et al. (2015) formulated the flexible flow-shop scheduling problem with unrelated machines as a mixed-integer model and later introduced a simulated annealing heuristic to handle large-scale cases. Lin et al. (2015) evaluated preventive maintenance policies using classical and Bayesian deterioration models for locomotive wheelsets, illustrating that reliability-based policy design substantially enhances system performance.

Studies in aerospace, energy, and mechanical systems have also contributed to maintenance optimization literature. Regattieri et al. (2015) introduced a heuristic framework for optimizing aircraft maintenance policies, validated through an A320 case study. Ruiz and Maroto (2016) extended scheduling research by integrating unrelated parallel machines with sequence-dependent setups, machine eligibility constraints, and limited machine availability—features reflective of real-world shop-floor conditions. Similarly, Yang et al. (2017) modeled preventive maintenance under external shocks, highlighting the need to tailor maintenance policy to equipment aging profiles.

Integration-focused research has also expanded in recent years. Liu et al. (2017) proposed a mathematical model linking maintenance and production planning by explicitly accounting for sequence-dependent setup costs and downtimes. Miyata et al. (2019) combined time-dependent processing and maintenance scheduling into an integrated job-shop formulation solved via heuristic methods. Amiri and Honarvar (2018) investigated joint maintenance and scheduling within energy hubs under stochastic equipment failures using ε-constraint optimization.

Advances in predictive maintenance have further reshaped the literature. Tokoli-Moghadam et al. (2022) applied reinforcement learning for predictive maintenance-aware scheduling, demonstrating superior performance over traditional methods including neural and heuristic models. Similarly, recent works in Persian-language literature (e.g., Khaaksari & Ghandi-Bidgoli, 2023) addressed no-wait flow-shop scheduling under preventive maintenance constraints, proposing hybrid metaheuristics for large-scale NP-hard problem instances. Shahbazi and Vahidi (2024) extended the discussion by integrating simulation-based optimization for determining machine counts in uncertain job-shop environments with budget and space limitations.

Collectively, these studies indicate extensive progress in maintenance strategy formulation, reliability modeling, and scheduling optimization. However, a critical gap persists: most prior research has either optimized maintenance policies or enhanced scheduling performance in isolation, with limited attention to the criteria that drive effective integration between maintenance and production—particularly in Open Shop systems characterized by high routing flexibility and operational uncertainty.

Consequently, the present research contributes to the literature by systematically identifying, structuring, and prioritizing the criteria that influence maintenance–production integration using a hybrid DEMATEL–OPA framework. The outcome of this review informs the development of a criteria set (Table 1) validated through expert judgment and grounded in the theoretical and empirical insights from preceding studies.

3. Research Methodology

This section delineates the research methodology employed in the present study. Considering the defined research objectives, the current investigation is classified as applied research with a descriptive data collection approach. As previously indicated, this study adopts a hybrid DEMATEL–Sequential Prioritization framework. The research implementation steps are summarized as follows:

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/

Research Article

1. Formation of an expert committee
2. Identification and compilation of criteria through an extensive literature review, complemented by expert opinions
3. Application of the DEMATEL approach to identify causal and effect relationships among the criteria
4. Utilization of the Ordered Priority Approach (OPA) for ranking the causal criteria
5. Formulation of managerial recommendations

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3.1 DEMATEL Method

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is widely employed to reveal interdependencies among variables and to identify causal relationships in complex systems. Inter-variable influences are represented through a causal diagram, where the strength of influence is measured on a 0–4 scale, with 0 indicating no influence and 4 representing a very strong influence (Sharma et al., 2020).

The implementation of the DEMATEL method in this study follows these steps:

1. Identification of Influential Criteria: Relevant criteria are selected based on a comprehensive literature review and expert consultations. These criteria are positioned as nodes in a directed graph representing the system under study.
2. Construction of Pairwise Influence Matrix: Experts evaluate the direct influence of each criterion on every other criterion, forming a pairwise comparison matrix. This matrix captures the perceived causal relationships among criteria, which can be expressed mathematically as:

$$Z = \begin{array}{c} \\ C_1 \\ C_2 \\ \cdot \\ \cdot \\ C_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & \dots & \dots & C_n \end{array} \\ \begin{bmatrix} R_{11} & R_{12} & \dots & \dots & R_{1n} \\ R_{21} & R_{22} & \dots & \dots & R_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ R_{m1} & \dots & \dots & \dots & R_{mn} \end{bmatrix} \end{array} \qquad (1)$$

3. Formation of the Direct Relation Matrix (M):

The matrices obtained from the pairwise comparison are examined, and the existence or absence of direct influence between each pair of criteria is determined based on the majority opinion of experts.

Journal of Information Systems Engineering and Management
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Research Article

The resulting direct relation matrix, M, is then constructed as the average of expert evaluations, capturing the consensus on inter-criterion relationships.

4. Construction of the Causal Diagram:

A directed graph corresponding to the matrix M is developed. In this diagram, nodes represent the criteria, while edges indicate the presence and direction of direct influence between criteria. The weight of each edge corresponds to the score assigned to the respective direct influence, allowing for a visual representation of causal relationships within the system.

5. Normalization of the Direct Relation Matrix:

To facilitate comparability and subsequent analysis, the direct relation matrix M is normalized. First, the row sums of M are computed, and the inverse of the maximum row sum is used to scale the entries of M. This step produces a normalized matrix in which the relative strength of direct relationships among criteria is appropriately represented.

In the present study, this normalization process is further refined by incorporating expert weighting and sensitivity analysis, ensuring that both dominant and subtle influences are adequately captured. This enhances the robustness and reliability of the DEMATEL causal analysis, providing a strong foundation for subsequent prioritization of critical criteria.

$$N = \alpha \times M$$
$$\alpha = \frac{1}{Max \sum_{j=1}^{n} a_{ij}} \tag{2}$$

6. Calculation of the Total Relation Matrix:

In this step, the total relation matrix (S), which captures both direct and indirect relationships, is constructed according to the following equation:

$$S = N + N^2 + N^3 + \cdots + N^t = \frac{N(I - N^t)}{I - N} = \frac{N}{I - N} = N(1 - N)^{-1}$$
$$\lim_{t \to \infty} N^t = 0 \tag{3}$$

The potential intensity of indirect relationships (i.e., the influence of elements on each other through indirect paths) is calculated using the geometric series summation, following a reasoning analogous to that used for direct relationships, as expressed in Equation (4).

$$T_{t \to \infty} = N^2 + N^3 + \cdots + N^t = N^2(1 - N)^{-1} \tag{4}$$

7. Drawing the Causal Diagram:

The following principles are applied to construct the causal diagram:

- R (Row Sum): For each criterion, the sum of the row elements represents the total influence exerted by that criterion on all other elements in the system.
- D (Column Sum): For each criterion, the sum of the column elements indicates the total influence received by that criterion from other elements in the system.
- R + D (Prominence Vector): Represented on the horizontal axis, this vector reflects the overall interaction of a criterion within the system. A higher R + D value indicates that the criterion has greater connectivity and significance in the system.
- R – D (Relation Vector): Represented on the vertical axis, this vector shows the net causal effect of each criterion on the system. Positive values indicate causal factors, while negative values indicate effect factors.

Journal of Information Systems Engineering and Management
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Research Article

$R \succ D \Rightarrow$ R-D $\succ 0 \Rightarrow$	A criterion with a positive R − D value is considered a definite influential factor and is classified as a cause (driver) variable in the system.
$R \prec D \Rightarrow$ R-D $\prec 0 \Rightarrow$	A criterion with a negative R − D value is considered a definite influenced factor and is classified as an effect (dependent) variable in the system.

Consequently, the causal diagram can be derived by plotting the ordered pairs (R + D, R − D), providing valuable insights for decision-making.

8. Determination of Hierarchy or Possible Structure of Criteria

In this step, by arranging the criteria based on their R, D, R + D, and R − D values obtained from the total relation matrix (S), a possible ranking and hierarchical structure of the criteria can be established.

9. Drawing the Network Relationship Map (NRM)

A Network Relationship Map (NRM) can be constructed to visually represent the relationships among criteria. To draw the NRM, the threshold value of relationships is calculated using the average values of the total relation matrix (S). This enables the identification of significant interactions among system elements.

3.2 Ordered Priority Approach (OPA)

Considering the research objective, the Ordered Priority Approach (OPA) proposed by Attaie et al. (2020) is employed. Prior to describing the procedural steps of the approach, the sets, indices, parameters, and variables of the model are defined as follows (Attaie et al., 2020):

Table 1- Sets, indicators and variables in the OPA approach

Sets	
I	Experts' Set $\forall\, i \in$ I
J	Criteria Set $\forall\, j \in$ J
K	Option Set $\forall\, k \in$ K
Criteria	
i	Expert-based criteria (1, 2, …, p)
j	Criterion-based indicators (1, 2, …, n)
k	Option-based criteria (1, 2, …, m)
Variables	
Z	Objective functio
${W_{ijk}}^{r}$	Weight of the k-th alternative for the j-th criterion by the expert at rank r.
${A_{ijk}}^{r}$	The k-th alternative with respect to the j-th criterion by expert i at rank r.

Journal of Information Systems Engineering and Management
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Research Article

Model Design

In the decision-making process, alternatives, criteria, and experts can be considered as the three vertices of a decision-making triangle, interacting simultaneously to determine the relative importance of each element. In the proposed model, it is suggested that the characteristics of all three vertices be simultaneously utilized in the decision-making process. This allows experts to provide evaluations of alternatives based on criteria in a simplified and structured manner, ultimately leading to the determination of the importance (weight) of each component.

Assume that the ranking is performed across k available alternatives according to the following steps:

- Ranking of experts: based on organizational position, academic degree, experience, etc.
- Ranking of criteria: provided by each expert
- Ranking of alternatives: based on each criterion, provided by each expert

With the above framework and by solving Model (5), it is possible to obtain the appropriate weights (importance values) for each rank of each alternative, taking into account both the criteria ranking and the expert ranking.

Max: Z

s.t:

$$Z \leq i\left(j\left(r\left({W_{ijk}}^{r} - {W_{ijk}}^{r+1}\right)\right)\right) \qquad \forall\, i,j,r$$

$$Z \leq \ ijm{W_{ijk}}^{m} \qquad \forall\, i,j \quad , \ r = m$$

$$\sum_{i}\sum_{j}\sum_{k} {W_{ijk}}^{r} = 1 \qquad \forall\, r$$

$${W_{ijk}}^{r} \geq 0$$

Figure 1. Illustration of the direct relationship between the causal variable as the source of influence and the affected variable as the outcome.

(5)

Journal of Information Systems Engineering and Management
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Research Article

It should be noted that the decision variable of this linear mathematical model ${W_{ijk}}^{(r)}$ represents the cardinal weight of the k-th option with respect to the j-th index as assigned by the i-th expert at rank r. By solving the linear mathematical model (5) for expert i and index j, multiple values will be obtained for each option. Therefore, the weights of the options, indices, and experts are expressed according to equations (6), (7), and (8) as follows:

Weight of options:

$$\sum_{k} {W_{ijk}}^{r} \qquad \forall\, i, j, r \tag{6}$$

Weight of indicators:

$$\sum_{j} {W_{ijk}}^{r} \qquad \forall\, i, k, r \tag{7}$$

Experts' weight:

$$\sum_{i} {W_{ijk}}^{r} \qquad \forall\, j, k, r \tag{8}$$

In the following section, the proposed framework for group decision-making is presented based on the aforementioned relationships. The procedure consists of the following steps:

Step 1: Selection and ranking of domain experts

Experts with relevant knowledge and experience in the decision-making context are identified and ranked according to their expertise. Criteria for ranking may include organizational position, years of experience, prior involvement in similar decision-making processes, and demonstrated proficiency in the subject matter. This step ensures that the most qualified individuals contribute effectively to the decision-making process.

Step 2: Identification of decision criteria

Key decision criteria are selected in accordance with the decision-making problem. If criteria include sub-criteria, these should be explicitly incorporated into the analysis, allowing experts to evaluate options at a more granular level. This hierarchical structuring enhances the precision and robustness of the model.

Step 3: Expert ranking of criteria

Each expert prioritizes the identified criteria based on their domain knowledge. Experts may assign different levels of importance to criteria, and if certain criteria are deemed irrelevant by an expert, they may be excluded from that expert's evaluation. This flexibility captures the diversity of expert judgments and avoids imposing uniform weights that may not reflect actual expertise.

Step 4: Expert ranking of alternatives with respect to each criterion

In this step, experts are asked to rank the alternatives according to each criterion. This procedure allows the model to incorporate expert opinions for every criterion individually, enhancing the granularity and accuracy of the resulting decision matrix. The formal representation of this step is provided in Equation (9).

the model allows dynamic inclusion/exclusion of criteria per expert, integrates hierarchical criteria structures, and generates multi-perspective weighted rankings. This approach not only enhances the transparency of group decision-making but also improves the adaptability of the model across different industrial contexts.

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/
Research Article

$$A_{ijk}{}^{(1)}, A_{ijk}{}^{(2)}, \dots, A_{ijk}{}^{(m)} \tag{9}$$

$A_{ijk}{}^{(r)}$ It represents the ranking of the option COM based on the jth index by the expert.

Step 5. Finding the optimal weight) $\mathbf{W_{ijk}{}^{(1)}, W_{ijk}{}^{(2)}, \dots, W_{ijk}{}^{(m)}}$)

As the final step, the linear mathematical model (5) is employed to determine the optimal weight of the k-th alternative with respect to the j-th criterion as assigned by the i-th expert at rank r. Subsequently, the final weights of alternatives, criteria, and experts are calculated using Equations (6), (7), and (8), respectively, which then enable the ranking of alternatives based on these computed weights (Ataei et al., 2020). It is noteworthy that, in addition to the described model, one of the key advantages of this approach is its implementation using the OPA Solver software, which is utilized in the present study to solve the proposed model efficiently.

4. Research Findings

This section presents the results obtained from the study. Prior to detailing the findings, the demographic information of the participants—comprising managers and specialists from the production and maintenance departments of Nakoubehineh Factory—is summarized in Table 2.

Table 2- Demographic information of the research

Education	Years of Service	Organizational post	Experts
Master's degree	21	Production and Operations Deputy	E_1
Master's degree	19	Maintenance Planning Manager	E_2
Bachelor's degree	11	Maintenance and Repair (M&R) Specialist	E_3
Bachelor's degree	3	Maintenance and Repair (M&R) Specialist	E_4
P.h.D	18	Technical and Support Deputy	E_5
Bachelor's degree	14	Production Department Specialist	E_6
Bachelor's degree	5	Production Department Specialist	E_7

Following the defined steps, after establishing the expert committee, the process proceeds to the identification and collection of decision criteria. These criteria, derived from a comprehensive literature review and expert opinions, are summarized in Table 3.

Table 3- Factors affecting the integration of maintenance and repairs

References	Symbol	Factor	No.
Moreno-Trejo et al., (2012)	C01	Determination of maintenance and repair costs	1
	C02	Determination of production operational costs	2
	C03	Line downtime costs due to maintenance and repair activities	3
	C04	Available tools, materials, spare parts, and other equipment	4
Jasiulewicz-Kaczmarek. (2018)	C05	Management of spare parts and consumables	5
	C06	Collaboration with machinery and equipment manufacturers/suppliers	6

Journal of Information Systems Engineering and Management
2024, 9(4)
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Research Article

	C07	Collaboration between maintenance and R&D department	7
	C08	Collaboration between maintenance and production & quality departments	8
Sahu et al., (2008)	C09	Personnel training	9
Jandali & Sweis (2018)	C10	Considering and analyzing the equipment lifecycle	10
	C11	Qualified maintenance manager	11
Darestani et al., (2020)	C12	Equipment installation and commissioning time	12
	C13	Workforce capabilities and competencies	13
Azadeh & Jebreili, (2013)	C14	Facility layout optimization	14
	C15	Validation and approval of facility layout	15
Wang et al., (2024)	C16	Machine maintenance cycle	16
	C17	Equipment failure rate determination	17
Oliveira & Lopes. (2020)	C18	Planning and scheduling of maintenance activities	18
Expert opinion	C19	Setup time of parts on equipment and machines	19
Expert opinion	C20	All production and maintenance personnel	20

After collecting, sorting, and finalizing the decision criteria based on the opinions of the current study's experts, the next step involves applying the DEMATEL approach to categorize the criteria into two groups: influential and influenced criteria. Following the defined DEMATEL procedure, the results obtained in this stage are as follows:

Initially, a direct-relation matrix among the criteria is constructed based on expert judgments. Once the direct-relation matrix is established, it is normalized. Subsequently, the total-relation matrix, representing both direct and indirect influences, is derived by calculating the matrix (I - N)^{-1}, where I is the identity matrix and N is the normalized direct-relation matrix. The resulting total-relation matrix captures the overall influence structure among the criteria.

Finally, considering a threshold value of 0.363, the sum of rows and columns of the total-relation matrix is calculated to determine the degree of influence (D) and the degree of being influenced (R) for each criterion. The outcomes of these calculations are presented in Table 4.

Table 4- The degree of influence and effectiveness of indicators

	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C01	0	1	1	1	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
C02	1	0	1	0	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	0

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/

Research Article

C03	1	0	0	0	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1
C04	1	1	1	0	1	0	1	1	1	0	1	1	0	1	1	1	0	1	1	1
C05	1	1	1	0	0	0	1	1	1	0	1	1	0	1	1	0	0	1	1	0
C06	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
C07	1	0	1	0	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1
C08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C09	1	0	0	0	0	0	1	0	0	0	0	1	0	1	1	0	0	1	0	0
C10	1	0	1	1	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1
C11	1	0	1	1	1	0	1	1	1	0	0	1	0	1	1	0	0	1	1	1
C12	1	0	0	0	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1
C13	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0
C14	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1
C15	1	1	1	0	1	0	1	1	1	0	1	1	0	1	0	0	0	1	1	1
C16	1	1	1	1	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1
C17	1	0	1	0	1	0	1	1	1	1	1	1	0	1	1	1	0	1	1	1
C18	1	0	1	1	1	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1

Journal of Information Systems Engineering and Management
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Research Article

C 19	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0
C 2 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

To construct the cause-and-effect diagram, the values of D-R and D+R must be determined. The D+R values, represented on the horizontal axis of the diagram, indicate the overall prominence of each criterion, while the D-R values, plotted on the vertical axis, reflect the net influence of a criterion. A positive D-R value signifies that the criterion is primarily influential, whereas a negative D-R value indicates that the criterion is primarily influenced. Table 5 presents the levels of influence and dependence of the criteria, along with their ranking and classification into the two groups of cause and effect.

Table 5- Index sorting based on D, R, D+R and D-R values

Index	**R**	**D**	**R+D**	**R-D**	**Cause/Effect**
C01	7/99	7/60	15/59	0/39	Cause
C02	7/07	6/73	13/80	0/34	Cause
C03	7/30	7/51	14/81	-0/22	Effect
C04	7/69	6/80	14/48	0/89	Cause
C05	7/53	7/62	15/16	-0/09	Effect
C06	6/40	6/18	12/58	0/22	Cause
C07	7/45	8/24	15/69	-0/79	Effect
C08	6/06	7/49	13/54	-1/43	Effect
C09	6/94	7/63	14/56	-0/69	Effect
C10	7/58	6/24	13/82	1/35	Cause
C11	7/47	7/53	15/00	-0/06	Effect
C12	7/36	8/12	15/49	-0/76	Effect
C13	6/47	6/42	12/90	0/05	Cause
C14	8/09	8/15	16/24	-0/06	Effect
C15	7/79	7/71	15/50	0/08	Cause
C16	7/99	6/64	14/63	1/35	Cause
C17	7/83	6/43	14/26	1/40	Cause
C18	7/87	7/71	15/57	0/16	Cause
C19	6/47	7/53	14/00	-1/06	Effect
C20	6/20	7/12	13/32	-0/93	Effect

Based on the data presented in Table 10, the cause-and-effect diagram is illustrated in Figure1.

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
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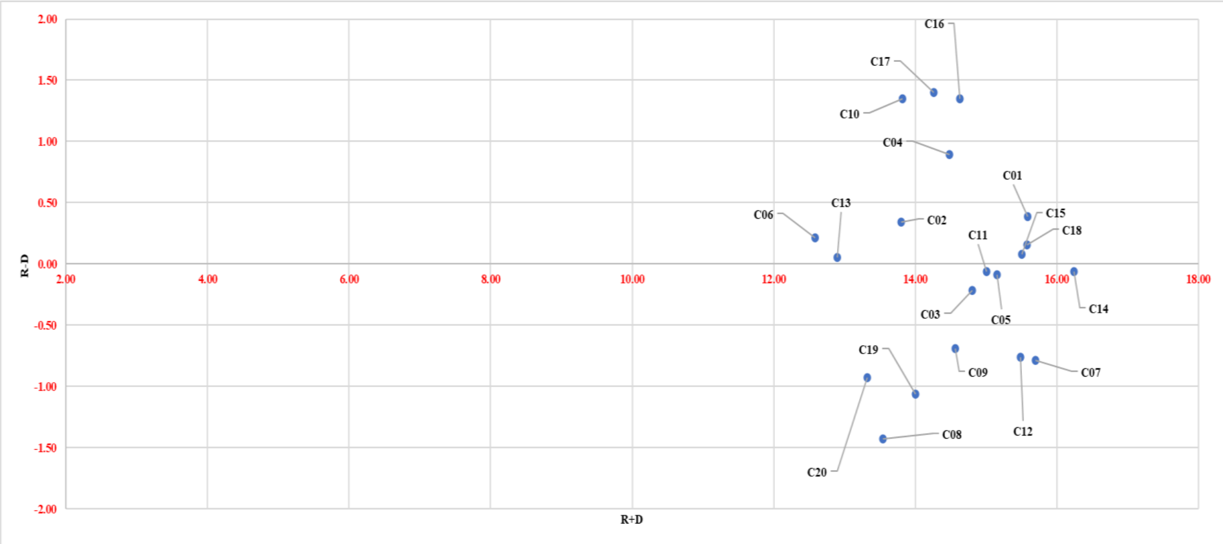

شکل 2- دیاگرام علت و معلولی معیارها

Figure 2- Cause and effect diagram of criteria

Considering the cause-and-effect diagram, the influential (cause) criteria are identified and presented in Table 6.

Table 6- Influential criteria (cause)

Symbol	Factor	No.
C01	Determination of maintenance and repair costs	1
C02	Determination of production operational costs	2
C04	Available tools, materials, spare parts, and other equipment	3
C06	Collaboration with machinery and equipment manufacturers/suppliers	4
C10	Considering and analyzing the equipment lifecycle	5
C13	Workforce capabilities and competencies	6
C15	Validation and approval of facility layout	7
C16	Machine maintenance cycle	8
C17	Equipment failure rate determination	9
C18	Planning and scheduling of maintenance and repair activities	10

According to the defined steps of the OPA approach, after identifying the criteria—which, in this study, correspond to the factors influencing the supply chain and the role of production line balancing— it is necessary to define factors for ranking the impact of these criteria. These factors are summarized in Table 7.

Table 7- Factors considered for rating criteria

Symbol	**Factor**	**No.**
F_1	Cost level	1
F_2	Profitability	2

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
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F_3	Proper resource management	3
F_4	Formulation of competitive strategies	4
F_5	Adoption of modern technologies	5

Considering the input presented in Tables 6 and 7, the execution steps and the results obtained at each stage are as follows:

Step 1: Ranking of experts (based on organizational chart, academic degree, experience, etc.)

Following the steps of the proposed approach, experts were initially ranked based on their years of service. In cases where years of service were equal, academic qualifications were used as a secondary criterion. Accordingly, the ranking of the seven experts participating in this study—comprising managers and specialists from the production and maintenance departments of Nakoubehineh Factory—is presented in Table 8, taking into account their demographic information.

Table 8- Ranking of experts

Rank	Education	Years of Service	Organizational post	**Experts**
1	Master's degree	21	Production and Operations Deputy	**E_1**
2	Master's degree	19	Maintenance Planning Manager	**E_2**
5	Bachelor's degree	11	Maintenance and Repair (M&R) Specialist	**E_3**
7	Bachelor's degree	3	Maintenance and Repair (M&R) Specialist	**E_4**
3	P.h.D	18	Technical and Support Deputy	**E_5**
4	Bachelor's degree	14	Production Department Specialist	**E_6**
6	Bachelor's degree	5	Production Department Specialist	**E_7**

Step 2: Ranking of factors by each expert

In this stage, the members of the expert committee were asked to rank the factors used for evaluating the criteria based on their professional experience. The results of this ranking process are summarized in Table 9.

Table 9- Rating of factors by experts

Factors / Experts	F_1	F_2	F_3	F_4	F_5
Expert 1	4	3	1	5	2
Expert 2	1	3	2	5	4

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
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Expert 3	4	1	2	3	5
Expert 4	5	3	1	2	4
Expert 5	5	3	2	4	2
Expert 6	3	1	2	5	4
Expert 7	2	5	1	4	3

Step 3: Ranking of criteria (factors influencing the supply chain) by each expert

In this stage of the OPA approach, the criteria targeted for ranking are evaluated and ranked by the experts. The results of this ranking process are presented in Table 10.

Table 10- Rating of criteria by experts

Factors / Experts	Criteria	C_{01}	C_{02}	C_{04}	C_{06}	C_{10}	C_{13}	C_{15}	C_{16}	C_{17}	C_{18}
Expert 1	F1	3	5	1	2	6	4	9	7	8	10
	F2	2	4	1	8	7	3	6	10	9	5
	F3	4	1	2	5	3	10	9	8	7	6
	F4	5	1	2	4	3	8	9	6	7	10
	F5	4	2	3	5	6	1	8	7	10	9
Expert 2	F1	1	3	2	6	7	4	5	9	8	10
	F2	4	5	1	2	3	7	9	10	6	8
	F3	6	5	2	1	3	4	10	9	7	8
	F4	5	2	6	1	4	3	9	10	7	8
	F5	4	5	2	1	3	9	7	10	6	8
Expert 3	F1	5	6	1	3	2	8	7	9	10	6
	F2	3	4	2	5	1	7	6	8	9	10
	F3	2	1	4	3	5	6	9	10	8	7
	F4	4	3	2	1	7	6	8	7	5	9
	F5	5	6	1	2	3	8	7	4	10	9
Expert 4	F1	3	5	6	1	2	4	9	8	7	10
	F2	3	6	5	2	1	8	7	9	10	4
	F3	2	1	6	4	5	9	8	7	3	10
	F4	4	3	5	2	1	8	7	9	3	10
	F5	2	5	1	3	4	6	7	10	8	9
Expert 5	F1	3	4	1	2	5	6	8	7	9	10
	F2	4	3	5	1	2	7	6	8	9	10

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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	F3	2	4	5	6	3	1	9	10	7	8
	F4	4	3	6	5	1	2	8	7	9	10
	F5	5	6	1	2	3	7	4	9	8	10
Expert 6	F1	4	5	1	3	2	6	7	9	10	8
	F2	2	3	1	4	5	7	6	8	9	10
	F3	4	3	2	1	6	7	9	10	5	8
	F4	2	3	4	1	5	8	7	9	10	6
	F5	1	2	4	6	7	8	9	10	3	5
Expert 7	F1	2	1	3	5	8	4	6	9	10	7
	F2	3	2	4	1	5	7	8	6	10	9
	F3	1	3	2	4	6	7	8	5	9	10
	F4	2	4	3	1	8	7	6	10	5	9
	F5	2	1	3	4	6	5	9	7	8	10

The results obtained from the proposed approach are presented through three outputs: the weights of experts, factors, and criteria, as follows:

a. Calculation of expert weights: The weights of the seven experts considered in this study are presented in Table 11.

Table 11- Weight of experts

Weight of experts	Rank	Organizational post	Experts
0/386117	1	Production and Operations Deputy	E_1
0/193058	2	Maintenance Planning Manager	E_2
0/076209	5	Maintenance and Repair (M&R) Specialist	E_3
0/055029	7	Maintenance and Repair (M&R) Specialist	E_4
0/128706	3	Technical and Support Deputy	E_5
0/096529	4	Production Department Specialist	E_6
0/064353	6	Production Department Specialist	E_7

b. Calculation of factor weights

In this stage of the approach, the weights of the factors are calculated based on expert judgments. The resulting weights, as determined by the experts, are presented in Table 12.

Journal of Information Systems Engineering and Management
2024, 9(4)
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Table 12- Index weights based on the OPA approach

Weight of experts	Synbol	**Factor**	No.
0/178556	F_1	Cost level	1
0/193125	F_2	Profitability	2
0/358134	F_3	Proper resource management	3
0/103676	F_4	Formulation of competitive strategies	4
0/166509	F_5	Adoption of modern technologies	5

c. Calculation of effective criteria weights (alternatives)

In the final step of the OPA approach, after determining the weights of experts and factors, the weights of the effective criteria (alternatives) are calculated. The resulting weights are presented in Table 13.

Table 13- Criteria weights based on OPA approach

Weight	Symbol	Factor	No.
0/148053	C01	Determination of maintenance and repair costs	1
0/167322	C02	Determination of production operational costs	2
0/194814	C04	Available tools, materials, spare parts, and other equipment	3
0/143633	C06	Collaboration with machinery and equipment manufacturers/suppliers	4
0/117217	C10	Considering and analyzing the equipment lifecycle	5
0/083409	C13	Workforce capabilities and competencies	6
0/042558	C15	Validation and approval of facility layout	7
0/031866	C16	Machine maintenance cycle	8
0/037174	C17	Equipment failure rate determination	9
0/033954	C18	Planning and scheduling of maintenance and repair activities	10

Based on the outputs of this stage, it is evident that the criteria “tools, materials, spare parts, and other available equipment,” “production operational costs,” and “maintenance and repair costs” ranked first to third in terms of importance, with weights of 0.194814, 0.167322, and 0.148053, respectively.

5. Conclusions and Recommendations

Production scheduling is a critical aspect of managing an open workshop system. Such systems typically comprise a large number of workers and diverse machinery operating in a dynamic and complex environment. Therefore, in an open workshop system, coordination among machine components, various production elements, and transportation processes is of paramount importance. Scheduling should be designed to optimize interactions between components without creating obstacles to the production flow. From this perspective, identifying factors influencing the integration of supply chain activities becomes essential.

This study aims to identify the criteria that significantly affect the integration of maintenance and repair activities in an open workshop system. Following the steps of the proposed hybrid approach, the initial set of criteria was compiled based on a comprehensive literature review and expert consultations. In the subsequent step, the DEMATEL approach was applied to determine cause-and-effect relationships among the criteria, facilitating their screening. Among the ten screened criteria, "tools, materials, spare parts, and other available equipment," "production operational costs," and "maintenance and repair costs" were identified as the most influential factors.

Based on these findings, several managerial recommendations are proposed. Managers and specialists in production units are well aware that maintenance and repair activities account for a significant portion of production system costs. Concurrently, information technology-based intelligent systems for maintenance and repair units have experienced remarkable growth. Therefore, considering the production system, the number of operators, and the machinery involved, the implementation of advanced maintenance methods—where an intelligent system determines whether to repair or replace components based on factors such as operating time and system reliability—is recommended.

Another critical issue in maintenance and repair decision-making is determining the optimal timing for the utilization of equipment, materials, and spare parts. Premature replacement results in unnecessary costs, whereas delayed replacement increases maintenance and repair expenses. Consequently, awareness of the equipment's useful life can facilitate asset management and prevent additional costs.

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