

Analysis and Prioritization of Strategic Factors Affecting Sustainable Production Continuity Using an Advanced BWM–DEMATEL Approach

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Abstract: In process industries, sustainable production continuity depends on preventing disruptions, limiting capacity losses, and sustaining reliable operation across strongly interdependent units. Despite extensive work on maintenance, reliability, human factors, and sustainability, few studies combine plant-level shutdown evidence with expert-based weighting and network influence analysis across human, organizational, technical-process, and environmental factors. This study developed and applied an integrated Pareto–Delphi–BWM–fuzzy DEMATEL framework at the Jajarm Alumina Complex. A 24-month dataset comprising 425 unplanned events was used to identify critical units; 24 initial factors were then screened to 15 final factors through two Delphi rounds with 18 experts using CVR, CVI, and Kendall’s coefficient of concordance. Factor importance was estimated using the Best–Worst Method, while fuzzy DEMATEL was used to map directional influence and cause–effect group positions. The four main critical units accounted for 56.94% of recorded events but 69.09% of total shutdown duration and 72.07% of lost production. Utility disruptions received the highest BWM weight (0.1091), and the technical-process and organizational dimensions together accounted for 74.80% of total importance. Management commitment to reliability had the largest positive D–R value (1.1900), identifying it as the strongest cause-group factor, whereas wear and failure of critical equipment was the most prominent and strongly effect-group factor ($D+R=2.7455$; $D-R=-1.2200$). Integration of BWM and DEMATEL identified five main strategic levers: management commitment to reliability, maintenance planning, availability of spare parts and specialized personnel, process fluctuations and bauxite quality, and utility disruptions; inter-unit coordination emerged as a central hidden driver. Robustness checks showed a minimum leave-one-expert-out rank correlation of 0.993, and the cause–effect classification remained unchanged when the DEMATEL threshold varied by $\pm 10\%$. These findings indicate that sustainable production continuity in alumina processing depends on coordinated technical reliability, maintenance planning, resource provision, process stability, utility management, and cross-functional coordination rather than on equipment repair alone.

Keywords: Sustainable Production Continuity, Strategic Factors, Alumina Production, Best–Worst Method, Fuzzy DEMATEL.

1. Introduction

Undoubtedly, production continuity in process industries is a prerequisite for the economical, safe, and sustainable operation of industrial assets. These industries are characterized by capital-intensive equipment, continuous processes, and strong interdependencies among operational units; therefore, a disruption in one piece of equipment can simultaneously affect the performance of several sections of the production chain. Unplanned shutdowns not only reduce availability and result in lost production, but also increase emergency maintenance costs, spare-parts consumption, overtime, and energy and material losses. Reduced operating speed should also be considered alongside complete shutdowns, as it can consume a substantial proportion of available capacity in process industries (Trattner et al., 2020; Holgado et al., 2020).

Alumina production is a prominent example of such systems because of the continuous and interconnected nature of the Bayer process. In this process, bauxite, following preparation and grinding, enters the caustic digestion stage and subsequently passes through red mud separation, caustic soda recovery, hydrate precipitation, filtration, calcination, and solution recirculation. These stages are interdependent through material, steam, water, caustic soda, and energy flows; therefore, fluctuations in one unit can reduce the capacity of other units. In a study, Sidrak (2001) showed that the Bayer process is characterized by recurrent disturbances, strong interactions among subprocesses, and considerable time delays. Similarly, Spiers et al. (2024) identified digestion trains as networked assets on the critical path, whose maintenance is constrained by production and maintenance-resource limitations.

The complexity of production in complexes such as Jajarm is further intensified by the characteristics of the bauxite feedstock. Chehrehchelgani and Jorjani (2009), through the analysis of 332 bauxite and red mud samples, showed that the chemical ratios of the feed are important predictors of alumina recovery during the digestion stage. Variability in bauxite quality can affect digestion recovery, precipitation, caustic soda and lime consumption, red mud generation, and the capacity of downstream units. Therefore, the analysis of shutdowns should encompass not only equipment failures but also speed losses and deviations in process conditions resulting from variations in feedstock.

However, shutdowns or capacity reductions cannot be attributed solely to mechanical, electrical, or instrumentation failures. Process industries are socio-technical systems whose performance emerges from the interaction of equipment, technology, operators, maintenance teams, and organizational procedures. In this regard, Zarei et al. (2021) showed that operations, maintenance, emergency management, and control-room activities are associated with factors such as training, workload, time pressure, decision-making, and the quality of procedures. Jha et al. (2024) also emphasized the lack of an integrated classification of factors shaping human performance. At the organizational level, management commitment, communication, risk assessment, resource allocation, and the quality of procedures can play causal roles; accordingly, Ghorbani et al. (2024) identified management commitment to safety as the most influential factor in process safety culture. Unplanned shutdowns are also linked to industrial sustainability. Severe failures and emergency maintenance can increase energy and material consumption, generate additional waste, increase the likelihood of chemical leaks, and expose employees to greater workload pressures and hazards. Therefore, shutdown severity should not be assessed solely on the basis of repair costs or hours lost; its economic, environmental, and social-safety consequences should also be evaluated. Boral et al. (2020) showed that the consequences of equipment failures can be distinguished across these three dimensions. The Maintenance 5.0 literature likewise emphasizes a transition from purely cost-oriented maintenance toward human-centered, resilient, and sustainable maintenance systems (Psarommatis et al., 2023).

The interactive nature of shutdown-related factors necessitates the use of methods that distinguish between the importance of a factor and its influence power. Numerous studies have shown that the Best–Worst Method (BWM), through a smaller number of comparisons and the possibility of consistency control, can determine the relative weights of factors (Rezaei, 2015). However, a factor with a high weight is not necessarily a root cause and may instead be a consequence of upstream factors. In contrast, DEMATEL calculates direct and indirect relationships and distinguishes factors according to their influence, dependence,

and membership in cause and effect groups. Accordingly, further investigations have emphasized that integrating BWM and DEMATEL can reveal both the relative importance and the causal structure of factors (Govindan et al., 2022).

A review of international studies shows that existing research has generally focused on one dimension of the issue, such as Bayer process control, maintenance of digestion units, human reliability, safety culture, or maintenance sustainability. Moreover, the relationships among shutdown frequency, shutdown duration, lost production, and the influence structure of human, organizational, technical-process, and environmental factors have rarely been examined within a single evidence framework. Among domestic studies, no study was identified that first screened the entire Jajarm alumina production line using actual shutdown data and then analyzed the importance and directional influence of factors affecting the critical units through an integrated BWM–DEMATEL approach. Accordingly, the present study aimed to identify and prioritize factors affecting unplanned shutdowns at the Jajarm Complex. The complete production chain was first screened through Pareto analyses of event frequency, shutdown duration, and lost production. The candidate factors were then extracted and validated through the literature, plant documents, expert interviews, and Delphi analysis; BWM was used to estimate relative importance, fuzzy DEMATEL to characterize the influence structure, and the outputs were integrated into an importance–influence matrix. The novelty of the study lies in combining actual operational evidence with expert judgments across four socio-technical dimensions and in distinguishing high-importance factors from upstream influence factors and effect-driven manifestations. The central research question was which units account for the largest share of production disruption, which factors are most important and influential in sustaining those disruptions, and how these priorities can inform resilience and sustainable production management.

2. Literature Review

2.1 *Unplanned Shutdowns and Reliability in Process Industries*

An unplanned shutdown refers to a situation in which equipment, a subsystem, or a production line is taken completely out of service outside the approved schedule, or its operating capacity falls below the expected level. From this perspective, a shutdown does not refer solely to a complete outage; it also encompasses speed losses, reduced production rates, and short but frequent interruptions. Reliability is defined as the probability of performing the intended function over a specified period and under specified conditions; maintainability refers to the ability to restore equipment to an operational state; and availability represents the proportion of time during which equipment is ready to perform its intended function. Indicators such as mean time between failures, mean time to repair, downtime duration, lost production rate, and overall equipment effectiveness represent complementary dimensions of performance. Therefore, the identification of critical units should not be based solely on the number of failures. A review of maintenance optimization models also indicates that the technical, economic, and functional interdependencies among components of multi-unit systems make independent decision-making for each piece of equipment insufficient (de Jonge & Scarf, 2020). In addition, speed losses in process industries can consume 9–15% of available capacity and may be associated with both technical and human factors (Trattner et al., 2020). Digital Transformation of Organised Crime

2.2 *Alumina Production Process Structure and Disruption Propagation*

The Bayer process consists of a network of operations including bauxite preparation and grinding, caustic digestion, solid–liquid separation, red mud washing, hydrate precipitation, filtration, calcination, and caustic solution recirculation. These units are interconnected through material, steam, water, caustic soda, condensate, and energy flows; consequently, the location where a shutdown is observed is not necessarily the location where its root cause originated. For example, a reduction in digestion capacity may result from poor feed quality, steam limitations, scaling, high-pressure pump failure, or delays in maintenance. In this regard, Spiers et al. (2024) identified digestion trains as networked assets located on the critical production path, whose maintenance planning is intertwined with production capacity, activity scheduling, and maintenance-resource constraints. This characteristic makes it necessary to examine the entire production line and distinguish among the “unit initiating the disruption,” the “shutdown unit,” and the “affected units.”

2.3 Human Factors Affecting Shutdowns

From a socio-technical perspective, human error is not regarded as an inherent and fixed characteristic of an individual but rather as an outcome of the interaction among individual capabilities, task characteristics, equipment design, working conditions, and the organizational context. Human reliability in process industries is particularly important in normal operations, maintenance activities, control-room operations, and the management of abnormal conditions. Inadequate training, limited experience, fatigue, time pressure, workload, poor situational awareness, incorrect diagnosis of failure signals, incomplete shift handovers, and non-compliance with procedures may increase the likelihood of inappropriate decisions or actions. The review by Zarei et al. (2021) indicates that human reliability analysis should move beyond a narrow focus on operator behavior and consider the interaction among humans, technology, and the organization in operations, maintenance, and emergency management. The systematic review by Jha et al. (2024) likewise emphasizes the need for a context-based classification of performance-shaping factors, as generic classifications do not fully reflect differences in tasks and hazards across industries.

2.4 Organizational Factors Affecting Shutdowns

Organizational factors are mechanisms that shape decision-making quality, operational readiness, and the speed of recovery following failures. Senior management commitment, maintenance budget allocation, adequacy of specialized personnel, maintenance planning, spare-parts management, the quality of computerized maintenance management system data, production–maintenance coordination, contractor management, learning from previous failures, and change control are among the key elements of this dimension. Organizational weaknesses may not constitute the initial technical cause of a failure, but they can increase the time required for diagnosis, parts procurement, permit issuance, mobilization of maintenance personnel, and stable return to production. Therefore, a distinction should be made between a “factor causing the failure” and a “factor prolonging the shutdown.” The study by Ghorbani et al. (2024) showed that management commitment and risk assessment and management play influential roles in the network of process safety culture factors. Similarly, Yang et al. (2024), through causal network modeling of organizational factors, showed that human–machine interaction reliability is particularly sensitive to adequate training and the quality of procedures.

2.5 Technical–Process Factors

Technical–process factors relate to the physical condition of assets and the stability of operating conditions. Wear, corrosion, erosion, scaling and blockage, rotating-equipment failures, instrumentation faults, inadequate process control, lack of redundancy, temperature and pressure fluctuations, changes in solution concentration, and feedstock variability can result in complete shutdowns or capacity reductions. In multi-unit systems, the importance of a failure depends not only on its occurrence rate but also on the equipment’s position within the production pathway, the possibility of substitution, the existence of intermediate buffers, and the potential for disruption propagation to other units. A review of maintenance approaches in chemical and process industries indicates that effective planning should simultaneously consider interdependencies among units, time-varying quantitative and qualitative data, condition-based maintenance, resource constraints, and spare-parts supply. Therefore, in the present study, technical factors are evaluated not as an independent list of equipment failures, but according to their role in causing, propagating, and sustaining shutdowns (Chin et al., 2020).

2.6 Environmental Factors and Working Conditions

The work environment affects shutdowns through two pathways: first, by intensifying the physical degradation of equipment and, second, by altering employee performance. Heat, dust, humidity and corrosive environments, noise, inadequate lighting, exposure to alkaline substances, water limitations, and climatic conditions can affect equipment life, the ability to detect failure indications, concentration, and employee response speed. In human reliability analysis, these conditions are considered performance-shaping factors, and their effects are not independent of individual and organizational factors. For example, thermal stress is more likely to increase the probability of error or delay when combined with understaffing, inadequate protective equipment, inappropriate rest schedules, or difficulty accessing equipment. Accordingly, the

environmental dimension in the present model encompasses natural and physical working-environment conditions and resource constraints and is not considered equivalent to the “environmental consequences of shutdowns” (Jha et al., 2024).

2.7 Production Shutdowns and Industrial Sustainability

Industrial sustainability in this study is interpreted across three dimensions: economic, environmental, and social–safety. Economically, shutdowns lead to reduced production, increased repair costs, spare-parts consumption, overtime, and disruption of production schedules. Environmentally, unstable operation, shutdown and restart activities, or emergency maintenance may increase specific energy and water consumption, waste, leakage, and waste generation. From the social–safety perspective, workload pressures, maintenance personnel’s exposure to abnormal conditions, and the likelihood of accidents may increase. In this regard, Boral et al. (2020) showed that the severity of failure consequences should be disaggregated into economic, environmental, and social dimensions rather than represented by a single overall score. Similarly, Holgado et al. (2020) characterized maintenance not merely as a cost-generating activity but as a factor influencing economic performance, energy management, and the social benefits of production. The Maintenance 5.0 framework further develops this connection by emphasizing human-centered strategies, smart technologies, and environmental indicators (Psarommatis et al., 2023).

2.8 Rationale for Using BWM and DEMATEL Methods

The research problem is multi-criteria and network-based. The Best–Worst Method (BWM) is appropriate for determining the relative importance of factors because the expert first identifies the most important and least important criteria and then expresses the preferences of the best criterion over the other criteria and of the other criteria over the worst criterion. This structure requires fewer pairwise comparisons and allows the consistency of judgments to be assessed. The linear BWM model obtains a unique set of criteria weights by solving an optimization problem (Rezaei, 2016). However, a high weight does not indicate that the factor is necessarily a root cause, as it may instead be strongly affected by upstream factors. DEMATEL, in contrast, constructs direct-relation and total-relation matrices to quantify the influence and dependence of each factor and classify factors into cause and effect groups. The use of fuzzy logic also helps address the ambiguity inherent in experts’ linguistic judgments. In this regard, studies by Govindan et al. (2022) and Ghorbani et al. (2024) have shown that integrating BWM and DEMATEL is suitable for problems in which criteria differ in importance and exhibit mutual interdependence. Table 1 provides a summary of the relevant previous studies.

Study	Scope and Method	Specific and Applicable Finding for the Present Study
Rezaei (2015)	Introduction of the BWM method	The Best–Worst Method reduces the number of comparisons by comparing the best criterion with the other criteria and the other criteria with the worst criterion, while also allowing the consistency of judgments to be assessed.
Patil (2020)	Failure and repair data, expert perspectives, and Weibull and Lognormal fitting	Experience, training, and behavior were among the most important human factors, while safety culture, problem-solving resources, corrective-action programs, and training programs were key organizational factors. Although human and organizational factors accounted for a smaller share of failures, they produced substantial changes in reliability and maintainability indicators.
McDonnell et al. (2018)	Integration of human and organizational factors into maintenance prognostics models	Human-factor indicators and performance-shaping factors should be incorporated as quantitative variables alongside technical, process, and sensor data in reliability models to reduce uncertainty in failure prediction.

Ghasemi et al. (2022)	Integration of HFACS, fuzzy sets, and Bayesian networks	Conflict among organizational units, weak safety culture, inadequate equipment, insufficient inspection, and safety violations were among the major factors contributing to a process accident, reinforcing the role of inter-unit coordination and organizational factors in the present model.
Don et al. (2024)	Alumina refinery, SIPOC framework, and Weibull analysis	Refinery performance deviations may result from unexpected shutdowns, supply-chain disruptions, human-resource availability, process-input variations, and environmental conditions; therefore, shutdown analysis should not be limited to equipment failures.
Hiltunen et al. (2008)	Availability analysis of large alumina calciners	Design, refractory materials, valves and moving equipment, instrumentation, process control, operator performance, and maintenance planning affect calciner shutdowns. This study supports the criticality of the calcination unit and the need to integrate technical, operational, and human factors.
Uddin et al. (2019)	Root-cause analysis and Weibull analysis in the alumina precipitation section	A highly alkaline environment and improper pressure-gauge installation caused failures, repair costs, production losses, and HSE consequences; correcting the installation increased equipment life from several weeks to several years.
Bouabid et al. (2024)	Review of sustainable maintenance in high-risk process industries	Maintenance performance should be evaluated simultaneously in terms of economic, environmental, and social consequences, and maintenance should be considered as a means of achieving sustainability throughout the asset life cycle.
Barbieri and Hernandez (2024)	Integration of sustainability indicators and RAM analysis	Sustainability indicators, together with reliability, availability, and maintainability, can be used to compare maintenance alternatives from technical, economic, and environmental perspectives.
Sun et al. (2022)	Resilience-based maintenance cost planning in a refinery	Maintenance assessment should not focus solely on failure prevention; recovery capacity and recovery time following disruptions should also be evaluated using minimum acceptable resilience levels and maximum acceptable recovery times.
Hosseinpour et al. (2024)	Fuzzy Delphi, fuzzy BWM, and fuzzy DEMATEL	Delphi was used for identification and screening, BWM for determining importance, and DEMATEL for identifying internal and causal relationships among criteria; this study supports the rationale for the combined methodological framework used in the present study.
Ren et al. (2021)	Fuzzy hierarchical BWM, fuzzy DEMATEL, and TOPSIS	BWM determines criterion importance and short-term priorities, whereas DEMATEL reveals causal relationships and upstream factors influencing long-term sustainability improvement.

Table 1. Literature Review

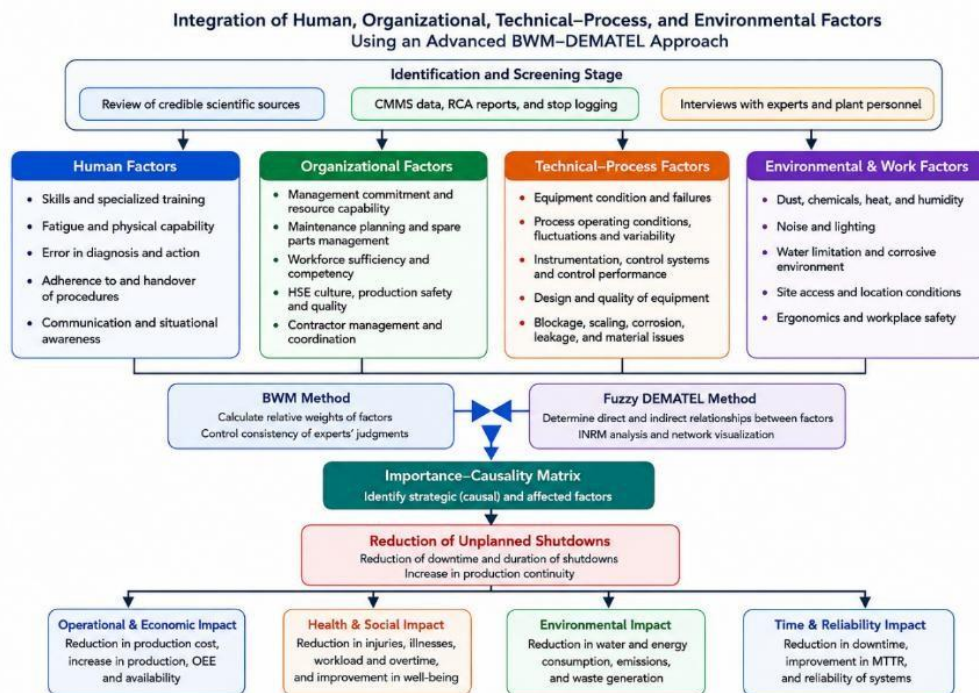
The synthesis of the literature and theoretical background indicates that alumina production shutdowns do not result from a single cause; rather, they emerge from the interaction of four groups of factors: human, organizational, technical–process, and environmental factors. Maintenance and reliability studies have primarily focused on equipment failures and maintenance policies; human-factor studies have mainly examined the probability of error; and sustainability research has often assessed production consequences independently of the network of causes underlying shutdowns. Therefore, the main gap in the existing literature is the absence of an integrated framework that first identifies critical units using actual data on the number of shutdowns, shutdown duration, and lost production, and then analyzes the importance and causal relationships of the four groups of factors.

From an operational perspective, the proposed model distinguishes among three concepts that may be

conflated in industrial reports: the source of disruption, the location where the shutdown occurs, and the factor that increases recovery time. For example, the source of a disruption may be a utility failure or feedstock quality, the shutdown may be observed in the digestion unit, while a shortage of spare parts or a delay in maintenance authorization may prolong its duration. This distinction allows the results of critical-unit identification and Pareto analysis to be correctly interpreted alongside expert-based causal analysis and prevents the unit with the highest number of shutdown hours from being incorrectly regarded as the primary source of the problem without examining upstream causes.

Accordingly, the initial conceptual model of the study consists of three main layers: factors causing and sustaining shutdowns; unplanned shutdowns and capacity losses; and economic, environmental, and social–safety consequences. In this model, the four dimensions of human, organizational, technical–process, and environmental factors constitute the first layer. BWM determines the relative weight and importance of these factors, while DEMATEL determines their influence and dependence structure. Integrating the two outputs makes it possible to distinguish strategic and causal factors, critical but effect-driven problems, hidden levers, and low-priority factors. Within this structure, sustainability consequences are regarded as outcomes of shutdowns and are therefore not placed at the same level as the environmental factors that contribute to causing shutdowns. The initial conceptual model developed based on this framework is presented in Figure 1.

Figure 1. Initial Conceptual Model of Factors Affecting Unplanned Alumina Production Shutdowns with an Industrial Sustainability Approach (Source: Developed by the author based on the theoretical foundations)



3. Materials and Methods

3.1 Research Design

The present study was applied–developmental in purpose and employed a multi-stage mixed-methods design. In the first stage, recorded shutdown data were analyzed to identify critical units; in the second stage, factors affecting shutdowns were extracted and refined through an integration of the literature review, technical documents, and expert perspectives; and in the third stage, factor importance was determined using the Best–Worst Method (BWM), while directional influence relationships were assessed using fuzzy DEMATEL. The unit of analysis in the first stage was a “shutdown or capacity-loss event,” whereas in the

expert-based stages it was a “factor affecting the occurrence or continuation of a shutdown.” Distinguishing between these two levels reduced the risk of treating the location where a shutdown was observed as its root source without examining the initiating disruption and the factors prolonging recovery.

3.2 Case Study Description

The research setting is the Jajarm Alumina Complex. The formal alumina production structure of the complex consists of the bauxite and lime, digestion, red mud separation, precipitation, calcination, caustic soda and evaporation, and utility units. These units are interdependent through flows of bauxite, lime, caustic soda, water, steam, condensate, and hydrate. Therefore, the entire production chain is included in the screening process without any prior assumption regarding the criticality of a particular unit. For the initial analysis, the process is coded into eight clusters: feed preparation; lime and grinding; digestion; red mud separation and caustic soda recovery; precipitation; calcination; caustic soda and evaporation; and utilities. This analytical classification, while preserving the actual structure of the plant, enables a comparable assessment of the number and duration of shutdowns across units.

3.3 Collection and Preparation of Shutdown Data

Twenty-four months of data covering the period from March 20, 2024 to March 21, 2026 were extracted from the computerized maintenance management system, shift reports, maintenance work orders, production reports, and HSE documents. For each event, the start and end times, initiating unit, affected units, equipment, shutdown type, direct cause, root cause, net repair time, waiting time, lost production, and safety or environmental consequences were recorded.

Under the proposed approach, scheduled shutdowns, duplicate records resulting from multiple entries for the same incident, and events without a direct connection to production were excluded. Partial shutdowns and speed losses were retained provided that the extent of capacity reduction could be measured. For chain events, the first demonstrable disruption was recorded as the “source of the shutdown,” while the other units were recorded as “affected units.” Waiting time for spare parts, permits, contractors, or specialized personnel was also separated from net repair time so that factors causing equipment failure could be distinguished from factors increasing shutdown duration.

3.4 Identification of Critical Units

The screening of units was conducted using three complementary Pareto analyses based on the number of events, total shutdown duration, and lost production. The share of each unit for criterion j was calculated using the following equation:

$$S_{ij} = (X_{ij}/(\sum_i X_{ij})) \times 100 \quad (1)$$

Where X_{ij} represented, respectively, the number of shutdowns, shutdown hours, or amount of lost production for unit i under criterion j . Units falling within the cumulative 80% range for at least two of the three criteria were selected as the initial critical units. This rule was specified before analysis to reduce post hoc selection bias.

Subsequently, the frequency–duration matrix classified units into four groups: “high-frequency–long-duration,” “high-frequency–short-duration,” “low-frequency–long-duration,” and “low-frequency–short-duration.” When lost production was not directly recorded, it was estimated using the following equation:

$$L_i = T_i \times Q_i \times R_i \quad (2)$$

In this equation, T_i denoted shutdown duration, Q_i the baseline hourly production rate, and R_i the capacity-reduction coefficient, ranging from zero to one; for a complete shutdown, $R_i=1$.

The results of this stage were used to limit the scope of subsequent expert-based analyses to units that, based on operational evidence, accounted for the largest share of production disruption.

3.5 Extraction and Validation of Factors

The initial list of factors was developed from three sources: peer-reviewed articles, plant root-cause analysis reports, and semi-structured interviews with experts in production, mechanical engineering, electrical engineering, instrumentation, process engineering, HSE, planning, and procurement. Factors with similar meanings were consolidated, and the final candidates were classified into four dimensions: human, organizational, technical-process, and environmental.

The final Delphi panel consisted of 18 experts, each with at least seven years of direct experience in production, maintenance, or safety in process industries. The Delphi process was conducted in two rounds. The a priori consensus criteria were at least 75% agreement, a median of four or higher on a five-point scale, and an interquartile range of no more than one. Establishing the consensus threshold a priori increased the transparency and reproducibility of the Delphi process.

The necessity of each factor was evaluated using the Content Validity Ratio (CVR), as presented in Equation (3):

$$CVR = ((ne - N/2))/((N/2)) \quad (3)$$

In this equation, ne denoted the number of experts who considered the factor “essential,” and N represented the total number of experts. The resulting value was compared with the critical threshold corresponding to the panel size (Lawshe, 1975).

3.6 Factor Weighting Using the BWM Method

After the factors were finalized, each expert identified the most important factor (B) and the least important factor (W) and completed two vectors—the “Best-to-Others” vector and the “Others-to-Worst” vector—using a 1–9 scale. Factor weights were then calculated using the linear BWM model:

$$\text{Min } \xi \quad (4)$$

Subject to:

$$|wB - aBj \times wj| \leq \xi$$

$$|wj - ajW \times wW| \leq \xi$$

$$\sum_j wj = 1$$

$$wj \geq 0$$

In these equations, aBj denoted the preference of the best factor over factor j , and ajW denoted the preference of factor j over the worst factor. The optimal value ξ represented the degree of deviation from perfect consistency; smaller values therefore indicated more consistent judgments. The model was solved independently for each expert and, after consistency checking, the individual weights were aggregated using the arithmetic mean as the primary estimate. Normalized geometric means were also calculated as a sensitivity check. In general, BWM requires $2n-3$ comparisons for n factors, and its linear model produces a unique solution (Rezaei, 2015, 2016).

3.7 Analysis of Directional Influence Relationships Using Fuzzy DEMATEL

To assess the direct influence of each factor on the other factors, a five-level linguistic scale—“no influence,” “low,” “moderate,” “high,” and “very high”—was used, and the judgments were converted into triangular fuzzy numbers. The average of the judgments provided by K experts constituted the fuzzy direct-

relation matrix:

$$\hat{z}_{ij} = (1/K) \times \sum_k x_{ij}(k) \quad (5)$$

After normalization of the direct-relation matrix, the total-relation matrix was calculated using the following equation:

$$T = X \times (I - X)^{-1} \quad (6)$$

The fuzzy values were defuzzified into crisp values using the Center of Area (Centroid) method:

$$t_{ij} = ((l_{ij} + m_{ij} + u_{ij}))/3 \quad (7)$$

The row sum D_i and column sum R_i were then calculated. The index D_i+R_i indicated prominence, whereas D_i-R_i indicated the direction of influence within the expert-judgment network: a positive value placed a factor in the cause group and a negative value placed it in the effect group. The threshold for displaying the DEMATEL network was set equal to the mean of the off-diagonal elements of the total-relation matrix. Fuzzy logic was used to reduce ambiguity in linguistic judgments, while DEMATEL was used to reveal direct and indirect influence relationships among the factors (Ghorbani et al., 2024). Cause/effect labels were interpreted as directional influence classifications based on expert judgments and not as experimentally established causality.

3.8 Integration of Results, Robustness Analysis, and Ethical Considerations

The BWM and DEMATEL outputs were integrated into an importance–influence matrix. Factors with above-threshold BWM weights and positive D_i-R_i values were treated as high-priority strategic levers; important but effect-group factors were treated as critical manifestations requiring attention to upstream influences; and factors with moderate weights but high network prominence and positive D_i-R_i values were treated as hidden levers for improvement.

Robustness was assessed by sequentially removing each expert, comparing arithmetic-mean and geometric-mean BWM aggregation, varying the DEMATEL threshold by $\pm 10\%$, and calculating Spearman's rank correlation coefficient. Industrial data were analyzed after removing personal identifiers and sensitive equipment codes. The research objectives, confidentiality provisions, voluntary nature of participation, and the experts' right to withdraw were explained before completion of the research instruments, and informed consent was obtained. These sensitivity analyses were used to evaluate ranking stability and the robustness of the cause/effect group classification.

4. Findings

4.1 Formation, Refinement, and Description of the Dataset

To test the proposed framework, an event-based dataset was compiled for a 24-month period from 1403/01/01 to 1405/01/01. The dataset is structured and includes shutdown reports, computerized maintenance management system records, production reports, and HSE documents. The variables include start and end times, unit and equipment, shutdown type, immediate and root causes, recovery-time components, capacity reduction, lost production, costs, additional resource consumption, and safety consequences.

Initially, 480 records were generated. After excluding 42 planned shutdowns, eight duplicate records, and five events without a direct connection to production, a total of 425 unplanned shutdowns remained for the main analyses. The descriptive results of these findings are presented in Tables 2 and 3.

Record Status	Number	Percentage of Initial Records
Initial records	480	100.00
Planned shutdowns excluded	42	8.75
Duplicate records excluded	8	1.67
Non-production events excluded	5	1.04
Unplanned events included in the analysis	425	88.54

Table 2. Data Refinement Specifications

Event Type	Number	Share (%)	Total Shutdown Duration (h)	Mean Duration (h)	Mean Recovery Time to 90% Capacity (h)	Lost Production (t)	Share of Lost Production (%)
Complete shutdown	128	30.12	960.67	7.51	2.23	28,818.11	63.39
Partial shutdown	174	40.94	796.48	4.58	1.79	13,422.84	29.53
Speed loss	123	28.94	436.67	3.55	1.53	3,221.24	7.09
Total	425	100.00	2,193.81	5.16	1.84	45,462.18	100.00

Table 3. Distribution Characteristics of Events Included in the Analysis

Based on Table 3, partial shutdowns, with 174 events accounting for 40.94% of all events, were the most frequent type of disruption. However, despite their lower frequency, complete shutdowns accounted for 63.39% of total lost production. The mean duration of each event was estimated at 5.16 hours, while the mean recovery time to 90% of capacity was 1.84 hours. This difference indicates that event frequency alone is not an adequate criterion for determining criticality, as less frequent shutdowns may have substantially greater consequences in terms of duration, capacity loss, and lost production. Therefore, in the next stage, the number of shutdowns, total shutdown duration, and lost production will be examined simultaneously using Pareto analysis.

4.2 Pareto Analysis and Identification of Critical Units

In the next step, the 425 unplanned events were aggregated by operational unit. To prevent the selection of critical units based solely on event frequency, three independent Pareto analyses were conducted based on the number of shutdowns, total shutdown duration, and lost production. The total duration of the events was 2,193.83 hours, and total lost production amounted to 45,462.80 tons. In each Pareto analysis, units falling within the cumulative 80% range were identified as the main contributors, while the first unit crossing this threshold was identified as the boundary unit. A unit was considered a “primary critical unit” if it was located within the 80% threshold in at least two of the three criteria. The results of the Pareto analyses and the identification of critical units are presented in Table 4.

Cod e	Operation al Unit	Numbe r of Events	Share of Event s (%)	Shutdow n Duratio n (h)	Share of Duratio n (%)	Lost Productio n (t)	Shar e of Loss (%)	Frequenc y– Duration Matrix	Final Status
U8	Utilities	78	18.35	418.41	19.07	9,999.21	21.99	High- frequency –long- duration	Main critical
U3	Digestion and high- pressure pumps	71	16.71	467.84	21.33	9,574.77	21.06	High- frequency –long- duration	Main critical
U4	Red mud separation and caustic soda recovery	66	15.53	314.76	14.35	5,776.31	12.71	High- frequency –long- duration	Main critical
U6	Calcination	27	6.35	314.64	14.34	7,413.68	16.31	Low- frequency –long- duration	Main critical
U5	Hydrate precipitation and filtration	45	10.59	204.48	9.32	4,240.35	9.33	Low- frequency –short- duration	Importa nt borderli ne
U2	Lime and grinding	47	11.06	148.62	6.77	2,491.41	5.48	Low- frequency –short- duration	Single- criterion
U1	Bauxite preparation and transfer	55	12.94	136.88	6.24	2,468.75	5.43	High- frequency –short- duration	Single- criterion
U7	Caustic soda and evaporatio n	36	8.47	188.20	8.58	3,498.32	7.69	Low- frequency –short- duration	Single- criterion borderli ne
Tota l	—	425	100.0 0	2,193.83	100.00	45,462.80	100.0 0	—	—

Table 4. Results of the Triple Pareto Analysis and Classification of Operational Units

The results of the analyses showed that utilities had the highest frequency, with 78 events, and accounted for the greatest amount of lost production, at 9,999.21 tons. In contrast, the digestion and high-pressure pump unit had the longest total shutdown duration, accounting for 467.84 hours. The classification of both units as high-frequency–long-duration indicates their simultaneous role in the recurrence and severity of disruptions in the study scenario. The red mud separation and caustic soda recovery unit also fell within the main Pareto range across all three criteria. Although calcination accounted for only 6.35% of the events, it represented 14.34% of the total shutdown duration and 16.31% of lost production; therefore, it represents an example of low-frequency but long-duration and high-consequence events. The four main critical units accounted for only 56.94% of all events, but their combined shares of total shutdown duration and lost production reached 69.09% and 72.07%, respectively. The hydrate precipitation and filtration unit was also retained as an important borderline unit because it was located at the Pareto boundary for event frequency and lost production. Accordingly, the factors examined in the Delphi, BWM, and DEMATEL stages were primarily extracted with a focus on the five units U8, U3, U4, U6, and U5. The results of the triple Pareto analysis and the final classification of the operational units are presented in Table 4.

4.3 Results of Factor Screening and Delphi Analysis

Following the integration of the theoretical foundations, the conceptual model structure, and the results of the critical-unit identification, 24 initial factors across four dimensions—human, organizational, technical–process, and environmental—were entered into two rounds of Delphi analysis. The analytical panel consisted of 18 expert profiles from the fields of production, mechanical and electrical maintenance, instrumentation, process engineering, HSE, energy, planning, reliability, and asset management. The factor-acceptance criteria were defined as a median of at least 4, an interquartile range of no more than 1, agreement of at least 75%, a minimum Content Validity Ratio (CVR) of 0.444, and a minimum Content Validity Index (CVI) of 0.78. Based on the results, 15 factors met all acceptance criteria, while 9 factors were excluded because of insufficient content validity, conceptual overlap, or borderline status.

Kendall’s coefficient of concordance (W) increased from 0.304 in the first round to 0.578 in the second round. The corresponding chi-square values were 125.75 and 239.49, respectively, with 23 degrees of freedom, indicating statistically significant agreement among the experts. The increase in the coefficient of concordance indicates that the controlled feedback provided after the first round reduced the dispersion of judgments and resulted in greater convergence among the expert profiles. The mean content validity index of the final factors was 0.963. The final factors confirmed through the two Delphi rounds are presented in Table 5.

Code	Dimension	Final Factor	Mean Round 1	Mean Round 2	Median	IQR	Agreement (%)	CVR	I-CVI
H1	Human	Specialized skills and training	4.06	4.22	4	0.00	100.0	0.778	1.000
H2	Human	Fatigue and shift workload	4.33	4.00	4	0.00	100.0	0.556	0.944
H3	Human	Operator diagnostic and response error	4.22	4.11	4	0.00	100.0	0.667	0.944

O1	Organizational	Management commitment to reliability	4.67	4.67	5	1.00	100.0	0.778	1.000
O2	Organizational	Maintenance planning	4.61	4.72	5	0.75	100.0	0.889	1.000
O3	Organizational	Availability of spare parts and specialized personnel	4.33	4.78	5	0.00	100.0	0.889	1.000
O4	Organizational	Coordination among production, maintenance, process, and HSE	4.17	4.22	4	0.00	100.0	0.778	0.944
T1	Technical–process	Wear and failure of critical equipment	4.83	4.94	5	0.00	100.0	1.000	1.000
T2	Technical–process	Scaling and line blockage	4.22	4.56	5	1.00	100.0	0.889	0.944
T4	Technical–process	Instrumentation and control-system failures	4.39	4.44	4	1.00	100.0	0.778	1.000
T5	Technical–process	Process fluctuations and bauxite quality	4.61	4.39	4	1.00	100.0	0.778	0.944
T6	Technical–process	Electricity, steam, water, and compressed-air disruptions	4.67	4.83	5	0.00	100.0	1.000	1.000
E1	Environmental	Thermal stress, dust, noise, and lighting	3.83	4.00	4	0.00	100.0	0.556	0.889
E3	Environmental	Alkaline and corrosive environment	4.39	4.06	4	0.00	100.0	0.667	0.944
E4	Environmental	Industrial water limitations and quality	4.28	4.00	4	0.00	100.0	0.556	0.889

Table 5. Final Factors Confirmed Through the Two Delphi Rounds

The results showed that the final set consisted of three human factors, four organizational factors, five technical–process factors, and three environmental factors. The highest Round 2 mean scores were obtained for wear and failure of critical equipment, utility disruptions, availability of spare parts and specialized personnel, and maintenance planning, respectively. However, these means represent only the screening results, and the final ranking of the factors will be determined in the next stage based on the structured BWM comparisons.

In the subsequent analysis, the factors of shift communication and handover, compliance with procedures, CMMS data quality, change management, corrosion and erosion, condition monitoring, climatic conditions, and ergonomics were mainly excluded because their CVR values were below the acceptance threshold. The factor “lack of redundancy and reserve capacity,” with a CVR of 0.444, was at the acceptance threshold; however, its I-CVI was 0.778, and it was therefore not included in the final set. The exclusion of this factor does not imply that it is unimportant; rather, it indicates that, in the present scenario, there was insufficient consensus to retain it as an independent factor.

4.4 Factor Weighting and Ranking Using the BWM Method

After the 15 factors were confirmed through the Delphi stage, the linear Best–Worst Method model was solved independently for each of the 18 expert profiles. Each profile first identified the most important and least important factors and then performed the “Best-to-Others” and “Others-to-Worst” comparisons using a 1–9 scale. After solving the model, the individual weights were aggregated using the arithmetic mean; normalized geometric means were also calculated to assess the sensitivity of the rankings.

The mean optimal value of ξ^* was 0.0499, while the mean and maximum consistency ratios were 0.0361 and 0.0640, respectively, and all 18 sets of judgments fell within the acceptable range. The low values indicate a high degree of internal consistency in the expert judgments. The final BWM weights and ranking of the factors affecting shutdowns are presented in Table 6.

Rank	Code	Dimension	Factor	Group Weight	Share of Total (%)	Standard Deviation
1	T6	Technical–process	Electricity, steam, water, and compressed-air disruptions	0.1091	10.91	0.0132
2	T1	Technical–process	Wear and failure of critical equipment	0.1062	10.62	0.0149
3	O2	Organizational	Maintenance planning	0.0966	9.66	0.0119
4	O3	Organizational	Availability of spare parts and specialized personnel	0.0908	9.08	0.0116
5	T2	Technical–process	Scaling and line blockage	0.0866	8.66	0.0136

6	O1	Organizational	Management commitment to reliability	0.0738	7.38	0.0145
7	T5	Technical–process	Process fluctuations and bauxite quality	0.0677	6.77	0.0154
8	T4	Technical–process	Instrumentation and control-system failures	0.0653	6.53	0.0135
9	H1	Human	Specialized skills and training	0.0552	5.52	0.0055
10	O4	Organizational	Coordination among production, maintenance, process, and HSE	0.0519	5.19	0.0042
11	H3	Human	Operator diagnostic and response error	0.0513	5.13	0.0048
12	H2	Human	Fatigue and shift workload	0.0438	4.38	0.0071
13	E3	Environmental	Alkaline and corrosive environment	0.0369	3.69	0.0035
14	E4	Environmental	Industrial water limitations and quality	0.0356	3.56	0.0026
15	E1	Environmental	Thermal stress, dust, noise, and lighting	0.0292	2.92	0.0030

Table 6. Final Weights and Ranking of Factors Affecting Shutdowns Based on BWM

The results of this stage showed that electricity, steam, water, and compressed-air disruptions had the highest priority, with a weight of 0.1091. This finding is consistent with the Pareto results, as utilities accounted for the highest number of shutdowns and the greatest amount of lost production in the second stage. Wear and failure of critical equipment ranked second, with a weight of 0.1062. The small difference between these two factors indicates that, from the experts' perspective, they were nearly equal in terms of importance. Maintenance planning and the availability of spare parts and specialized personnel ranked third and fourth, respectively, indicating that organizational factors, in addition to technical failures, play an important role in sustaining and prolonging shutdowns. Scaling and line blockage, management commitment to reliability, process fluctuations and bauxite quality, and instrumentation and control-system failures occupied the subsequent ranks.

According to the results presented in Table 6, technical–process factors had the highest cumulative

weight, at 0.4349. The organizational, human, and environmental dimensions had weights of 0.3131, 0.1504, and 0.1016, respectively. Overall, the technical–process and organizational dimensions accounted for approximately 74.80% of the total importance. This finding indicates that reducing shutdowns in the examined scenario cannot be explained solely by improving equipment or solely by changing employee behavior; rather, the interaction between technical reliability and organizational capabilities must be considered.

4.5 Influence-Structure Analysis Using Fuzzy DEMATEL

To determine the influence structure among the factors, 3,780 directed relationships were evaluated based on the judgments of 18 expert profiles and the 15 final factors, using a five-level scale ranging from 0 to 4. The linguistic scores were converted into triangular fuzzy numbers and, after aggregation, the fuzzy direct-relation matrix was constructed. The normalization coefficient was 9.4306. Subsequently, the total-relation matrix was calculated and defuzzified into crisp values using the Center of Area method. The threshold for displaying relationships in the network was set equal to the mean of the off-diagonal elements of the total-relation matrix, yielding 0.0681. Accordingly, 76 of the 210 possible relationships had strengths greater than the threshold. Ultimately, 10 factors were classified into the causal group and five factors into the effect group. The results of the causal–effect analysis using fuzzy DEMATEL are presented in Table 7.

Prominence Rank	Code	Factor	D	R	D+R	D–R	Role
1	T1	Wear and failure of critical equipment	0.7628	1.9828	2.7455	–1.2200	Effect
2	O4	Coordination among production, maintenance, process, and HSE	1.4600	1.0730	2.5330	0.3870	Cause
3	T4	Instrumentation and control-system failures	0.7443	1.5791	2.3234	–0.8348	Effect
4	O3	Availability of spare parts and specialized personnel	1.2479	1.0725	2.3204	0.1754	Cause
5	H3	Operator diagnostic and response error	0.7223	1.5900	2.3122	–0.8677	Effect
6	O2	Maintenance planning	1.3299	0.9786	2.3084	0.3513	Cause
7	T6	Electricity, steam, water, and compressed-air disruptions	1.1499	1.0346	2.1844	0.1153	Cause

8	O1	Management commitment to reliability	1.6611	0.4711	2.1323	1.1900	Cause
9	T2	Scaling and line blockage	0.7402	1.2668	2.0070	-0.5266	Effect
10	H2	Fatigue and shift workload	0.8113	1.1801	1.9915	-0.3688	Effect
11	H1	Specialized skills and training	0.9498	0.7319	1.6817	0.2179	Cause
12	T5	Process fluctuations and bauxite quality	0.8990	0.6406	1.5396	0.2585	Cause
13	E4	Industrial water limitations and quality	0.9418	0.5028	1.4446	0.4390	Cause
14	E3	Alkaline and corrosive environment	0.8677	0.4667	1.3344	0.4010	Cause
15	E1	Thermal stress, dust, noise, and lighting	0.7411	0.4585	1.1996	0.2826	Cause

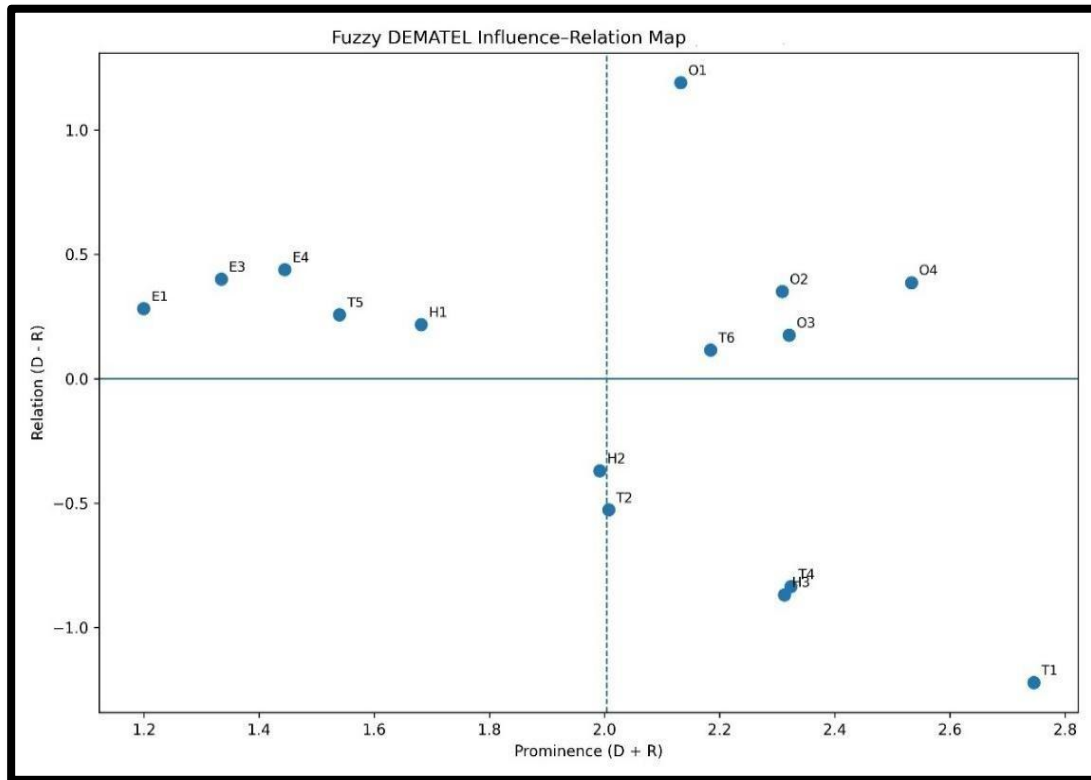
Table 7. Results of the Causal–Effect Analysis of Factors Using Fuzzy DEMATEL

According to Table 7, management commitment to reliability ($D-R=1.1900$) had the strongest cause-group position in the expert-judgment network. Industrial water limitations and quality, the alkaline and corrosive environment, coordination among units, and maintenance planning followed among the positive $D-R$ factors. These results indicate stronger net outward influence within the modeled network, rather than experimentally demonstrated causality.

In contrast, wear and failure of critical equipment ($D-R=-1.2200$) was the strongest effect-group factor and, simultaneously, the most prominent factor in the network ($D+R=2.7455$). Within the modeled influence structure, this pattern suggests that equipment failure is strongly connected to upstream organizational, maintenance, utility, and environmental conditions. Operator diagnostic errors, instrumentation failures, scaling and line blockage, and shift fatigue were also classified in the effect group.

The strongest modeled influence links included $O1 \rightarrow T1$, $O2 \rightarrow T1$, $O3 \rightarrow T1$, $T6 \rightarrow T1$, $O4 \rightarrow H3$, and $O2 \rightarrow T4$. This pattern suggests that focusing only on the immediate failed equipment may overlook upstream conditions identified by the expert network. The INRM map illustrates each factor according to prominence and cause/effect group position; the fuzzy DEMATEL map is presented in Figure 2. These results were subsequently integrated with the BWM weights.

Figure 2. Fuzzy DEMATEL Map



4.6 Integration of Importance–Influence and Robustness Analysis

In the final stage, the BWM weight was used as the baseline importance measure, $D+R$ as the network prominence index, and $D-R$ as the direction of net influence. To avoid double-counting expert judgments, these indices were not directly multiplied in the primary classification. The importance threshold was set to the equal weight of the 15 factors ($1/15=0.0667$), while the prominence threshold was set to the mean $D+R$ (2.0039). Five factors—management commitment to reliability, maintenance planning, availability of spare parts and specialized personnel, process fluctuations and bauxite quality, and utility disruptions—were classified as main strategic levers because they combined above-threshold importance with positive $D-R$ values.

Coordination among production, maintenance, process, and HSE, despite having a BWM weight below the equal-weight threshold, showed high network prominence and a positive $D-R$ value and was therefore classified as a central hidden driver. Wear and failure of critical equipment and scaling and line blockage were classified as critical effect-driven manifestations because of their relatively high weights and negative $D-R$ values. Instrumentation and control-system failures and operator diagnostic errors, although slightly below the BWM importance threshold, exhibited high prominence and were classified as critical dependent indicators. The final importance–influence classifications are presented in Table 8.

Code	Factor	BWM Weight	D+R	D–R	Final Classification
T1	Wear and failure of critical equipment	0.1062	2.7455	–1.2200	Critical and effect-driven consequence

T6	Electricity, steam, water, and compressed-air disruptions	0.1091	2.1844	0.1153	Main strategic lever
O2	Maintenance planning	0.0966	2.3084	0.3513	Main strategic lever
O3	Availability of spare parts and specialized personnel	0.0908	2.3204	0.1754	Main strategic lever
T2	Scaling and line blockage	0.0866	2.0070	−0.5266	Critical and effect-driven consequence
T4	Instrumentation and control-system failures	0.0653	2.3234	−0.8348	Critical dependent indicator
O1	Management commitment to reliability	0.0738	2.1323	1.1900	Main strategic lever
O4	Coordination among production, maintenance, process, and HSE	0.0519	2.5330	0.3870	Central hidden driver
H3	Operator diagnostic and response error	0.0513	2.3122	−0.8677	Critical dependent indicator
T5	Process fluctuations and bauxite quality	0.0677	1.5396	0.2585	Main strategic lever
H2	Fatigue and shift workload	0.0438	1.9915	−0.3688	Dependent factor requiring monitoring
H1	Specialized skills and training	0.0552	1.6817	0.2179	Supporting causal condition
E4	Industrial water limitations and quality	0.0356	1.4446	0.4390	Supporting causal condition
E3	Alkaline and corrosive environment	0.0369	1.3344	0.4010	Supporting causal condition

E1	Thermal stress, dust, noise, and lighting	0.0292	1.1996	0.2826	Supporting causal condition
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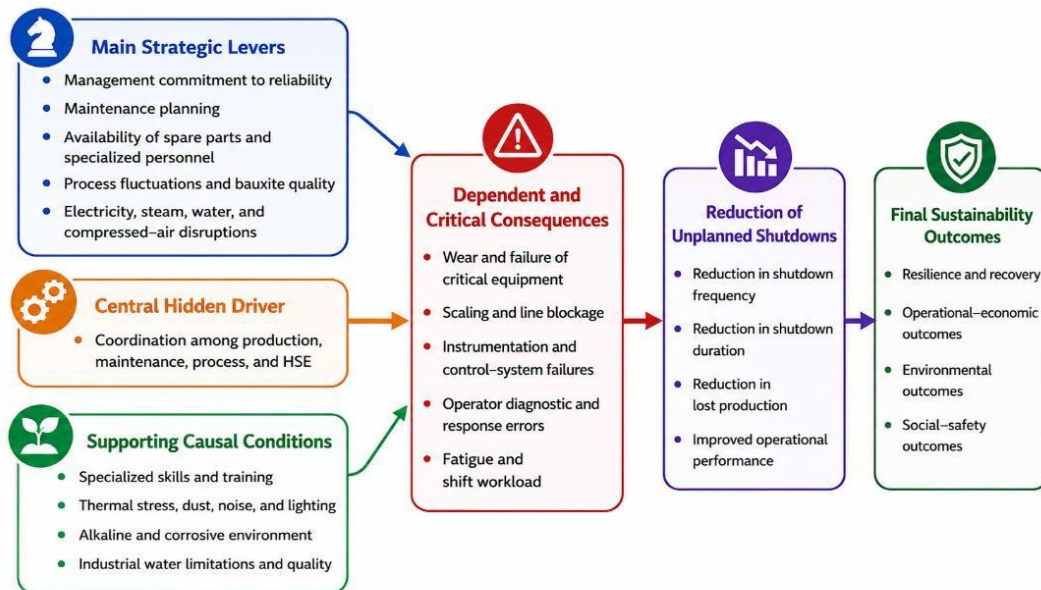
Table 8. Final Outputs of the Importance–Influence Matrix

The robustness analysis supported the stability of the main rankings and influence classifications. The BWM rankings obtained using arithmetic-mean and normalized geometric-mean aggregation were identical. In the leave-one-expert-out analysis, the lowest Spearman correlation with the original ranking was 0.993 and the maximum rank displacement was one position. When the DEMATEL threshold was varied by $\pm 10\%$, the number of displayed network relationships ranged from 73 to 81, while the classification of factors into cause and effect groups remained unchanged.

4.7 Final Empirical Conceptual Model

The final model summarizes the empirically derived influence structure: the main strategic levers and the central driver are linked to dependent technical and human manifestations, which in turn are associated with shutdown frequency, duration, and lost production. These disruptions have implications for resilience, operational–economic performance, environmental performance, and social–safety outcomes. The model should be interpreted as an expert-informed structural representation rather than as experimental proof of causal effects. The empirically revised model is presented in Figure 3.

Figure 3. Final Conceptual Model of the Study (Source: Developed by the author)



5. Conclusions and Recommendations

The present study identified and prioritized factors affecting unplanned shutdowns in alumina production and examined their directional influence structure using an integrated Pareto–Delphi–BWM–fuzzy DEMATEL framework. The analysis of 425 unplanned events over a 24-month period showed that event frequency alone is insufficient for identifying critical units; total shutdown duration and lost production must also be considered. Utilities, digestion and high-pressure pumps, red mud separation and caustic soda recovery, and calcination were identified as the main critical units, while hydrate precipitation and filtration was an important boundary unit. The four main critical units accounted for 56.94% of events but 69.09% of total shutdown duration and 72.07% of lost production, demonstrating that criticality is strongly shaped by severity and process-chain position in addition to frequency.

This finding is consistent with the interconnected nature of the Bayer process. A disruption in one section can propagate to other units through material, caustic, water, steam, and energy flows. Accordingly, as Sidrak (2001) also emphasized, the alumina refining process is characterized by multiple disturbances, extensive interactions among subprocesses, and difficulties in maintaining stable operating conditions. Similarly, Spiers et al. (2024) showed that digestion equipment is located on the critical path of the Bayer process and that its maintenance scheduling should be coordinated with the network dependencies of production.

The results of the two-round Delphi screening reduced the initial list of 24 factors to 15 final factors across four dimensions: human, organizational, technical–process, and environmental. The increase in Kendall's coefficient of concordance from 0.304 to 0.578 and the achievement of an S-CVI/Ave of 0.963 confirmed the internal consistency of the process. In the BWM stage, electricity, steam, water, and compressed-air disruptions, with a weight of 0.1091; wear and failure of critical equipment, with a weight of 0.1062; maintenance planning, with a weight of 0.0966; and availability of spare parts and specialized personnel, with a weight of 0.0908, received the highest importance scores. At the dimensional level, technical–process and organizational factors together accounted for 74.80% of the total weight. Therefore, shutdowns cannot be regarded solely as consequences of physical equipment failures; weaknesses in planning, resource provision, and organizational coordination can also contribute to their occurrence or prolongation.

The DEMATEL analysis added an influence-structure perspective to the BWM ranking. Management commitment to reliability ($D-R=1.1900$) had the strongest cause-group position, whereas wear and failure of critical equipment ($D-R=-1.2200$) was the strongest effect-group factor and the most prominent factor in the network. Coordination among production, maintenance, process, and HSE, despite a below-average BWM weight, emerged as a central hidden driver because of its high prominence and positive $D-R$ value. These classifications represent directional influence patterns derived from expert judgments and should not be interpreted as experimentally established causal effects.

In the final empirical model, management commitment, maintenance planning, provision of spare parts and specialized personnel, process stability, and utilities were identified as the main strategic levers. Inter-unit coordination played the role of a central driver, while equipment wear and failure, scaling, instrumentation failures, diagnostic errors, and shift fatigue were classified as dependent consequences. Skills and training, workplace conditions, the alkaline environment, and water quality were identified as supporting causal conditions. The simultaneous importance of technical, human, and organizational factors is consistent with the analysis by Zarei et al. (2021), who regarded human reliability in operations, maintenance, and control of process industries as an integral component of risk management.

From a sustainability perspective, the results indicate that production disruptions can extend beyond lost output to affect resource use, environmental performance, employee workload and safety, and recovery capability. The present study did not apply a separately validated quantitative sustainability-burden index; therefore, these implications are interpreted qualitatively and should be quantified in future work using directly measured environmental, economic, resilience, and social–safety indicators.

Practical recommendations should therefore target both observable failures and upstream organizational conditions. In the short term, shutdown-recording quality, separation of repair time from waiting time, utility-event review, and critical spare-parts control should be prioritized. In the medium term, criticality-based maintenance planning, condition monitoring, structured shift handover, and a formal coordination mechanism among production, maintenance, process, and HSE should be strengthened. In the longer term, redundancy for critical utilities, modernization of high-risk assets, integration of CMMS with production and energy data, and predictive analytics can be evaluated through field implementation and before–after performance indicators.

The main theoretical contribution of the study is the distinction among factor importance, network

prominence, and cause/effect group position, thereby avoiding the assumption that the highest-weighted factor is necessarily an upstream driver. Methodologically, the study integrates shutdown Pareto analysis, Delphi screening, BWM weighting, and fuzzy DEMATEL within a reproducible decision-support framework. The principal limitations are the single-site design, the 24-month observation window, reliance on an 18-expert judgment panel, and the fact that DEMATEL influence directions do not constitute experimental causal identification. In addition, quantitative sustainability consequences were not independently validated using a dedicated burden index.

Future research is recommended to apply the proposed framework using at least 36–48 months of CMMS, production, and HSE data and a larger expert panel. Independent coding of causes with calculation of Cohen's Kappa, comparison of expert groups, validation of the results through a focus-group session, and assessment of changes in indicators such as MTTR, Availability, lost production, and specific resource consumption could be used to examine the external validity of the model.

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Ethical Approval

This study was conducted in accordance with research ethics principles and standards. Prior to the interviews, the objectives of the study, the participation procedures, and the intended use of the interview data were explained to all participants. Their participation was informed and voluntary.

Conflict of Interest

The author declares no conflict of interest in connection with this research.

Author's Contribution

The author was solely responsible for the study conception and design, data collection, methodology, analysis and interpretation of the findings, manuscript preparation, and final approval of the submitted version.

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