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Adaptive OEE: A FUCOM-TOPSIS Framework for Context-Driven Equipment Effectiveness

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Abstract

Overall Equipment Effectiveness (OEE) measures manufacturing productivity as the product of Availability (A), Performance (P), and Quality (Q). Despite its widespread adoption, the classical OEE formula embeds a structural limitation, i.e., the three components are treated as equally important regardless of operational context. This fixed-weight assumption distorts maintenance prioritisation in environments where one component dominates operational losses. To the best of the authors' knowledge, no published framework has formally addressed this limitation through a structured, auditable multi-criteria weighting model. This paper proposes Adaptive OEE, a FUCOM–TOPSIS framework that replaces the fixed A $\times$ P $\times$ Q product with a context-driven weighting model. FUCOM derives context-specific weights for A, P, and Q from expert judgement with minimum elicitation effort and mathematically guaranteed consistency. TOPSIS is adapted from its classical formulation by replacing data-derived ideal solutions with fixed reference poles defined independently of the observed data, ensuring that the effectiveness score of each asset is not influenced by the performance of other assets in the dataset. Three illustrative case studies covering availability-dominant, performance-dominant, and quality-dominant industrial scenarios suggest that classical OEE rankings are not preserved under asymmetric weight configurations, with ranking divergence being most severe when one component carries strongly asymmetric weight, precisely the condition that equal weighting cannot accommodate. The principal contributions are the formalisation of the equal-weight assumption as a formal methodological limitation, the replacement of multiplicative aggregation with a weighted distance measure, and the adaptation of TOPSIS with fixed reference poles for context-independent asset scoring. The framework is directly applicable by maintenance managers and industrial engineers seeking operationally justified equipment rankings without specialised analytical expertise.

Keywords: adaptive OEE; overall equipment effectiveness; FUCOM; TOPSIS; multi-criteria decision making; context-driven weighting; maintenance prioritisation; equipment effectiveness measurement; asset management

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1. Introduction

Overall Equipment Effectiveness (OEE) is widely recognised as the gold standard for measuring manufacturing productivity. Introduced by Nakajima [1] within the Total Productive Maintenance (TPM) framework, OEE decomposes equipment losses into three multiplicative components, i.e., Availability (A), Performance (P), and Quality (Q), yielding the composite score OEE = A $\times$ P $\times$ Q. Since its formalisation in the late 1980s, OEE has achieved broad adoption across discrete and process manufacturing, serving as a foundational key performance indicator in lean manufacturing, Six Sigma, World Class Manufacturing, and Industry 4.0 initiatives [2,3]. Academic interest in OEE has grown substantially over the past decade, with research keywords evolving from maintenance and production toward lean manufacturing and optimisation [3]. An OEE score of 85% is widely cited as the world-class benchmark for discrete manufacturing, while the global average across most industrial sectors lies between 55% and 65% [4,5], indicating persistent gaps between actual and potential equipment performance.

Despite its widespread use, the classical OEE formula embeds a structural assumption that has received insufficient critical attention. The three components A, P, and Q are treated as equally important, combined with implicit fixed weights of 1/3 each, regardless of the operational context. This assumption is not operationally neutral. Wudhikarn [6] was among the first to formalise this limitation, noting that the classical OEE assigns equivalent weights to elements that are fundamentally different in nature. Subsequent work confirmed that this equal-weight structure is not suitable for comparing equipment across different machine types, capacities, and production environments [7,8] and that the significance of each OEE component varies with the specific operational context [9]. Dal et al. [10] further observed that OEE appears differently across sectors and industries, a limitation that has persisted in the literature [2]. Metrics such as Production Equipment Effectiveness (PEE) emerged precisely to address this gap, weighting quality, performance, and availability differently to reflect sector-specific priorities [11].

To illustrate this structural issue, three representative industrial contexts are examined, each characterised by a distinct dominant loss factor.

For instance, in pharmaceutical manufacturing, Quality is the operationally critical component. Regulatory frameworks enforced by agencies such as the Food and Drug Administration impose strict conformance requirements on every production unit; non-conforming batches are subject to mandatory quarantine, investigation, and disposal [12,13]. Reported industry data indicate that the average quality score in pharmaceutical manufacturing is approximately 94%, implying a non-conformance rate that may trigger regulatory inspections or product recalls [5]. The financial and reputational consequences of quality failures are disproportionate relative to equivalent losses in Availability or Performance. The classical OEE formula assigns equal weight to all three components and fails to reflect this asymmetry.

In other context, for example, in continuous-flow refinery operations, Availability is the operationally critical component. Process shutdowns propagate simultaneously across interconnected upstream and downstream units, generating economic losses that are structurally incomparable to equivalent performance or quality degradations [14]. Restart procedures incur additional costs associated with energy consumption, material losses, and equipment thermal cycling [15]. Performance and quality variations in refinery operations are typically absorbed within operational tolerances. The equal-weight OEE formulation does not capture this difference in loss severity between components.

In a third distinct context, in high-speed automotive assembly, Performance is the operationally critical component. These systems are engineered around a defined cycle time, and minor speed reductions or micro-stoppages generate cumulative throughput

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deficits across tightly synchronised stations [16]. Automated inspection systems maintain quality losses at negligible levels, and predictive maintenance programmes limit unplanned downtime [2,16]. Assigning equal weight to A, P, and Q in this environment systematically underestimates the contribution of performance losses to total production inefficiency.

In each context, the dominant loss factor differs, yet the classical OEE formula assigns identical weight to all three components. This fixed-weight assumption constitutes a structural limitation with direct and measurable consequences for maintenance prioritisation decisions.

Significant efforts have been made to extend the original OEE framework. Extensions such as Total Equipment Effectiveness Performance (TEEP), Production Equipment Efficiency (PEE), Overall Asset Effectiveness (OAE), Overall Factory Effectiveness (OFE), and Overall Production Effectiveness (OPE) have emerged to address broader perspectives on equipment and factory-level performance [2]. While PEE introduces differential weights to A, P, and Q, no structured method is prescribed for deriving those weights from the operational context. Weight assignment in PEE remains ad hoc, expert-dependent, and unsupported by any consistency validation mechanism.

While some authors have proposed weighting methods for the OEE components, including Rank-Order Centroid approaches [6], these modify the OEE calculation directly without replacing the multiplicative aggregation structure. Extensions such as TEEP, OAE, OFE, and OPE broaden the scope of measurement but do not address the weighting of A, P, and Q in a given operational context [2,10]. To the best of the authors' knowledge, no published work has proposed a distance-based ranking model that simultaneously derives context-specific weights with guaranteed consistency, incorporates fixed reference poles for cross-asset comparability, and supports auditable equipment ranking across heterogeneous industrial environments. This methodological gap motivates the present work.

To address this gap, this paper pursues three research questions. The first concerns the formal characterisation of the structural limitations of the classical OEE formula and the theoretical basis upon which a multi-criteria weighting approach is justified. The second examines how FUCOM and TOPSIS can be integrated to derive context-sensitive weights for the OEE components with minimum expert elicitation burden and mathematically guaranteed consistency. The third investigates the conditions under which the proposed Adaptive OEE framework produces rankings that differ materially from those obtained under classical OEE and analyses the implications of such divergence for maintenance prioritisation decisions.

This paper makes three original contributions. First, the equal-weight assumption embedded in the classical OEE formula is formally characterised as a structural limitation, and its quantifiable consequences for maintenance prioritisation decisions are systematically identified. Second, the Adaptive OEE framework is proposed as a FUCOM–TOPSIS model for context-driven equipment effectiveness measurement, applicable across heterogeneous industrial environments. Third, three illustrative and representative case studies involving equipment assets evaluated across availability-dominant, performance-dominant, and quality-dominant operational contexts are presented.

The proposed Adaptive OEE framework enables maintenance managers to rank equipment assets based on the operational priorities that matter in their specific context rather than treating availability, performance, and quality as equally important. This produces more accurate prioritisation decisions, reducing the risk of misallocating maintenance resources to assets whose losses are operationally less critical.

It should be noted that the Adaptive OEE does not invalidate the classical formula as a diagnostic instrument. It proposes a structural replacement specifically for maintenance prioritisation decisions across multiple assets in contexts with asymmetric operational priorities.

The remainder of this paper is organised as follows. Section 2 reviews the classical OEE framework and its documented limitations. Section 3 presents the Adaptive OEE framework and introduces the FUCOM and TOPSIS methods that form the methodological basis of the proposed approach, detailing its architecture, weighting procedure, and scoring mechanism. Section 4 describes the case studies, reports the results obtained across the three operational contexts, and compares Adaptive OEE rankings against those produced by the classical formula. Section 5 discusses the findings and addresses the practical implications for industrial asset management. Section 6 concludes the paper and identifies directions for future research.

2. Literature Review

2.1. Documented Limitations of Classical OEE

Despite the OEE's widespread adoption across manufacturing sectors, a substantial body of critical literature has documented structural deficiencies that constrain its validity as a standalone decision-support instrument, particularly when the aim is to reflect operational priorities with sufficient fidelity to support maintenance and resource-allocation decisions.

The first and most fundamental limitation concerns false precision through equal weighting. The classical OEE formula assigns equal implicit weight to availability, performance and quality, contrary to the well-established operational reality that these three dimensions of loss are qualitatively and strategically distinct [17,18]. There is no theoretical or empirical basis for asserting that a one-percentage-point deterioration in availability is equivalent in strategic impact to a one-percentage-point deterioration in quality. Several authors have noted that the rationale underlying the multiplication of the three sub-indicators remains unspecified in the original formulation and that the relative importance of each dimension is simply not considered [19]. Baykasoğlu demonstrated that, when all three OEE variables individually exceed 0.70, the multiplicative formula can yield a composite score that does not faithfully represent actual equipment performance and systematically understates it relative to any weighted-sum formulation [19]. Muchiri and Pintelon [2], whose review in the International Journal of Production Research remains the most comprehensive treatment of the metric's genealogy, showed both where the measurement framework captures production losses and where it diverges from actual industrial practice. The absence of a principled weighting mechanism means that OEE produces a single composite score that may simultaneously conceal and misrepresent the operational criticality of individual loss categories, a problem not resolved by any algebraic manipulation of the basic $A \times P \times Q$ structure.

The second class of limitations involves systematic blind spots in the measurement scope. Muchiri and Pintelon [2] explicitly noted that the OEE framework does not capture losses attributable to external causes such as logistics failures, supplier disruptions, utility shortages or lack of commercial demand. Planning delays, which render equipment idle for intervals not classifiable under any of the six canonical losses, are similarly invisible to the OEE lens. Stefana et al. [20], in their 2024 development of the Resource Overall Equipment Cost Loss (ROECL) indicator published in the International Journal of Productivity and Performance Management, confirmed that costs and organisational losses outside the A, P, Q triplet remain invisible to OEE-based assessments and demonstrated that the lowest-OEE machine is not necessarily responsible for the largest economic losses. Raju et al. [21] further identified that organisational and planning causes of sub-optimal performance fall entirely outside OEE's measurement perimeter in multi-machine environments.

A third limitation is the aggregation distortion arising from the multiplicative structure of the formula. Because OEE is computed as a product rather than a weighted sum, a marginal deterioration in one factor is amplified non-linearly in the composite score. Different combinations of A, P and Q values can yield identical OEE scores, meaning that the metric is not injective: the same output can correspond to fundamentally different operational states, thereby undermining its diagnostic utility [19]. Tsarouhas [22], in a detailed eight-month case study on an automated production line published in the International Journal of Productivity and Performance Management, confirmed that speed losses and equipment breakdowns collectively account for more than 90% of total OEE losses in food manufacturing contexts, illustrating precisely the kind of structural dominance that the multiplicative formula amplifies rather than contextualises.

The fourth structural limitation is context insensitivity. The classical 85% world-class benchmark was developed for high-volume, dedicated discrete manufacturing lines in the Japanese automotive sector. Applied across industries, this threshold is widely acknowledged to be inapplicable without contextual adjustment [17,23]. Ng Corrales et al. [3], in their systematic review of 186 peer-reviewed articles published in Applied Sciences, confirmed that OEE benchmarks vary significantly across manufacturing verticals and that the same numerical value carries different operational meaning depending on product mix, batch complexity, automation level and regulatory regime. In pharmaceutical manufacturing, process industries exhibit inherently lower availability due to mandatory cleaning cycles and batch validation, circumstances under which a value of 70% may represent excellent performance. Lucantoni et al. [24], in their 2024 machine-learning-based OEE improvement framework published in the International Journal of Quality and Reliability Management, further confirmed that the inability to contextualise OEE values across different process types is a persistent barrier to its effective deployment as a decision-support tool.

Taken collectively, these four documented limitations establish that classical OEE, while operationally useful as a first-pass diagnostic tool, is insufficient as the sole basis for informed strategic decisions on maintenance prioritisation, resource allocation or continuous improvement.

2.2. Extensions of OEE in the Literature

The documented inadequacies of classical OEE have stimulated a substantial body of work producing alternative metrics, each addressing a specific perceived deficiency while leaving the fundamental equal-weighting problem substantially intact. The systematic review by Ng Corrales et al. [3] confirmed that academic interest in OEE-derived models has grown substantially but identified no established consensus on an inter-component weighting methodology that is simultaneously theoretically grounded, empirically validated and practically applicable.

The earliest and most widely adopted extension is Total Effective Equipment Performance (TEEP), which modifies the denominator of the formula to encompass total calendar time rather than merely planned production time [2]. TEEP captures planned downtime as an additional loss category, giving visibility to utilisation losses that OEE by design excludes, and is routinely employed as a strategic capacity-planning metric. While TEEP expands the measurement scope, it retains the equal-weight multiplicative structure within the operational time window it shares with OEE.

Production Equipment Effectiveness (PEE), proposed by Raouf [25] in the International Journal of Operations and Production Management, represents the first formal recognition of the weighting problem within the OEE family. Raouf argued that quality, performance and availability should not be treated as equally important and proposed the use of the Analytic Hierarchy Process (AHP) to assign differential weights, yielding the weighted exponentiation formula PEE = $A^{w1} \times P^{w2} \times Q^{w3}$. Critically, however, while PEE acknowledges the unequal-weight problem, Raouf did not specify a rigorous computational procedure for deriving the weights, leaving the method dependent on expert judgement without a structured elicitation framework [19].

Overall Asset Effectiveness (OAE) and Overall Production Effectiveness (OPE) were developed to extend the measurement scope from individual equipment to the asset or production-system level, explicitly incorporating commercial and logistical losses that OEE ignores [2]. These metrics represent a change in measurement scope but preserve the multiplicative structure and do not revisit the equal-weighting assumption applied within each sub-category.

Overall Equipment Effectiveness of a Manufacturing Line (OEEML), introduced by Braglia, Frosolini and Zammori [26] in the Journal of Manufacturing Technology Management, extends OEE to jointly operated machine sets by proposing an alternative losses classification that separates losses directly attributable to individual equipment from those distributed across the line. OEEML successfully highlights bottleneck inefficiencies and supports root-cause identification at the line level. However, as the authors themselves acknowledged, the metric fails to account for the extent to which effectiveness is sustained by in-process inventories and requires complementary metrics to estimate associated costs [26]. In these works, the inter-component weighting issue is not addressed.

Overall Resource Effectiveness (ORE), proposed by Garza-Reyes [27] in the Journal of Quality in Maintenance Engineering, recognised that factors such as raw material efficiency and the wider production environment may contribute significantly to process performance in ways not captured by OEE's three conventional factors. Empirical and simulation-based investigation confirmed that ORE provides more complete diagnostic information for some processes [27]. Stefana et al. [20] extended this cost-based direction through ROECL but similarly did not address the weighting of A, P and Q relative to one another.

Overall Weighting Equipment Effectiveness (OWEE), introduced by Wudhikarn [6] at the IEEE International Conference on Industrial Engineering and Engineering Management, applied the Rank-Order Centroid (ROC) method to assign differential weights to OEE elements. While OWEE represents a meaningful advance in recognising the need for weighting, the ROC method produces weights that are insensitive to tie-breaking when factors share the same rank, and its approximation error increases with the number of criteria ranked [19]. Extensions incorporating fuzzy logic for weighted OEE computation have more recently been proposed precisely because neither PEE nor OWEE adequately handles the uncertainty and context-dependence inherent in expert weight elicitation [19].

The Schiraldi [28] review and compatible weighting approach, published in the Lecture Notes in Production Engineering series in 2024, provides the most recent systematic treatment of OEE weighting methods and concludes that FUCOM-based approaches represent a theoretically superior alternative to both AHP-based PEE- and ROC-based OWEE, given FUCOM's ability to guarantee mathematical consistency with only $n - 1$ pairwise comparisons. Pamucar, Stevic and Sremac [29] formally established FUCOM in 2018 in the journal Symmetry as a method that simultaneously minimises expert elicitation burden and guarantees the deviation from full consistency, properties directly relevant to the OEE weighting problem.

The critical observation that unifies all of these extensions is that, while each addresses real and important deficiencies of classical OEE, none resolves the fundamental equal-weighting limitation from a multi-criteria decision-making perspective. Extensions such as TEEP, OAE and ORE modify the scope or the numerator of the measurement framework but retain the implicit equal-weight assumption within the core multiplicative structure.

PEE and OWEE acknowledge the weighting problem but rely on methods that are either insufficiently specified or theoretically limited in their ability to represent the relative importance of operational dimensions in a structured, replicable and context-sensitive manner [3,19,28].

2.3. Critical Analysis

The literature review identifies three gaps that directly motivate the proposed framework.

Although the structural limitations of classical OEE have been documented across multiple contributions [2,19–22,24,25], no prior work has formalised the conditions under which the equal-weight assumption is statistically and operationally inadmissible. The present work provides that formal argument, establishing the theoretical basis for replacing the multiplicative A $\times$ P $\times$ Q composite with a weighted formulation.

Moreover, existing weighting approaches are individually deficient: PEE [25] introduced AHP-based weights but without a rigorous elicitation procedure; ROC-based OWEE [6] captures only rank ordering and cannot represent cardinal preference intensities; and fuzzy extensions [19] address uncertainty without guaranteeing consistency. None satisfies simultaneously the three requirements of minimum expert elicitation burden, mathematical consistency guarantee, and context-sensitivity. Pamucar et al. [29] demonstrated that FUCOM meets all three conditions; its integration with TOPSIS for equipment ranking has no precedent in the OEE literature.

Also, divergence between weighted and unweighted OEE rankings has been observed empirically [24,26,27], but no study has characterised the threshold conditions under which this divergence becomes materially consequential for maintenance prioritisation decisions. The present work fills this gap, bridging the theoretical justification of weighting and the practical specification of the FUCOM-TOPSIS procedure.

3. Adaptive OEE Framework Proposal

The Adaptive OEE framework produces a new equipment effectiveness indicator, the Adaptive OEE score, defined as the weighted proximity of an equipment asset to a theoretically perfect performance state.

The framework follows a four-step procedure. First, the decision-maker identifies the operational context and determines which OEE component is dominant for the asset under evaluation. Second, FUCOM elicits context-specific weights through a structured pairwise comparison requiring only $n - 1$ comparisons, with mathematical consistency guaranteed. Third, the weighted criteria are used as inputs to the modified TOPSIS model, where the positive and negative ideal solutions are defined as fixed reference poles rather than derived from the observed data, ensuring that each asset's score is independent of the performance of other assets. Fourth, the resulting closeness coefficients rank the equipment assets, and the ranking is compared against the classical OEE ranking to assess divergence.

The framework may be re-executed whenever the operational context changes, generating a revised weight vector and updated Adaptive OEE scores. Figure 1 illustrates the proposed framework. The procedure is fully replicable and requires no specialised software beyond a standard spreadsheet environment.

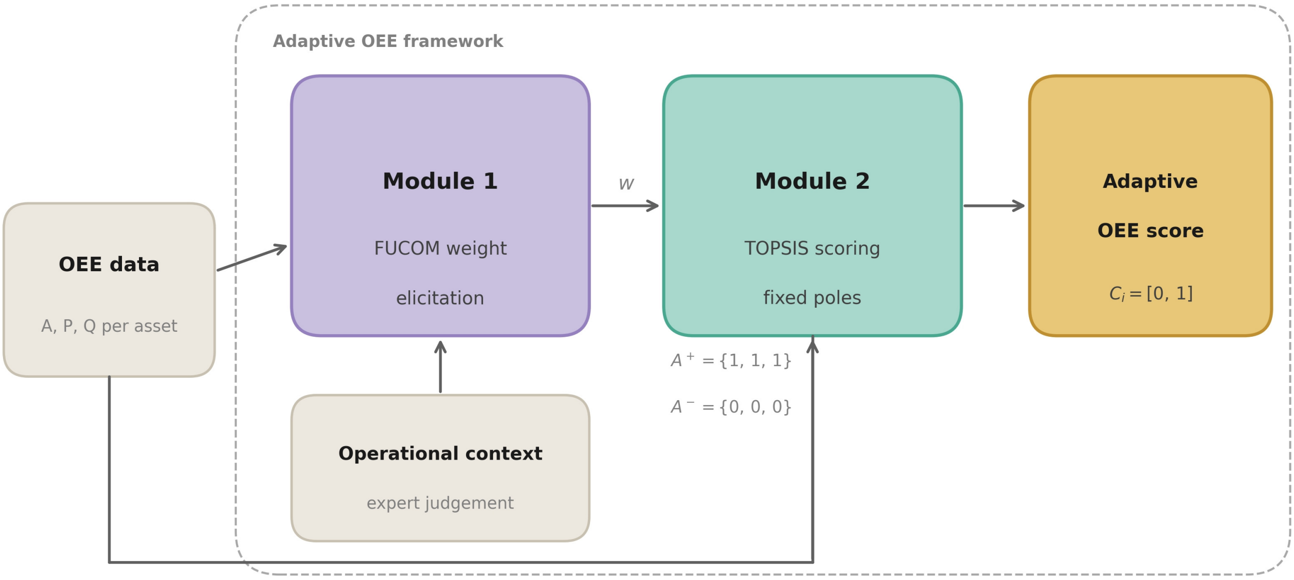

Figure 1. Adaptive OEE framework architecture. OEE component measurements (A, P, Q) feed both modules. Module 1 (FUCOM) derives the context-specific weight vector w from expert judgement. Module 2 (TOPSIS) computes the Adaptive OEE score C_i using the weight vector and fixed ideal poles $A^+ = \{1, 1, 1\}$ and $A^- = \{0, 0, 0\}$. The two modules are strictly sequential.

3.1. Framework Architecture

The framework consists of two sequential modules. The first module applies the Full Consistency Method to derive a context-specific weight vector $w = (w_A, w_P, w_Q)$ reflecting the relative strategic importance of the three OEE components in the operational context under analysis. The second module applies a modified TOPSIS formulation with fixed ideal poles to compute a closeness coefficient C_i that constitutes the Adaptive OEE score for the asset. The weight vector produced by the first module enters the second module as a required input; no scoring is performed prior to weight elicitation. The framework may be re-executed whenever the operational context changes, generating a revised weight vector and revised Adaptive OEE scores. Figure 1 illustrates the proposed framework.

The proposed framework addresses three of the four structural limitations identified in Section 2 as follows.

The equal weighting limitation is addressed by replacing the implicit uniform weight structure of classical OEE with a context-specific weight vector $w = (w_A, w_P, w_Q)$ derived through FUCOM. The weight vector satisfies a mathematical consistency condition and reflects the operational priorities of the context under analysis.

The aggregation distortion limitation is substantially mitigated by replacing the multiplicative formula with a TOPSIS-based closeness coefficient. Unlike the scalar OEE product, the closeness coefficient C_i distinguishes component profiles that yield identical classical OEE values but differ in their A, P, Q composition, a diagnostic distinction that the multiplicative formulation systematically suppresses. In practice, distinct A, P, Q profiles that differ substantially in composition yield distinct values of C_i, preserving the diagnostic granularity of the decomposition.

The context insensitivity limitation is addressed by grounding the scoring model in a context-specific weight structure rather than a universal performance threshold.

The score C_i is interpretable as the relative weighted proximity of an asset to the theoretically perfect performance state {1, 1, 1}, without reference to any industry-derived benchmark. Individual score values may vary marginally when the asset set changes due to Euclidean column normalisation; however, the ranking order remains stable, which constitutes the operationally relevant output of the framework.

3.2. Module 1—FUCOM Weight Elicitation

Let C = {A, P, Q} denote the set of OEE components. The decision-maker first establishes a priority ranking of the components consistent with the operational context, expressed as an ordered sequence:

$$C_{j(1)} > C_{j(2)} > C_{j(3)} \tag{1}$$

where $C_{j(k)}$ denotes the component ranked *k*-th and > denotes strict preference. Where two components are judged equally important, they occupy the same rank position. For each pair of consecutively ranked components, the decision-maker assigns a comparative priority ratio:

$$\varphi_k = \frac{w_{j(k)}}{w_{j(k+1)}},\ k = 1, 2, \ldots \tag{2}$$

where $\varphi_k \in [1, 9]$ expresses how many times more important component $C_{j(k)}$ is relative to $C_{j(k+1)}$. The full set of ratios {φ_1, φ_2} constitutes the comparative priority vector. The FUCOM optimisation model derives the weight vector w = (w_A, w_P, w_Q) by minimising the degree of full consistency χ subject to the following constraints:

$$\left| \frac{w_{j(1)}}{w_{j(2)}} - \varphi_1 \right| \leq \chi \tag{3}$$

$$\left| \frac{w_{j(2)}}{w_{j(3)}} - \varphi_2 \right| \leq \chi \tag{4}$$

$$\left| \frac{w_{j(1)}}{w_{j(3)}} - \varphi_1 \cdot \varphi_2 \right| \leq \chi \tag{5}$$

$$w_A + w_P + w_Q = 1 \tag{6}$$

$$w_j > 0,\ \forall j \in \{A, P, Q\},\ \chi \geq 0 \tag{7}$$

The optimal solution w* = (w_{A^*}, w_{P^*}, w_{Q^*}) is obtained at χ^* = 0 when the elicited ratios satisfy exact transitivity and at χ^* > 0 otherwise. The scalar χ^* constitutes the degree of full consistency of the elicited judgements. To better understand the FUCOM applicability, the following illustrative example is used. Consider a context in which availability is judged most important, followed by performance, followed by quality. The decision-maker elicits:

$$\varphi_1 = \frac{w_A}{w_P} = 2,\ \varphi_2 = \frac{w_P}{w_Q} = 3 \tag{8}$$

The transitivity condition requires $\varphi_1 \cdot \varphi_2$ = 2 · 3 = 6, therefore w_A/w_Q = 6. Substituting into the normalization constraint w_A + w_P + w_Q = 1 and imposing exact consistency (χ = 0):

$$w_A = 6w_Q,\ w_P = 3w_Q \tag{9}$$

$$6w_Q + 3w_Q + w_Q = 1 \Rightarrow w_Q = \frac{1}{10} \tag{10}$$

The resulting weight vector is:

$$w^* = (w_A, w_P, w_Q) = (0.6,\ 0.3,\ 0.1), \qquad \text{DFC} = 0 \tag{11}$$

This solution is unique and obtained without iteration. The deviation from full consistency (DFC) of zero confirms that the elicited ratios {φ_1 = 2, φ_2 = 3} are mutually consistent and no approximation is required.

3.3. Module 2—Modified TOPSIS Formulation

TOPSIS [30] was selected among other MCDM models to address the OEE limitations because its simultaneous use of positive and negative reference poles, combined with a geometrically transparent distance measure, makes it particularly suited for incorporating externally derived weights and producing directly interpretable asset scores. This distance-based aggregation structure is a natural replacement for the multiplicative A × P × Q formula, as it accommodates differential weighting of the three OEE components while preserving their individual contribution to the final score.

To ensure score comparability for single-asset evaluation across time and operational contexts, the conventional TOPSIS formulation is herein modified by replacing the endogenous ideal and anti-ideal solutions with fixed exogenous reference poles. Unlike the original TOPSIS method, in which the reference poles are derived from the contemporaneous decision matrix and therefore vary with the set of evaluated alternatives, this adapted formulation employs invariant benchmark poles that substantially reduce score distortions caused by changes in the composition of the asset set, supporting ranking stability across evaluation periods. Note that Euclidean column normalisation introduces a residual dependency on the asset set at the level of individual score values; however, this does not affect the ranking order, which constitutes the primary output of the framework.

Unlike weighted-sum aggregation, which assumes full compensability among criteria and lacks an explicit notion of distance to an ideal state, the modified TOPSIS formulation preserves information on both achievement and deficiency relative to benchmark conditions through simultaneous minimisation of distance to the ideal and maximisation of distance from the anti-ideal. In contrast, weighted geometric mean approaches impose a strictly multiplicative structure that may over-penalise low criterion values and introduce restrictive non-linear effects not required in the present operational context.

Accordingly, the proposed modified TOPSIS formulation provides a more balanced aggregation framework by combining multi-criteria evaluation with explicit benchmarking. This integration ensures consistent, comparable, and interpretable scoring over time. While simpler aggregation methods such as weighted sum or weighted geometric mean could also produce comparable scores given that A, P, and Q are measured on a common [0, 1] scale, the modified TOPSIS formulation is preferred because it explicitly benchmarks each asset against both a theoretically perfect and a theoretically worst state simultaneously, providing richer diagnostic information than a single-pole aggregation approach.

Let $I = \{1, \ldots, m\}$ denote the set of equipment assets under evaluation. Each asset i is characterised by its observed OEE component values (A_i, P_i, Q_i), where each component is defined on [0, 1] in accordance with the standard OEE measurement framework. The decision matrix $\mathbf{X}$ is constructed as:

$$\mathbf{X} = \begin{pmatrix} A_1 & P_1 & Q_1 \\ A_2 & P_2 & Q_2 \\ \vdots & \vdots & \vdots \\ A_m & P_m & Q_m \end{pmatrix} \tag{12}$$

Step T1—Augmented decision matrix. Two reference rows are appended to $\mathbf{X}$: a positive ideal solution $A^+ = \{1, 1, 1\}$ and a negative ideal solution $A^- = \{0, 0, 0\}$. The augmented matrix $\widetilde{\mathbf{X}}$ of dimension $(m + 2) \times 3$ is:

$$\widetilde{\mathbf{X}} = \begin{pmatrix} 1 & 1 & 1 \\ A_1 & P_1 & Q_1 \\ \vdots & \vdots & \vdots \\ A_m & P_m & Q_m \\ 0 & 0 & 0 \end{pmatrix} \tag{13}$$

Step T2—Normalisation. Each element of $\widetilde{\mathbf{X}}$ is normalised by the Euclidean norm of its column:

$$r_{ij} = \frac{\widetilde{x}_{ij}}{\sqrt{\sum_k \widetilde{x}_{kj}^2}},\ \forall i,j \tag{14}$$

Step T3—Weighted normalised matrix. The FUCOM weight vector $\mathbf{w}^* = (w_A, w_P, w_Q)$ from Module 1 is applied uniformly across all rows of $\mathbf{R}$, including the ideal poles:

$$v_{ij} = w_j \cdot r_{ij},\ \forall i,j \tag{15}$$

Step T4—Distances to ideal solutions. For each asset i:

$$d_i^+ = \sqrt{\sum_j \left(v_{ij} - v_j^+\right)^2} \tag{16}$$

$$d_i^- = \sqrt{\sum_j \left(v_{ij} - v_j^-\right)^2} \tag{17}$$

where v_j^+ and v_j^- denote the weighted normalised values of A^+ and A^-, respectively.

Step T5—Adaptive OEE score.

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-},\ C_i \in [0,1] \tag{18}$$

3.4. Conceptual Positioning of the Adaptive OEE Framework

The Adaptive OEE is not intended as a general replacement for the classical OEE formula. The classical OEE retains its value as a diagnostic tool for quantifying individual loss categories within a single asset. The Adaptive OEE addresses a different and complementary question, namely, given a set of assets operating in a specific context, which asset should be prioritised for maintenance intervention? For this purpose, the classical equal-weight formula is structurally inadequate. The Adaptive OEE replaces the multiplicative A × P × Q aggregation with a weighted distance-based model that reflects the operational priorities of the decision-maker.

4. Illustrative Numerical Examples

To evaluate the performance of the proposed Adaptive OEE framework and demonstrate its behaviour relative to classical OEE, three illustrative case studies are presented. Each case study represents a distinct operational context characterised by a different strategic priority, yielding a different FUCOM weight vector. The three contexts are designed to span the space of plausible weight configurations and to illustrate how identical equipment data can lead to materially different effectiveness assessments depending on the operational priorities of the decision-maker.

4.1. Case Study 1—Availability-Dominant Context

The first context represents a capital-intensive production environment in which unplanned equipment downtime constitutes the primary source of operational loss. In such settings, typical of continuous process industries, heavy manufacturing, or asset-critical infrastructure, the financial and operational consequences of availability failures are disproportionately severe relative to marginal losses in performance rate or product quality. Maintenance strategy is oriented towards maximising equipment uptime, and the organization's key performance targets are expressed primarily in terms of availability metrics.

Applying the FUCOM elicitation procedure, the decision-maker establishes the priority ranking $A > P > Q$ and provides comparative priority ratios reflecting a strong dominance of availability over the remaining components. The resulting weight vector assigns availability a weight of 0.667, acknowledging its dominant role as the primary driver of operational effectiveness. A unit reduction in availability produces a loss contribution six times greater than an equivalent reduction in quality and three times greater than an equivalent reduction in performance. Performance is assigned a weight of 0.222, acknowledging its secondary relevance in environments where throughput is constrained by equipment uptime rather than speed. Quality is assigned the lowest weight of 0.111, consistent with settings in which product conformance is maintained through process controls that operate largely independently of equipment scheduling decisions.

4.2. Case Study 2—Performance-Dominant Context

The second context represents a high-throughput discrete manufacturing environment operating under tight delivery schedules and sustained customer demand pressure. In such settings, characteristic of automotive supply chains, electronics assembly, or fast-moving consumer goods production, the primary operational concern is the rate at which equipment converts available running time into finished output. Equipment availability is managed through structured preventive maintenance programmes and, while necessary, does not represent the binding constraint on operational performance. Product quality is maintained through embedded process controls and is not the principal source of competitive differentiation.

Applying the FUCOM elicitation procedure, the decision-maker establishes the priority ranking $P > A > Q$ and provides comparative priority ratios reflecting the centrality of throughput in the organisation's operational objectives. The resulting weight vector assigns performance rate a weight of 0.667, reflecting its role as the dominant determinant of operational output. A unit reduction in performance produces a loss contribution twice as large as an equivalent reduction in availability and six times larger than an equivalent reduction in quality. Availability is assigned a weight of 0.222, acknowledging its necessary but non-dominant role in throughput-oriented environments where downtime is largely planned and predictable. Quality is assigned the lowest weight of 0.111, consistent with settings in which first-pass yield is structurally high and quality losses represent a residual rather than a principal source of effectiveness deterioration.

4.3. Case Study 3—Quality-Dominant Context

The third context represents a regulated manufacturing environment in which product conformance is the overriding operational requirement. In such settings, exemplified by pharmaceutical manufacturing, aerospace component production, or medical device assembly, quality failures carry regulatory, safety, and reputational consequences that far outweigh the costs associated with reduced throughput or episodic downtime. Equipment availability and performance rate are maintained at satisfactory levels through established maintenance and operational programmes, but any deterioration in quality rate triggers immediate corrective action, potential batch rejection, and regulatory notification obligations.

Applying the FUCOM elicitation procedure, the decision-maker establishes the priority ranking $Q > A > P$ and provides comparative priority ratios reflecting the non-negotiable primacy of product conformance in the organisation's operational context. The resulting weight vector assigns quality a weight of 0.667, reflecting its dominant role in regulated production environments. A unit reduction in quality produces a loss contribution twice as large as an equivalent reduction in availability and six times larger than an equivalent reduction in performance. Availability is assigned a weight of 0.222, acknowledging that equipment uptime remains operationally necessary but is subordinate to conformance requirements; in regulated environments, equipment is frequently taken offline voluntarily to preserve quality rather than run at the risk of non-conforming output. Performance is assigned the lowest weight of 0.111, consistent with settings in which operating speed is deliberately conservative to minimise process variability and protect product quality.

The weight vectors derived through the FUCOM elicitation procedure for each of the three operational contexts are summarised in Table 1. The classical OEE reference row is included to make explicit the uniform weight assumption implicit in the multiplicative formula, against which the context-specific weight vectors are contrasted.

Table 1. FUCOM weight vectors by operational context.

Context	wA	wP	wQ	DFC
CS1: Availability-dominant	0.667	0.222	0.111	0.000
CS2: Performance-dominant	0.222	0.667	0.111	0.000
CS3: Quality-dominant	0.222	0.111	0.667	0.000
Classical OEE (reference)	0.333	0.333	0.333	n.a.

4.4. Decision Matrix Definition and Classical OEE Baseline

The three assets are evaluated on the same observed OEE component values across all case studies. The raw decision matrix **X** is common to the three contexts; what varies across case studies is exclusively the FUCOM weight vector applied in Module 2.

The observed component values are defined as follows. Asset 1 presents high availability but moderate performance and quality, representing equipment that is consistently available but not fully optimised in speed or output conformance. Asset 2 presents moderate availability, high performance, and high quality, representing equipment that runs efficiently when available but is subject to more frequent downtime. Asset 3 presents moderate values across all three components, representing a balanced but unexceptional operational profile. The decision matrix **X** is:

$$\mathbf{X} = \begin{pmatrix} & A & P & Q \\ \text{Asset 1} & 0.95 & 0.62 & 0.72 \\ \text{Asset 2} & 0.62 & 0.95 & 0.74 \\ \text{Asset 3} & 0.74 & 0.65 & 0.95 \end{pmatrix}$$

The corresponding classical OEE scores, computed as $\text{OEE}_i = A_i \times P_i \times Q_i$, are:

$$\begin{aligned} \text{OEE}_1 &= 0.95 \times 0.62 \times 0.72 = 0.424 \\ \text{OEE}_2 &= 0.62 \times 0.95 \times 0.74 = 0.436 \\ \text{OEE}_3 &= 0.74 \times 0.65 \times 0.95 = 0.457 \end{aligned}$$

The ranking Asset 3 > Asset 2 > Asset 1 will serve as the reference against which the Adaptive OEE rankings under the three context-specific weight vectors are compared in Section 4.5.

4.5. Modified Technique for Order of Preference by Similarity to Ideal Solution

4.5.1. Case Study 1— Context with Availability as the Dominant Factor

This case study evaluates three equipment assets in an availability-dominant operational context. The FUCOM weight vector assigns dominant importance to Availability:

$$w^* = (w_A, w_P, w_Q) = (0.667,\ 0.222,\ 0.111),\ \mathrm{DFC} = 0$$

Step 1—Extended Decision Matrix

The decision matrix X is extended by appending the fixed ideal positive pole A+ = (1, 1, 1) as the first row and the fixed ideal negative pole A− = (0, 0, 0) as the last row, forming the extended matrix $\widetilde{\mathbf{X}}$:

$$\widetilde{\mathbf{X}} = \begin{pmatrix} 1 & 1 & 1 \\ A_1 & P_1 & Q_1 \\ A_2 & P_2 & Q_2 \\ A_3 & P_3 & Q_3 \\ 0 & 0 & 0 \end{pmatrix}$$

This modification ensures that normalisation and scoring remain independent of observed asset performance; Table 2 presents the values of the extended matrix X.

Table 2. Extended decision matrix $\widetilde{\mathrm{X}}$ with fixed reference poles.

	A	P	Q
A+	1.00	1.00	1.00
Asset 1	0.95	0.62	0.72
Asset 2	0.62	0.95	0.74
Asset 3	0.74	0.65	0.95
A−	0.00	0.00	0.00

Step 2—Column Normalisation

Each column norm is computed as the square root of the sum of squared values across all rows of $\widetilde{\mathbf{X}}$ (Table 3), including the fixed poles:

$$\mathrm{norm}_j = \sqrt{\sum_k \widetilde{x}_{kj}^2}$$

Table 3. Squared values and column norms.

	A	P	Q
A+	1.0000	1.0000	1.0000
Asset 1	0.9025	0.3844	0.5184
Asset 2	0.3844	0.9025	0.5476
Asset 3	0.5476	0.4225	0.9025
A−	0.0000	0.0000	0.0000
norm_j	1.6836	1.6460	1.7229

Step 3—Normalised and Weighted Matrix

Table 4 shows the normalised and weighted values of the extended matrix $\widetilde{\mathbf{X}}$. Each element is divided by its column norm and multiplied by the corresponding FUCOM weight:

$$v_{ij} = \frac{\widetilde{x}_{ij}}{\mathrm{norm}_j} \times w_j$$

Table 4. Normalised and weighted matrix V.

	A	**P**	**Q**
A+	0.3962	0.1349	0.0644
Asset 1	0.3764	0.0836	0.0464
Asset 2	0.2456	0.1281	0.0477
Asset 3	0.2932	0.0877	0.0612
A−	0.0000	0.0000	0.0000

Step 4—Distance to Ideal Positive Pole (D+)

Table 5 presents the distances to the ideal positive pole (d^+). The distance $d^+{}_i$ of each asset to the weighted ideal positive pole is computed as the Euclidean distance between the asset's weighted row and the weighted A+ row:

$$d_i^+ = \sqrt{\sum_j \left(v_{ij} - v_j^+\right)^2}$$

Table 5. Squared deviations from A+ and resulting d+ distances.

	$(\mathbf{v_A} - \mathbf{v_{A+}})^2$	$(\mathbf{v_P} - \mathbf{v_{P+}})^2$	$(\mathbf{v_Q} - \mathbf{v_{Q+}})^2$	**d+**
Asset 1	0.000392	0.002627	0.000325	0.0578
Asset 2	0.022664	0.000045	0.000281	0.1516
Asset 3	0.010610	0.002228	0.000010	0.1134

Step 5—Distance to Ideal Negative Pole (d^-)

Since A− = (0, 0, 0), the distance $d^-{}_i$ simplifies to the Euclidean norm of the weighted asset vector (Table 6):

$$d_i^- = \sqrt{\sum_j \left(v_{ij} - v_j^-\right)^2} = \sqrt{\sum_j v_{ij}^2}$$

Table 6. Squared values and resulting D− distances.

	$\mathbf{v_{A2}}$	$\mathbf{v_{P2}}$	$\mathbf{v_{Q2}}$	$\mathbf{d^-}$
Asset 1	0.141652	0.006992	0.002152	0.3883
Asset 2	0.060334	0.016416	0.002273	0.2811
Asset 3	0.085949	0.007685	0.003746	0.3121

Step 6—Closeness Coefficient and Ranking

Table 7 presents the Adaptive OEE scores. The C_i is computed as the ratio of $d^-{}_i$ to the total distance. A value of 1 indicates maximum proximity to the ideal positive pole; a value of 0 indicates minimum:

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-},\ C_i \in [0,1]$$

Table 7. Adaptive OEE scores (C_i), distances, and classical OEE scores—Case Study 1.

	d^+	d^-	C_i	Classical OEE
Asset 1	0.0578	0.3883	0.8704	0.4241
Asset 2	0.1516	0.2811	0.6496	0.4359
Asset 3	0.1134	0.3121	0.7335	0.4569

The classical OEE produces scores of 0.4241, 0.4359, and 0.4569 for Assets 1, 2, and 3, respectively. Although Asset 3 yields the highest classical OEE score, the scores are insufficiently differentiated to support reliable maintenance prioritisation. The Adaptive OEE produces differentiated scores of 0.8704, 0.6496, and 0.7335, yielding the ranking: Asset 1 > Asset 3 > Asset 2

This result is consistent with the availability-dominant weight configuration (w_A = 0.667): Asset 1, which has the highest availability score (A = 0.95), ranks first. Asset 3 ranks second ahead of Asset 2 because its availability score (A = 0.74) exceeds that of Asset 2 (A = 0.62), which is decisive under the dominant availability weight.

The ranking produced by the Adaptive OEE diverges from the classical OEE ranking, which would place Asset 3 first. This inversion demonstrates that the classical equal-weight formula misrepresents the operational priority of assets in contexts where one OEE component dominates.

4.5.2. Case Study 2—Context with Performance as the Dominant Factor

This case study applies the Adaptive OEE framework to the same three assets under a performance-dominant operational context. The asset profiles are unchanged; only the FUCOM weight vector is modified to reflect the new operational priority:

$$w^* = (w_A, w_P, w_Q) = (0.222,\ 0.667,\ 0.111),\ \text{DFC} = 0$$

Performance now carries the dominant weight (w_P = 0.667), as is the case in high-speed assembly environments where throughput losses have the greatest operational impact. Availability and Quality are assigned residual weights of 0.222 and 0.111, respectively. The extended matrix $\widetilde{\mathbf{X}}$ and column norms are identical to Case Study 1, as the asset profiles are unchanged. The weight vector, however, amplifies the Performance column and reduces the Availability column relative to Case 1. Table 8 shows the resulting normalised and weighted matrix V.

Table 8. Normalised and weighted matrix V—Performance-dominant context (w_P = 0.667).

	A	P	Q
$\mathbf{A}^+$	0.1319	0.4052	0.0644
Asset 1	0.1253	0.2512	0.0464
Asset 2	0.0818	0.3850	0.0477
Asset 3	0.0976	0.2634	0.0612
$\mathbf{A}^-$	0.0000	0.0000	0.0000

Applying the Modified TOPSIS procedure with the performance-dominant weights, the distances d^+ and d^- and the closeness coefficient Ci are obtained in Table 9:

Table 9. Adaptive OEE scores (C_i), distances, and classical OEE scores—Case Study 2.

	d^+	d^-	C_i	Classical OEE
Asset 1	0.1552	0.2845	0.6471	0.4241
Asset 2	0.0566	0.3964	0.8751	0.4359
Asset 3	0.1459	0.2875	0.6633	0.4569

Under the performance-dominant configuration, Asset 2—which has the highest performance score (P = 0.95)—ranks first with C_i = 0.8751. Asset 3 ranks second (C_i = 0.6633), and Asset 1 ranks third (C_i = 0.6471). The ranking is Asset 2 > Asset 3 > Asset 1.

4.5.3. Case Study 3— Context with Quality as the Dominant Factor

The third case study applies the Adaptive OEE framework to the same asset profiles under a quality-dominant operational context. The FUCOM weight vector is:

$$\mathbf{w}^* = (w_A, w_P, w_Q) = (0.222,\ 0.111,\ 0.677),\ \mathrm{DFC} = 0$$

Normalised and Weighted Matrix. The extended matrix $\widetilde{\mathbf{X}}$ and column norms are identical across all three case studies. The quality-dominant weight vector substantially amplifies the Q column in the normalised matrix V, as shown in Table 10:

Table 10. Normalised and weighted matrix V—Quality-dominant context (w_Q = 0.667).

	A	P	Q
A^+	0.1319	0.0674	0.3929
Asset 1	0.1253	0.0418	0.2829
Asset 2	0.0818	0.0641	0.2908
Asset 3	0.0976	0.0438	0.3733
A^-	0.0000	0.0000	0.0000

The closeness coefficients and final ranking are presented in Table 11:

Table 11. Adaptive OEE scores (C_i), distances, and classical OEE scores—Case Study 3.

	d^+	d^-	C_i	Classical OEE
Asset 1	0.1132	0.3122	0.7340	0.4241
Asset 2	0.1138	0.3088	0.7306	0.4359
Asset 3	0.0460	0.3883	0.8940	0.4569

Under the quality-dominant configuration, Asset 3, which has the highest quality score (Q = 0.95) ranks first with C_i = 0.8940. Assets 1 and 2 rank second and third with closely spaced scores of 0.7340 and 0.7306, reflecting the relatively balanced quality scores of the two assets (Q = 0.72 and Q = 0.74).

4.5.4. Cross-Case Comparison

Table 12 consolidates the results of all three case studies alongside the classical OEE ranking, providing a complete view of how the Adaptive OEE framework responds to changes in operational context across the full weight space.

Table 12. Ranking comparison across classical OEE and all three Adaptive OEE case studies.

	Classical OEE	Case 1 (w_A = 0.667)	Case 2 (w_P = 0.667)	Case 3 (w_Q = 0.677)
Asset 1	0.4241 (3rd)	0.8704 (1st)	0.6471 (3rd)	0.7340 (2nd)
Asset 2	0.4359 (2nd)	0.6496 (3rd)	0.8751 (1st)	0.7306 (3rd)
Asset 3	0.4569 (1st)	0.7335 (2nd)	0.6633 (2nd)	0.8940 (1st)

The cross-case comparison reveals a consistent and predictable pattern. In each case study, the asset with the highest score in the dominant component rises to the top of the Adaptive OEE ranking: Asset 1 (A = 0.95) under availability dominance, Asset 2 (P = 0.95) under performance dominance, and Asset 3 (Q = 0.95) under quality dominance. This behaviour confirms that the framework correctly encodes the operational context through the weight vector and produces rankings that are directly traceable to the decision-maker's stated priorities.

The classical OEE ranking, Asset 3 > Asset 2 > Asset 1, remains constant across all three contexts, confirming that the equal-weight formula is structurally insensitive to operational priorities. An organisation relying solely on classical OEE would identify Asset 3 as the maintenance priority regardless of whether the dominant loss factor is Availability, Performance, or Quality, which is operationally unjustifiable in the availability-dominant and performance-dominant scenarios.

A further observation concerns the proximity of Assets 1 and 2 in Case Study 3 (C_i = 0.7340 and C_i = 0.7306). The near-equal scores reflect the similar quality profiles of the two assets (Q = 0.72 and Q = 0.74), illustrating that the Adaptive OEE framework produces close rankings when the assets are genuinely similar in the dominant dimension, a property not captured by the classical formula, which assigns these same assets distinctly different OEE scores (0.4241 and 0.4359).

4.6. Behavioural Analysis of Weight Configurations

To characterise the behaviour of the Adaptive OEE framework across the full weight space, all weight combinations satisfying $w_A + w_P + w_Q = 1$ were systematically evaluated with a step of 0.05, yielding 231 combinations. For each combination, the C_i scores and the resulting asset ranking were computed.

Six distinct ranking configurations were identified (Table 13). Two configurations dominate the weight space: A1 > A3 > A2, observed in 66 combinations (28.6%), and A2 > A3 > A1, observed in 65 combinations (28.1%). The remaining four configurations cover the quality-dominant and transitional regions.

Table 13. Ranking Distribution Across All Weight Combinations (n = 231).

Ranking	Count	% of Total
A1 > A3 > A2	66	28.6
A2 > A3 > A1	65	28.1
A3 > A1 > A2	36	15.6
A3 > A2 > A1	35	15.2
A2 > A1 > A3	20	8.7
A1 > A2 > A3	9	3.9

Figures 2–4 show the evolution of C_i scores as each dominant weight increases from 0 to 1, with the remaining two weights held equal. Three threshold observations are consistent across all scenarios. When w_A exceeds approximately 0.50, Asset 1 ranks first. When w_P exceeds approximately 0.50, Asset 2 ranks first. When w_Q exceeds approximately

0.50, Asset 3 ranks first. In each case, the asset with the highest score in the dominant component rises to the top of the ranking at the same threshold.

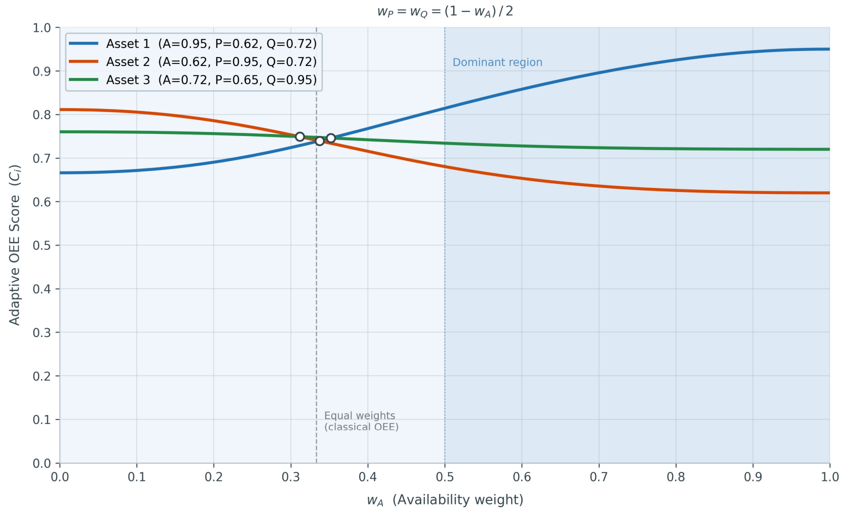

Figure 2. Evolution of Adaptive OEE scores (C_i) for the three assets as the Availability weight increases from 0 to 1, with Performance and Quality weights held equal.

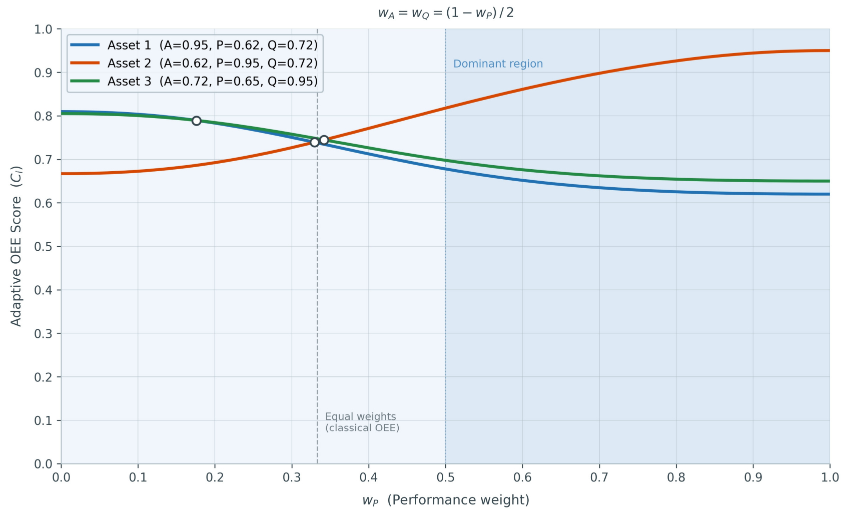

Figure 3. Evolution of Adaptive OEE scores (C_i) for the three assets as the Performance weight increases from 0 to 1, with Availability and Quality weights held equal.

Figure 2 shows that Asset 1, which has the highest availability score (A = 0.95), consistently benefits from increasing w_A. The ranking transition occurs at approximately $w_A = 0.50$, beyond which Asset 1 ranks first in all configurations. Below this threshold, the ranking is sensitive to the balance between w_P and w_Q.

Figure 3 shows Asset 2, which has the highest performance score (P = 0.95), rises progressively as w_P increases. The ranking transition occurs at approximately $w_P = 0.50$, beyond which Asset 2 ranks first. The crossover point is clearly visible and confirms that performance-dominant contexts systematically favour Asset 2 over the remaining assets.

Figure 4 shows Asset 3, which has the highest quality score (Q = 0.95), rises progressively as w_Q increases. The ranking transition occurs at approximately $w_Q = 0.50$, beyond which Asset 3 ranks first. The pattern is symmetric with Figures 2 and 3, confirming that the framework responds consistently and predictably to the dominant weight regardless of which component is prioritised.

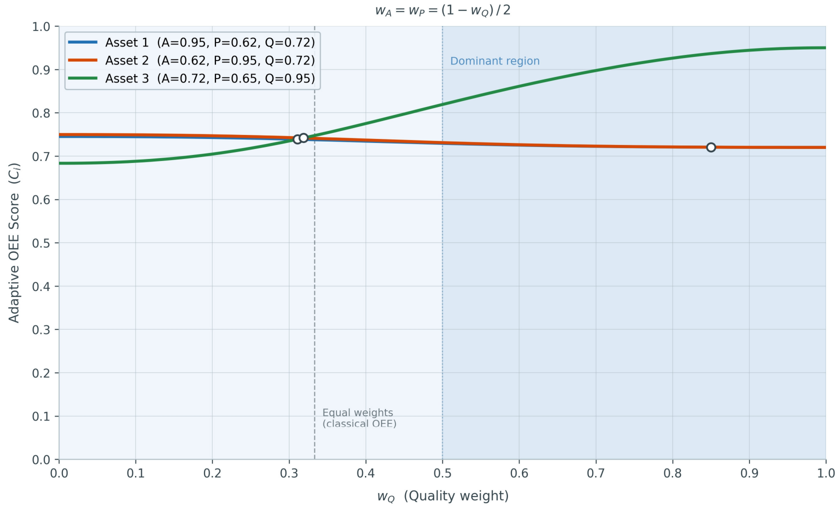

Figure 4. Evolution of Adaptive OEE scores (C_i) for the three assets as the Quality weight increases from 0 to 1, with Availability and Performance weights held equal.

The zone of greatest sensitivity occurs near w ≈ 0.333, which corresponds to the classical OEE equal-weight assumption. In this region, small weight perturbations are sufficient to alter the ranking. Outside this zone, rankings stabilise rapidly. This confirms that the equal-weight assumption is not a neutral modelling choice, it places the framework in the region of maximum ranking instability.

5. Discussion

The three case studies suggest that the Adaptive OEE framework produces rankings that respond directly and predictably to the operational context encoded in the weight vector. The classical OEE produces scores of 0.424, 0.436, and 0.457 for Assets 1, 2, and 3. These scores are too similar to support reliable maintenance prioritisation. The Adaptive OEE produces clearly differentiated scores in each context: 0.870, 0.650, and 0.734 under the availability-dominant configuration; 0.647, 0.875, and 0.663 under the performance-dominant configuration; and 0.734, 0.731, and 0.894 under the quality-dominant configuration. In each case, the asset with the highest score in the dominant component rises unambiguously to the top of the ranking.

The classical OEE and the Adaptive OEE serve different and complementary purposes. The classical formula remains useful for monitoring individual asset performance over time and identifying loss categories within a single asset. The Adaptive OEE addresses a different question: given a set of assets operating in a specific context, which asset should be prioritised for maintenance intervention? The two metrics operate at different levels of the decision-making process and are not in competition.

The results directly address the three research questions formulated in Section 1. The classical OEE ranking (Asset 3 > Asset 2 > Asset 1) is not preserved under any of the three weight configurations. The input matrix X is identical across all case studies. The ranking divergence is therefore attributable exclusively to the weight structure applied, not to differences in asset data. This confirms that the equal-weighting assumption constitutes a structurally consequential choice rather than a neutral default, addressing RQ1.

The FUCOM elicitation procedure produced fully consistent weight vectors (DFC = 0) in all three case studies from only two pairwise comparisons per context. This satisfies the minimum-comparison, guaranteed-consistency, and context-sensitivity requirements identified as absent from existing OEE extensions in Section 2.2. The integration of FUCOM with the modified TOPSIS yields a scoring model that is both formally rigorous and operationally tractable, addressing RQ2.

Rank inversions relative to the classical OEE ranking are observed in all three case studies, addressing RQ3. The most severe divergence occurs in the availability-dominant and performance-dominant contexts, where a single component carries a weight of 0.667. In the quality-dominant context, the first-ranked asset under classical OEE retains its position under Adaptive OEE, but the relative ordering of the remaining assets is inverted. Divergence is most severe when one OEE component carries strongly asymmetric weight, which is precisely the condition that the equal-weighting assumption is structurally unable to accommodate.

Limitations

The Adaptive OEE framework has a specific and well-defined objective: to provide a structured, auditable, and context-driven methodology for ranking equipment assets and supporting maintenance prioritisation decisions in environments where the three OEE components carry asymmetric operational importance. Within this scope, the framework performs as intended. The limitations described below do not compromise its primary contribution.

The case studies presented are illustrative in nature. The asset profiles and weight configurations were deliberately constructed to demonstrate the framework's behaviour across distinct operational contexts. Empirical validation using real industrial data and actual expert elicitation has not been conducted. This remains a primary direction for future research. This limitation does not affect the methodological validity of the framework or the analytical conclusions drawn regarding the structural inadequacy of the equal-weight assumption.

The framework relies on a decision-maker or a panel of experts to elicit the FUCOM weight vector. FUCOM minimises elicitation burden and guarantees mathematical consistency. However, the resulting weights remain subjective and context-dependent. In organisations where operational priorities are contested or unclear, the elicitation process may introduce bias that the DFC metric alone cannot detect. This is a general property of all preference-based weighting methods and does not represent a specific weakness of the proposed framework relative to existing approaches.

The Adaptive OEE score is sensitive by design to the weight configuration. This sensitivity is a deliberate and essential property of the framework, not a deficiency. It is precisely this property that enables the framework to encode operational context and produce differentiated rankings. It does, however, imply that scores are not directly comparable across different weight configurations. This limits their use as standalone benchmarks across organisational units with different operational priorities.

The framework evaluates assets on three fixed dimensions, Availability, Performance, and Quality, inherited from the classical OEE decomposition. Extensions to incorporate additional criteria such as maintenance cost, energy consumption, or safety indicators would require a reformulation beyond the scope of the present work. Within the OEE measurement paradigm, the A-P-Q decomposition remains the established standard, and the proposed framework operates fully within this convention.

6. Conclusions

This paper proposed the Adaptive OEE framework as a structured and context-driven alternative to the classical OEE formula for equipment effectiveness measurement and maintenance prioritisation. The framework addresses a fundamental structural limitation of classical OEE: the implicit equal weighting of Availability, Performance, and Quality, which produces rankings that are insensitive to the operational context in which assets are evaluated.

The proposed framework integrates two methodological components. FUCOM is used to elicit context-specific weights for the three OEE components with minimum expert burden and guaranteed mathematical consistency. A modified TOPSIS formulation with fixed reference poles replaces the multiplicative $A \times P \times Q$ aggregation with a weighted distance measure, producing a closeness coefficient that is stable, interpretable, and comparable across assets and contexts.

Three illustrative case studies were presented, covering availability-dominant, performance-dominant, and quality-dominant operational contexts. The classical OEE ranking was not preserved under any of the three weight configurations. Since the asset profiles were identical across all cases, the ranking divergence is attributable exclusively to the weight structure applied. This is consistent with the argument that the equal-weighting assumption is not a neutral modelling choice. It is a structurally consequential decision with direct implications for maintenance prioritisation.

The results address the three research questions formulated in the introduction. The equal-weighting assumption was formalised as a structural limitation with demonstrable consequences for asset ranking. The FUCOM-TOPSIS integration was shown to satisfy the requirements of minimum elicitation burden, guaranteed consistency, and context-sensitivity simultaneously. Rank inversions relative to the classical OEE ranking were observed in all three case studies, confirming that divergence is most severe when one OEE component carries strongly asymmetric weight.

The principal limitation of this work is the illustrative nature of the case studies. Empirical validation using real industrial data and actual expert elicitation remains the primary direction for future research. A second direction concerns the extension of the weight elicitation module to group decision-making settings, where weights are derived from multiple experts with potentially divergent operational priorities. This would require the integration of consensus mechanisms compatible with the FUCOM consistency framework. A third direction concerns a systematic comparative study benchmarking the Adaptive OEE framework against existing weighting approaches, including AHP-based PEE and ROC-based OWEE, across empirical industrial datasets.

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