Prescriptive Decision-Making for Sustainable Production Management: An Overall Sustainable Equipment Effectiveness (OSEE) Framework Using Causal AI

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Abstract

In response to the growing challenges posed by climate change and demographic shifts, industrial operations must move beyond traditional productivity metrics such as Overall Equipment Effectiveness (OEE). While OEE is a valuable key performance indicator, it fails to account for the ecological, social, and economic dimensions essential for long-term sustainability. This paper introduces an Overall Sustainable Equipment Effectiveness (OSEE) framework, designed to integrate sustainability factors into operational performance measurement, enabling a holistic assessment and optimization approach. Key sustainability factors and their interrelationships are identified through an extensive literature review and subsequently validated by industry experts to ensure practical relevance and applicability to real-world operational settings. To address the complexity of these interconnected factors, causal AI methods, in particular Dynamic Bayesian Networks (DBN) are employed. DBN allow a qualitative understanding of sustainability interrelationships (cause-effects) and enable a quantitative optimization of sustainability impacts on operational efficiency. The proposed OSEE framework offers a structured approach for balancing productivity with environmental and social factors, equipping decision-makers with insights for informed sustainable operational strategies. This research contributes to the broader agenda of twin transformation, aligning digitalization and sustainability, and provides a foundation for building resilient, future-ready industrial operations.

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1. Introduction

Manufacturing industries are responsible for approximately 30% of global emissions (World Economic Forum, 2023) and are critical to limiting global warming to 1.5°C (Core Writing Team, H. Lee and J. Romero (eds.), 2023). Simultaneously, demographic changes and a growing shortage of skilled workers present significant challenges to the industrial sector (Acemoglu and Restrepo, 2018). In response to these escalating challenges, global initiatives have been launched to address them, including the United Nations Sustainable Development Goals (United Nations, 2023) and regional strategies such as the European Green Deal (European Comission, 2019). In parallel, emerging concepts like the twin transition, integrating digitalization and sustainability, are gaining prominence (Fouquet and Hippe, 2022). At the same time, manufacturing enterprises increasingly implement corporate sustainability programs and engage in green and sustainability-linked financing to accelerate transformation efforts and align with global and regional sustainability targets. Despite advances, environmental and social sustainability considerations are frequently underemphasized (Göçoğlu *et al.*, 2025), particularly in the context of current economic pressures. Operational-level sustainability is therefore critical, as manufacturing processes have a direct impact on emissions, energy use, and working conditions. In manufacturing, a large proportion of the workforce is employed in operational roles (i.e. blue collars), highlighting the importance of this level for achieving substantive sustainability gains. When operational activities are overlooked, the effectiveness of corporate sustainability strategies is reduced, and key opportunities to mitigate environmental and social impacts are lost. Despite the growing importance of sustainability, operational planning and performance measurement in manufacturing continue to rely primarily on economic indicators, such as Overall

Equipment Effectiveness (OEE), which reflects equipment availability, performance, and product quality (Nakajima, 1988). Environmental and social dimensions are either typically excluded or not explicitly considered. As a result, operational performance is often optimized in isolation, without accounting for the interdependence of economic, environmental, and social factors (Madreiter and Ansari, 2024). This fragmented approach constrains the potential for integrated improvements that enhance resource efficiency, lower environmental impact, and strengthen working conditions at the operational level.

To enable measuring sustainability and assessing attainments of corporate sustainability goals at the operational level, two aspects are particularly relevant:

i. Integrating sustainability principles throughout all operational activities, and
ii. Extending conventional indicators such as OEE to encompass environmental and social dimensions

Yet, indicator expansion alone is not sufficient. Improving sustainability outcomes at the operational level requires a move from static reporting toward methods that support ongoing management. This includes tools that represent causal links between operational, environmental, and social variables, and can simulate the effects of internal changes or external disruptions over time. Such models allow operational teams to examine trade-offs, identify potential risks, and test interventions before implementation. A structured approach of this kind is necessary to make sustainability efforts more anticipatory and integrated. This requires a clear understanding of how sustainability has been addressed in operational contexts and how existing metrics, such as OEE, have been extended to support broader sustainability objectives. Operational sustainability in manufacturing requires integrating economic, environmental, and social objectives directly into production and maintenance processes at the shop floor level.

Existing work increasingly focuses on the comprehensive incorporation of sustainability dimensions into operational practices. Hoyos et al. (2023) propose a scoring system that combines environmental, economic, physical, and social criteria to evaluate welding processes for electric transport components. Wadood et al., (2023) show that aligning Lean and Sustainability Management produces stronger outcomes across all three dimensions than applying them separately. Afum et al. (2023) demonstrate that Lean Production Systems improve social sustainability and green competitiveness when mediated by green technology adoption and green product innovation. Franciosi et al. (2020) highlight that maintenance activities directly and indirectly affect all sustainability pillars and propose a framework linking maintenance processes to indicators across organizational levels. Building on these holistic approaches to operational sustainability, further developments have explored how key performance indicators can be expanded to reflect environmental and social objectives at the operational level.

In parallel, several studies have explored how OEE can be extended toward sustainability by linking operational performance with energy, resource efficiency, and broader sustainability outcomes. Technology-based approaches enhance OEE via machine learning, IoT monitoring, and predictive diagnostics (Thiede, 2023; Da Costa *et al.*, 2024; Ademujimi and Prabhu, 2024). Conceptual extensions integrate sustainability indicators into performance metrics, e.g., Sustainable Overall Throughput Effectiveness (Durán *et al.*, 2018) and Overall Sustainable Equipment Effectiveness (Madreiter and Ansari, 2024). Maintenance-focused strategies further align reliability, energy efficiency, and operational effectiveness, demonstrated in studies on Industry 4.0-enabled maintenance frameworks and resource-optimized material handling systems (Jena *et al.*, 2024; Seyed Hosseini *et al.*, 2024; Ghafoorpoor Yazdi *et al.*, 2018). Finally, system-level and business-oriented models formalize the integration of operational performance and sustainability outcomes, particularly in automotive manufacturing and lean-green compliance frameworks (Zehra *et al.*, 2024; Abreu *et al.*, 2024). Although significant progress has been made, many of the existing approaches remain conceptual in nature and are not yet fully integrated into operational decision-making processes based on expanded sustainability performance indicators.

While these contributions mark important progress, most remain static and descriptive. They often fail to capture the dynamic interdependencies between operational, environmental, and social factors, and are not yet fully integrated into operational decision-making. Consequently, anticipatory, scenario-based management at the shop floor level remains underdeveloped. This paper addresses this gap by developing a dynamic causal model for operational sustainability, building on an extended OEE framework.

The rest of the paper is structured as follows. Chapter 2 presents the theoretical foundations of causal AI. Chapter 3 outlines the methodology for causal modeling of operational sustainability within the OSEE framework. Chapter 4 applies the proposed model in a simulation study. Finally, Chapter 5 concludes the paper with a summary of key findings and directions for future research.

2. THEORETICAL FOUNDATIONS: CAUSAL AI AND PROBABILISTIC MODELING

2.1. Structural Causal Models and Dynamic Bayesian Networks

Causal Artificial Intelligence (Causal AI) focuses on finding and understanding cause-and-effect relationships between system variables. Unlike traditional statistical methods that describe associations, Causal AI provides tools to model interventions, dependencies, and hypothetical alternatives

(Pearl, 2010, 2009). At the core of causal reasoning is the Structural Causal Model (SCM), which describes how variables relate to each other using structural equations and directed acyclic graphs (DAGs) (Pearl, 2010). In these graphs, each node represents a variable, and the arrows represent direct causal influences. Together, the structural equations and the graph structure encode the system's behavior (Pearl, 2010). SCMs allow to answer three types of questions: (i) associational questions about correlations, (ii) interventional questions about the effects of actions, and (iii) counterfactual questions about what might have happened under different circumstances (Pearl, 2009). Bayesian Networks (BNs) are one way to apply these ideas in practice. A BN is a graphical model where nodes represent random variables, and edges represent conditional dependencies between them (Ben‐Gal, 2007). Each variable's probability depends only on its parent nodes, which makes it possible to express the full joint probability distribution in a compact way (Ben‐Gal, 2007). When the structure of a BN is based on causal assumptions, it can be used to reason about cause and effect (Pearl, 2009). However, many real-world systems change over time, and static models are not enough to capture their dynamics. To handle this, Dynamic Bayesian Networks (DBNs) extend BNs by repeating the network structure over multiple time steps, allowing both current and future dependencies to be modeled (Koller and Friedman, 2009). A DBN typically consists of an initial model that describes the system at time $t=0$, and a two-slice temporal model that defines how the system evolves from one time step to the next (Koller and Friedman, 2009). DBNs generally assume a first-order Markov property, meaning the state at time $t+1$ depends only on the state at time t (Koller and Friedman, 2009).

2.2. Applications of Causal AI Models in Sustainability and Manufacturing

Recent work has applied Causal AI methods to sustainability challenges in manufacturing. This section reviews how BNs and DBNs are used for energy efficiency, predictive maintenance, and decision-making under uncertainty. Nannapaneni et al. (2016) apply BNs to aggregate uncertainty from manufacturing processes for robust energy consumption predictions. Nannapaneni et al. (2020) extend this to real-time monitoring and control in cyber-physical manufacturing systems, integrating sensor and computational uncertainties to support energy-efficient decision-making. Building on this, applications of DBNs have emerged. Han et al. (2022) combine fuzzy Quality State Task Networks with DBNs to predict Remaining Useful Life at the system level, improving maintenance and resource efficiency. (Ansari et al., 2020) propose a prescriptive maintenance model for CPPS that integrates multimodal data using DBNs to support predictive decision-making and optimal maintenance planning. Nannapaneni et al. (2020) apply DBNs for sequential decision-making under uncertainty in cyber-physical systems, while Chang et al. (2023) highlight DBNs' broader potential for modeling dynamic environmental impacts.

3. MODELING OPERATIONAL SUSTAINABILITY USING THE OSEE-DBN

The shop floor constitutes a system where social, environmental, and economic factors interact closely with operational processes (Zackrisson *et al.*, 2017). Managing these interdependencies requires integrated approaches that balance production efficiency with environmental and social objectives, a central challenge in sustainable operations management. To support integrated prescriptive decision-making, the OSEE framework extends the traditional OEE by including environmental and social indicators relevant to the shop floor level. To bridge this gap Madreiter and Ansari (2024) proposed the OSEE framework as an extension to prescriptive maintenance (Prima) framework (Ansari *et al.*, 2019).

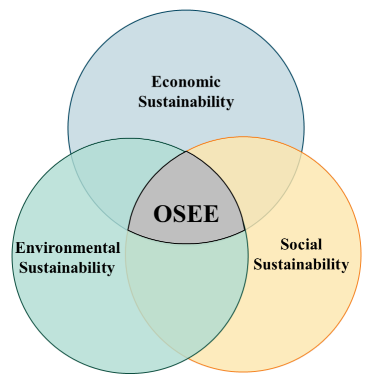

Figure 1: Sustainability Pillars in the OSEE Framework

The OSEE (see Figure 1) extends the classical OEE concept by incorporating environmental and social performance indicators into operational assessments (cf. Table 1), thereby offering a more holistic view of equipment effectiveness. The framework is modular in structure, allowing for the selection and adaptation of relevant indicators across different industry contexts. Although the OSEE framework establishes a comprehensive set of sustainability indicators at the operational level, it does not capture the causal interdependence between economic, environmental, and social performance dimensions.

To address this limitation, a Dynamic Bayesian Network (DBN) is developed to enable causal reasoning and scenario-based simulation. Figure 2 outlines the modeling process, from indicator selection to causal structure and DBN implementation. The following sections explain each step.

3.1. Deriving the Causal Structure

To enable causal inference and scenario-based simulation, a directed acyclic graph structure representing hypothesized causal relations between the sustainability indicators of the OSEE is derived. This structure serves as the foundation for the DBN described in the following section.

Table 1: OSEE Factors (Madreiter and Ansari, 2024)

Indicators			**Description**
OEE	Availability	A	The proportion of planned production time during which the equipment is actually running
	Performance	P	The ratio of actual output speed to the maximum possible speed
	Quality	Q	The proportion of good units produced out of the total units
Environmental (Env.)	Resource Efficiency	RE	The resource efficiency compares targeted and actual resource consumption across energy, water and materials
	Recycling Share	RS	The recycling share incorporates the Percentage of water, materials, and waste that is successfully recycled or reused
	Emission Efficiency	EE	The emission efficiency compares targeted and actual emissions, covering Greenhouse gases, NOx, SOx, and total air emissions
	Waste Efficiency	WE	Waste efficiency compares the ratio between the target and actual percentages of hazardous/harmful waste generated
Social (Soc.)	Employee Satisfaction	ES	Workers with positive workplace satisfaction as a percentage of workforce
	Employee Diversity	ED	Percentage of gender balance in the workforce to a defined target value
	Employee Training	ET	Percentage of completed training hours against planned training hours
	Employee Safety	S	Percentage of time or operations completed without work-related injuries or incidents
	Employee Health	EH	Percentage of scheduled hours worked without any unintended employee absences

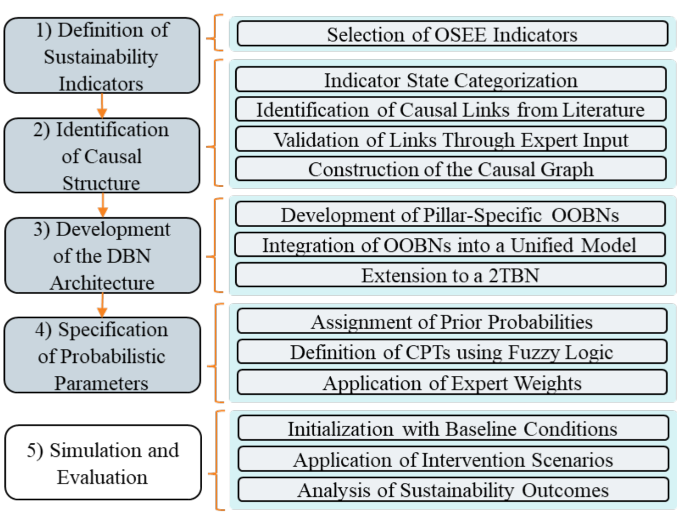

Figure 2: Overview of the modeling and parameterization steps for the OSEE-DBN

The derivation follows a four-stage process, i) identification of candidate causal relations via structured literature review, ii) expert-based evaluation of relevance and influence strength, iii) operationalization of OSEE indicators into model variables with discrete state definitions, and iv) graph construction based on validated relationships. In the literature review, targeted searches were conducted in manufacturing, maintenance, and sustainability domains to extract recurring interdependencies. Qualitative content analysis was applied to identify cause-effect linkages through co-occurrence and contextual discussion of OSEE-aligned constructions. This yielded a preliminary set of unidirectional relations between indicator pairs. To assess the causal relations among OSEE indicators, expert elicitation was conducted with a balanced group of domain specialists, including industry practitioners and academic researchers with expertise in production, manufacturing, and sustainability. The group represented multiple companies and sectors to reduce bias and avoid company-specific perspectives. Drawing on their professional experience, they rated the strength and relevance of potential links in a structured questionnaire complemented by semi-structured interviews, using a Likert scale. The aggregated results were used to validate the causal structure and to parameterize the DBN. Respondent ratings were normalized to a [0,1] scale and served two purposes: they determined which relations to include in the causal graph and provided quantitative influence weights for probabilistic modeling. The resulting validated interrelations were then represented as a directed graph, in which each node corresponds to a discretized OSEE indicator and each edge represents a confirmed causal influence.

Constructing the OSEE-Dynamic Bayesian Network

Building on the causal graph structure, a knowledge-based DBN was developed to represent the temporal and probabilistic dependencies among OSEE indicators. The DBN enables the evaluation of sustainability trajectories over time and supports scenario-based analysis of operational interventions. To manage the complexity of the full system while preserving the distinct characteristics of each sustainability pillar, the model construction followed a modular, three-stage approach (illustrated in Figure 3):

1. Object-Oriented Bayesian Networks (OOBNs) were developed for each of the three sustainability pillars: economic (OEE indicators), environmental, and social. Each OOBN encapsulated the relevant indicators defined within the OSEE framework, reducing overall network complexity while preserving domain-specific characteristics.
2. The pillar-specific models were integrated into a unified BN by identifying interface nodes that connect the different sustainability dimensions. For example, the social indicator "Employee Training" was linked to the operational indicator "Availability," highlighting how workforce development can influence equipment utilization and system performance.

3. The unified BN was extended into a two-slice DBN (2TBN) to model indicator evolution between consecutive time steps. This temporal extension allows the evaluation of sustainability trajectories over time and the simulation of operational interventions.

Following the construction of the network structure, the conditional probability tables (CPTs) were specified to quantify the probabilistic dependencies between variables, as described in the next section.

3.2. Defining Conditional Probabilities for the Model

While the causal structure was developed in Section 3.1, based on literature and expert validation of directional relationships, the present section focuses on quantifying those relationships using conditional probabilities and fuzzy logic. Each node in the BN is characterized by a probability distribution over discrete states. Together, all individual distributions form the joint probability distribution of the network. To develop the conditional probability tables (CPTs) for the OSEE framework, all possible states of each indicator were considered. Indicators were defined based on the OSEE framework and categorized into three qualitative states: High, Medium, and Low.

This discretization was selected to maintain a low model complexity while ensuring sufficient expressiveness of the sustainability dimensions. The use of three states for each indicator limits the exponential growth of CPTs and ensures practical interpretability, especially when the model is applied in operational settings. Thresholds for state classification were aligned with OEE industry standards, with values above 85% classified as High, 60–85% as Medium, and below 60% as Low. These thresholds were adapted consistently across operational, environmental, and social indicators to maintain coherence with typical industrial benchmarks. For variables without parent nodes, prior marginal distributions were assigned uniformly across the three states, each initialized at a probability of 33%. Given the limited availability of large-scale empirical Given the limited availability of large-scale empirical datasets in the context of operational sustainability, a qualitative and literature-based approach supported by expert input and fuzzy logic techniques was applied to define the conditional probabilities.

Fuzzy logic provides a mathematical framework for dealing with uncertainty and vagueness, and is particularly suited for scenarios where precise numerical data is lacking, and expert judgments or qualitative assessments are predominant (Zimmermann, 2010). System states were represented by degrees of membership in the categories High, Medium, and Low. The fuzzification process mapped normalized indicator values to a continuous membership scale between 0 and 1, allowing smooth transitions between qualitative states. To define the membership functions, symmetric triangular shapes were employed, which are commonly used in fuzzy modeling due to their interpretability and suitability for expert-based systems. Each input variable was normalized over the interval [0,1], and the sum of membership degrees across all categories was constrained to equal 1, maintaining internal consistency.

For nodes with multiple parents, conditional probability tables were constructed using a weighted aggregation approach based on both literature-derived and expert-validated relationships. Where strong and unambiguous causal relations were identified in the literature, these were directly encoded into the model. For other interdependencies not clearly established, expert assessments were used to evaluate the relative influence strength of each parent on its child indicator. These scores were normalized and combined with fuzzy membership degrees of the parent variable states to compute the conditional probability distributions for the child nodes. The causal links from the three pillar nodes (OEE, Environmental Sustainability, Social Sustainability) to

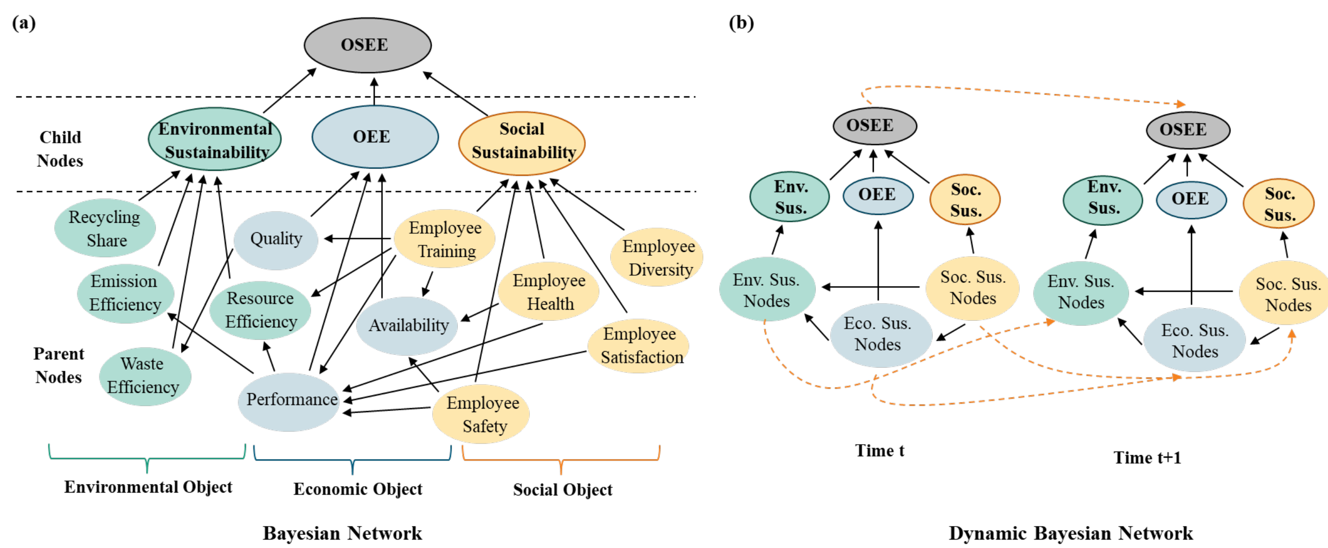

Figure 3: (a) BN consisting of OOBNs for the three sustainability pillars. (b) DBN with two-slice temporal links (t, t+1) showing dependencies across time

the OSEE node are assigned equal weight. This reflects the conceptual basis of the Triple Bottom Line (Elkington John, 1996), in which the economic, environmental, and social dimensions are considered equally important for sustainability performance. Equal weighting at this aggregation level ensures balanced representation of the three pillars, while all intra-pillar dependencies retain the weighted structure derived from literature and expert scoring. To derive the conditional probability distributions, the fuzzy membership degrees of parent variable states were combined with influence weights from expert assessments or literature. The probability of the child variable assuming a given state *Sj* was calculated using a weighted aggregation of these inputs as in equation (1), where w_i is the normalized influence weight of parent *i* (from literature and expert scoring) and $\mu_{i,j}$ is the fuzzy membership degree of parent *i* to state *j*.

$$P(S_j) = \frac{\sum_{i=1}^{n} w_i * \mu_{i,j}}{\sum_{j'} \sum_{i=1}^{n} w_i * \mu_{i,j'}} \quad (1)$$

This dual-sourcing approach ensured that CPTs reflect both established scientific knowledge and practice-informed insights, enabling a transparent and context-sensitive modeling of sustainability interdependencies in the OSEE-DBN.

4. SIMULATION STUDY: EVALUATING SUSTAINABILITY INTERVENTIONS

A simulation study was conducted using the OSEE-DBN to evaluate how an operational intervention influences sustainability performance over time. The scenario involved implementing a revised maintenance strategy aimed at improving equipment availability and employee training. These two factors were expected to have a direct effect on OEE and to influence environmental and social outcomes through the modeled dependencies in the network. This simulation represents a level 2 causal inference in Pearl's hierarchy, approximating *P(Y | do(X))* by explicitly setting selected node states and propagating their effects through the DBN structure.

The model was initialized with industry data for the OEE-related indicators. Environmental and social variables were populated with synthetic values that reflect realistic operating conditions. All variables were discretized into three qualitative states: High, Medium, and Low, based on the threshold definitions used in the model. At the baseline (t = 0), when the strategy was inactive, the probability of achieving a high OSEE score was 58%. The probabilities for medium and low scores were 31% and 11%, respectively. At t = 1, an exogenous variable ("New maintenance strategy") is set to True, fixing the indicators *Availability* and *Employee Training* to the "High" state. This intervention represents a maintenance-oriented operational adjustment, and its effects are transmitted through the validated, weighted causal dependencies described in Sections 3.1 and 3.3, with weights derived from literature evidence and expert scoring. As a result, the probability of a high OSEE score increases to 64%, while medium and low scores decline to 29% and 7%. By t = 2, the probability of a high OSEE rises further to 66%, with medium and low probabilities reduced to 28% and 6%. The changes over time reflect the lagged response of environmental and social indicators compared to the immediate operational effects. Figure 4, visualizes how the "New maintenance strategy" affects the three sustainability pillars and the aggregated OSEE score over the simulation period, comparing baseline and intervention results. A sensitivity analysis was carried out for $OSEE_1$ = High (t = 1, after the intervention) using the DBN's conditional probability structure. In each scenario, specific variables or combinations were fixed to defined states, while the remainder stayed at baseline. The resulting probability ranges for the target were compared, and configurations were ordered by their net influence relative to the baseline value of

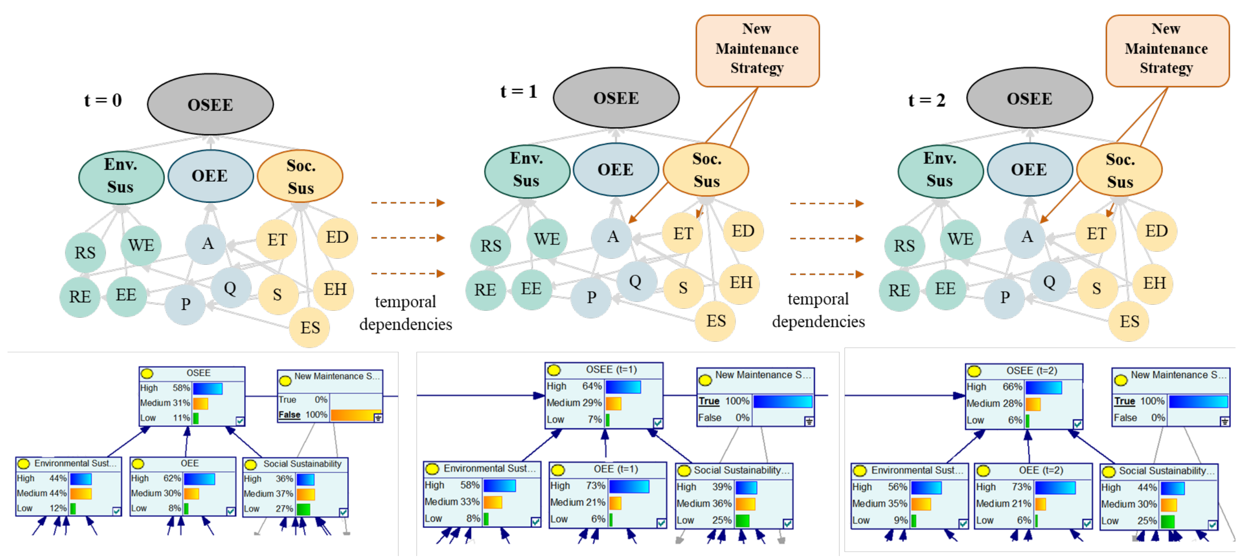

Figure 4: Simulation Results: Effects of Maintenance Strategy on Sustainability Performance

0.643 (range 0.634–0.652). In Figure 5, the green segment of each bar indicates the share of the range above baseline, the red segment the share below. The highest-ranked configuration sets Env., OEE, and Soc. to High along with OSEE$_0$ High, producing the largest positive shift but still allowing for some outcomes below baseline due to unfixed variables. In contrast, a configuration limited to environmental subfactors (WE, RE, EE, RS High) ranks lowest, showing only modest gains when operational and social factors remain unimproved. Intermediate ranks illustrate how partial or uneven improvements in the three pillars affect the probability of achieving $OSEE_1$ = *High*. In the context of the OSEE simulation, these results indicate that sustained and simultaneous improvements in all three pillars, supported by strong prior performance, have the greatest impact on future sustainability outcomes.

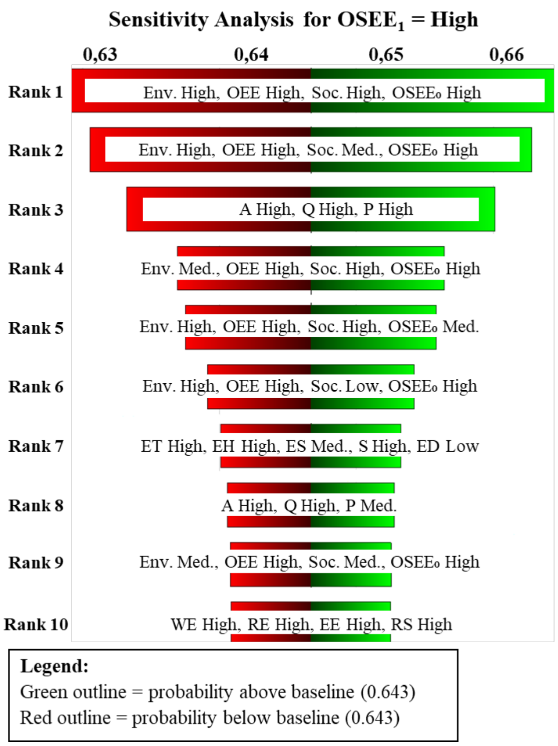

Figure 5: Sensitivity analysis results for OSEE$_1$ = High at t = 1 after intervention

5. CONCLUSION AND OUTLOOK

This paper developed a causal modeling approach for operational sustainability by extending the OSEE framework using DBNs. While existing OEE extensions incorporate environmental and social indicators, they typically treat these domains independently. The OSEE-DBN addresses this limitation by modeling causal relationships among operational, environmental, and social indicators. This enables scenario-based simulations and supports forward-looking prescriptive decision-making at the shop floor level. By providing an evidence-based approach, it helps decision-makers identify and prioritise high-impact interventions, test alternative strategies through what-if simulations, and integrate operational, environmental, and social considerations into a single sustainability perspective. The model explicitly accounts for time-dependent effects and cross-domain interactions, fac ilitating more anticipatory and coordinated management. Future research will focus on advancing the model and demonstrating its applicability in industrial practice. Empirical validation in real manufacturing environments is essential to test the plausibility of the assumed relationships and to assess the model's predictive performance. The current specification of conditional probability tables, derived from expert judgment and literature, should be complemented with actual operational, environmental, and workforce data to support a robust, data-driven formulation. Furthermore, the model's scalability should be systematically evaluated across a range of manufacturing contexts and organizational settings to assess its generalizability and practical relevance. The OSEE-DBN provides a structured and causally grounded method for integrating sustainability into operational decision-making. By modeling the dynamic interactions among sustainability indicators, it enables systematic evaluation of interventions and supports sustainability-aligned planning at the shop floor level. Continued empirical development and broader application are essential to establish its utility in industrial contexts.

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