

# Optimization of OEE and Energy Efficiency in Glass Manufacturing Using an Energy-Centric TPM Framework

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**Abstract:** Achieving equipment efficiency improvements without significant increases in energy consumption is crucial in the continuous glass industry, one of the most energy-intensive and thermally constrained industries. While Total Productive Maintenance (TPM) and Total Equipment Efficiency (OEE) are widely used to reduce losses, energy efficiency is often viewed as an external cost rather than an operational variable, creating a gap between equipment efficiency and energy intensity. This paper proposes a global TPM framework focused on energy in continuous glass production, integrating: (1) real-time remote energy measurement, (2) contextual realistic outcomes mechanism (CMO) logic, (3) qualitative comparative fuzzy ensembles analysis (fsQCA), and (4) dynamic interaction modeling between total equipment efficiency and energy. This framework identifies alternative Total Productive Maintenance (TPM) configurations linked to sustainable improvements in Total Equipment Effectiveness (OEE). It models the temporal correlation between downtime, production line speed, quality loss, and specific energy consumption, and generates optimal trade-offs based on Pareto principle between OEE and energy per unit of output to support management decision-making. This proposed approach promotes energy-sensitive maintenance governance within the context of the Fourth Industrial Revolution and provides a model applicable to continuous, energy-intensive processes.

**Keywords:** Energy efficiency, Energy telemetry; fuzzy-set Qualitative Comparative Analysis fsQCA, Overall Equipment Effectiveness (OEE); Total Productive Maintenance (TPM).

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## 1. Introduction

Improving operational efficiency while managing energy consumption remains a key challenge in continuous glass manufacturing. This study therefore examines how energy-oriented TPM practices can contribute to improving Overall Equipment Effectiveness (OEE) in such production systems. Accordingly, the study aims to develop and evaluate an energy-centric TPM approach for improving OEE in continuous glass manufacturing environments.

### This study therefore proposes

There is considerable interest in energy consumption in the glass industry, therefore Continuous glass manufacturing is among the most energy-intensive process industries due to the need to maintain furnaces at temperatures exceeding 1500 °C under stable thermal conditions. Any interruption to furnace operation, unexpected downtime, or unstable line speeds may result in significant productivity losses, quality defects, and increased energy

consumption [1]. In continuous glass production systems, both hot-end and cold-end operations must therefore operate with high reliability and stable process control to maintain production efficiency and thermal balance [2].

Total Productive Maintenance (TPM) has been widely adopted as a systematic approach to improving equipment reliability, reducing operational losses, and enhancing manufacturing performance [3]. TPM integrates multiple organizational and technical practices including autonomous maintenance, planned maintenance, focused improvement, and early equipment management. Within this framework, Overall Equipment Effectiveness (OEE) has become a widely used indicator for evaluating production performance by combining availability, performance, and quality into a single operational metric [3].

Despite the widespread application of TPM and OEE in manufacturing systems, a significant limitation remains in energy-intensive industries such as glass production. In most TPM implementations, energy consumption is treated as an external cost factor rather than an operational performance variable. Consequently, improvements in OEE may occur alongside increased energy intensity, while energy-saving strategies may not be reflected in traditional maintenance performance indicators. This disconnect creates a critical gap between maintenance governance and energy performance management [5].

OEE is the most widely used metric to quantify production losses, combining availability, performance, and quality into a single percentage value. Studies in continuous and semi-continuous processes frequently report OEE improvements of 10–20 percentage points following TPM programmes [7]. Yet, these improvements are typically reported without explicit consideration of energy performance. In continuous glass manufacturing, the strong coupling between thermal behaviour, downtime, and quality suggests that OEE metrics should be evaluated alongside energy intensity Fig.1[5].

Recent research highlights several limitations in existing studies on glass manufacturing performance. First, few studies explicitly integrate energy telemetry into TPM decision-making architectures. Second, most empirical analyses rely on static before-and-after comparisons rather than examining dynamic interactions between downtime, production performance, and energy consumption. Third, configurational analytical approaches such as fuzzy-set Qualitative Comparative Analysis (fsQCA) are increasingly used in operations management but remain under-utilized in process-industry maintenance research. Finally, integrated optimization models that simultaneously consider production effectiveness and energy efficiency remain limited in the glass manufacturing sector [9].

To address these gaps, this study proposes a Global Energy-Centric TPM Framework for continuous glass production that integrates energy monitoring, configurational analysis, dynamic interaction modelling, and multi-objective optimization. Rather than analyzing these components separately, the framework combines them into a unified analytical architecture capable of linking maintenance practices, operational performance, and energy efficiency.

With The study pursues the following research objectives:

- 1- To develop an integrated energy-centric TPM framework linking maintenance practices, operational performance indicators, and energy telemetry in continuous glass manufacturing systems.
- 2- To identify configurational pathways leading to significant OEE improvements using fuzzy-set Qualitative Comparative Analysis (fsQCA).
- 3- To analyses the dynamic interaction between OEE components and energy consumption, particularly the influence of downtime, production instability, and quality losses on specific energy intensity.
- 4- To formulate a multi-objective optimization model capable of identifying efficient operating regimes balancing production effectiveness and energy performance.

By integrating configurational analysis, dynamic modelling, and optimization within a unified framework, the study contributes to the development of energy-aware maintenance governance strategies suitable for Industry 4.0 environments and energy-intensive continuous manufacturing systems.

## 2. Literature Review

TPM has found extensive application in the discrete and processed industries as a systematic method of enhancing equipment reliability and minimizing losses. TPM pillars have also been demonstrated to mitigate the number of breakdowns, micro-stoppages, and defects in the glass industry when put in place properly, both in the hot-end and cold-end operations [3]. Autonomous Maintenance is an approach that helps to put the operators in charge of

the basic inspection and cleaning activities, whereas Planned Maintenance and EEM are aimed at improving systematic scheduling and design. Nevertheless, energy-intensive industries continue to use energy indicators as external cost measures when implementing TPM as opposed to using them as performance variables [6].

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Energy research in the glass sector highlights the role of thermal inertia, furnace design, and process control in determining energy consumption. Downtime events create reheating penalties, micro-stoppages reduce the effective utilisation of energy supplied to the furnace, and high defect rates impose a hidden energy cost through reprocessing and scrap [1,10]. Despite this, few TPM or OEE studies explicitly model the energy consequences of maintenance decisions.

fsQCA has emerged as a suitable method for examining complex causal configurations and equifinality in operations management [8,11]. In the manufacturing environment, it has been applied to find combinations of practices and conditions that are linked to high performance by using fsQCA [12,13]. Nevertheless, robustness testing, e.g., changing consistency levels or distorting set thresholds, is not invariably reported, making it difficult to put trust in certain configurational results.

Simultaneously, multi-objective optimization has emerged as a key instrument in managing to balance productivity with energy and environmental aims in manufacturing. Pareto-based methods enable the decision-maker to depict trade-offs between conflicting objectives like throughput and energy consumption [9,14]. However, there are a limited number of integrated optimization models, which directly correlate OEE, TPM decisions, and energy intensity in continuous glass manufacturing. These gaps inspire the thinking of a combined, energy-based TPM framework of the worldwide glass sector.

### **3. Methodological Workflow.**

Analysis, dynamic modelling, and optimization techniques in the analysis of glass manufacturing performance. The workflow links contextual reasoning, fsQCA analysis, dynamic OEE–energy interaction modelling, and multi-objective optimization within a unified analytical structure. Figure X illustrates the sequential analytical process used to identify operational configurations associated with improvements in OEE and energy, performance The overall methodological workflow adopted in this study is illustrated in Figure 1.

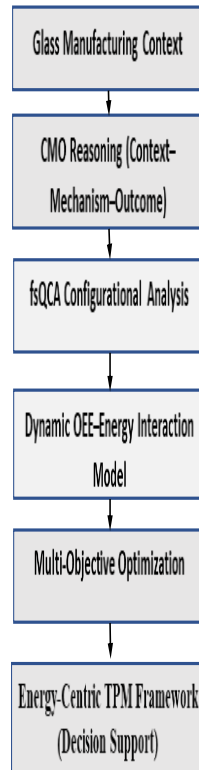


Figure 1. Methodological workflow illustrating the analytical sequence used in this Study.

#### 4. Methodology.

Overall Equipment Effectiveness (OEE) is used in this study as a key indicator of operational performance, representing the combined effects of availability, performance, and quality.

This research takes the mixed-method approach based on realist CMO logic, fsQCA configurational analysis, dynamic system modelling, and multi-objective optimization. The conceptualised relationship of the TPM mechanisms with contextual factors to induce High- $\Delta$ OEE results in continuous glass manufacturing is conceptualised using the realist CMO approach [15,16]. The methodological integration is consistent with the shift toward cyber-physical manufacturing systems where real-time sensing and analytics support maintenance decision-making and energy-aware operational control [16]. In addition, the choice of KPIs is aligned with international guidance on manufacturing performance measurement, including OEE-based indicator structures [12]. The CMO model differentiates between: (1) context, i.e., hot-end versus cold-end positioning, digital maturity, energy monitoring capabilities, and thermal constraints [2,17]; (2) mechanisms, i.e., TPM pillars, i.e., AM, FI, PM, EEM [3,18]; and (3) outcomes defined as High- $\Delta$ OEE, which are a significant increase in OEE over a sustained observation window. This reasoning underlies the identification of condition arrangements that result in better performance consistently.

fsQCA is used to model equifinality causal paths. Cases of continuous glass operations are coded into fuzzy sets of context (e.g., level of automation, the existence of energy monitoring), mechanisms (deployment of TPM pillars), and outcomes (the magnitude of OEE improvement), as per established protocols [11,19]. The theoretical anchors and empirical thresholds applied in the calibration process are based on published research in the glass and associated industries [7,20]. Truth tables are built and minimized to obtain adequate configurations of High- $\Delta$ OEE.

The robustness and sensitivity tests are conducted by modifying consistency thresholds, frequency cut-offs, and membership scores perturbation, which is consistent with recommendations provided by [8] and Schneider and Wagemann [21]. The tests ascertain that the identified settings can be maintained in the face of sensible changes in parameters.

Then, dynamic system identification techniques are used to model the time-dependent interaction between the OEE components and energy consumption. The analysis of the effect of downtimes, line-speed changes, and defect rates on particular energy consumption over time is analyzed with time-series, and it is an extension of previous process-industry methods [10,22].

The last step is to formulate a multi-objective optimization model to maximise OEE and specific energy minimisation, which are subjected to operational constraints. The model follows a Pareto-based approach, which enables the managers to choose operating points that optimally depict their strategic priorities [9,14].Table 1.

#### 4.1 Data sources and case definition

This study conceptualises cases as continuous glass production settings (hot-end and/or cold-end) characterised by (i) available OEE component data (availability, performance, quality), (ii) energy monitoring at plant or line level (electricity and fuel where applicable), and (iii) stable production runs observed over a defined time window. The energy-performance framing follows established sector guidance that identifies furnace energy intensity and heat-recovery effectiveness as dominant drivers of specific energy consumption in glass manufacturing [26]. The importance of robust measurement infrastructure and structured energy datasets for identifying improvement opportunities is widely documented in industrial energy-efficiency assessments [25]. Sector decarbonisation analyses further support treating energy use as a coupled operational variable that must be evaluated alongside throughput and quality, rather than as an independent cost metric [24]. Specific energy consumption is interpreted in physical units (e.g., kWh/ton of glass or GJ/ton) consistent with common practice in glass energy studies and process-industry reporting [23], [26]. Where optimisation results are presented using normalized indices, the index is explicitly linked to a physical baseline consistent with best-available-techniques benchmarking approaches used in the glass sector [26].

This study relies primarily on literature-informed operational configurations rather than proprietary plant-level datasets. Each analytical case represents a typical operational configuration derived from documented studies of continuous glass production systems. This approach allows the framework to synthesize empirical insights from multiple studies while avoiding confidentiality constraints associated with industrial production data. The cases therefore represent conceptualized operational environments reflecting typical hot-end and cold-end production conditions reported in prior research.

#### 4.2 fsQCA calibration and analysis procedure

The fsQCA calibration should report the three anchors for each condition (full membership, crossover, full non-membership) and the theoretical/empirical justification for each threshold. A calibration table is recommended. The truth-table construction should specify the frequency cut-off, the consistency threshold for sufficiency, and the approach to resolving logical remainders (e.g., intermediate solutions with directional expectations).[45]The analytical procedure of fsQCA used in this study is presented in Figure 2.



Figure 2. Analytical procedure of fsQCA used to identify[43]

Configurations leading to high OEE Performance.

Table ( 1 ) . Calibration scheme for fsQCA variables. [44].

Condition / Outcome	Observed data range	Full membership (1)	Crossover (0.5)	Full non-membership (0)	Threshold justification / Source
High OEE (Outcome)	0.45 – 0.90	0.85	0.65	0.50	Based on OEE benchmarks (Muchiri & Pintelon, 2008)
Maintenance efficiency	0.40 – 0.88	0.80	0.60	0.40	Distribution-based calibration following Ragin (2008)
Process stability	0.35 – 0.85	0.80	0.60	0.40	Empirical distribution and theoretical expectations
Operator skill	0.50 – 0.92	0.85	0.65	0.45	Calibration following fsQCA guidelines (Ragin, 2008)

Calibration anchors (full membership, crossover, and full non-membership) are set using a combination of theory and sector-informed empirical logic, and the robustness of solutions is verified through standard sensitivity checks. This approach follows established methodological guidance on applying and reporting fsQCA in operations and management research, particularly with respect to transparency of calibration choices and solution robustness [32]. The calibration of fuzzy sets follows the three-anchor approach recommended in fsQCA methodology. Each condition is calibrated using thresholds representing full membership, crossover point, and full non-membership. The calibration scheme for the fsQCA variables is presented in Table 1.

High- $\Delta$ OEE is defined as a significant positive change in overall equipment effectiveness exceeding a predefined threshold (e.g.,  $\Delta$ OEE  $\geq$  0.10). In this study,  $\Delta$ OEE values are calibrated into fuzzy-set membership scores to distinguish between low, moderate, and high operational performance levels. The calibration of the conditions and outcome variables was conducted using the direct method commonly applied in fsQCA research. Three qualitative anchors were specified to transform the raw data into fuzzy-set membership scores: full membership (1), crossover point (0.5), and full non-membership (0). The calibration thresholds adopted in this study are summarized in Table 2.

Table 2. Table 2 Calibration anchors for fsQCA conditions. [41]

Condition	Full membership	Crossover point	Full non-membership	Justification
Automation level	0.85	0.50	0.15	Reflects highly automated cold-end

				production environments
Energy monitoring capability	0.90	0.55	0.20	Based on presence of real-time energy telemetry
Preventive maintenance intensity	0.85	0.50	0.20	Frequency of structured PM interventions
Autonomous maintenance implementation	0.80	0.50	0.20	Operator-level maintenance involvement
Early equipment management	0.80	0.50	0.20	Integration of design improvements
Outcome: High- $\Delta$ OEE	0.90	0.50	0.10	Significant improvement in OEE performance.

The simplified truth table used in the configurational analysis is presented in Table 3.

Table 3. Simplified fsQCA truth table.[40]

<b>Configuration</b>	<b>Automation</b>	<b>Energy monitoring</b>	<b>AM</b>	<b>PM</b>	<b>EEM</b>	<b>High-<math>\Delta</math>OEE</b>
<b>C1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>
<b>C2</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>1</b>
<b>C3</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>1</b>	<b>1</b>
<b>C4</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>

The truth-table analysis identifies multiple configurations linking contextual conditions and TPM mechanisms to significant OEE improvements. The analysis highlights the presence of equifinality, where different combinations of operational conditions can lead to similar performance outcomes.

In the fsQCA analysis, a consistency threshold of 0.80 was adopted to identify sufficient configurations associated with high OEE outcomes, following common practice in configurational comparative research.

#### 4.3 Robustness and sensitivity testing

To strengthen inferential credibility, report a robustness protocol that varies (i) calibration anchors within plausible ranges, (ii) the raw consistency threshold, and (iii) the frequency cut-off. Summarise the sensitivity range within which the solution terms remain stable and report any solution terms that are sensitive to parameter changes. Robustness is further assessed by comparing solution stability under alternative model specifications and perturbations of calibration anchors, consistent with recommended robustness protocols for set-theoretical analyses [32], [34]. Reporting these checks improves confidence in causal complexity claims (equifinality and conjunctural causation) and reduces risks of artefactual solutions driven by single calibration choices [33,34].

#### 4.4 Dynamic OEE–Energy Interaction Model.

The modelling rationale reflects well-established thermodynamic and operational characteristics of glass furnaces and regenerative heat-recovery systems, where stoppages and unstable operating regimes reduce thermal efficiency and increase specific energy demand [26], [28], [29]. The dynamic coupling between throughput, quality losses, and energy per good unit is also consistent with process-level evidence that energy penalties arise from reheating requirements, reduced effective utilisation, and defect-related scrap/rework burdens in continuous melting

operations [23], [24], [26]. The main components of OEE used in the dynamic interaction model are summarized in Table 4.

Table. 4. OEE Components[42].

<b>Component</b>	<b>Definition</b>	<b>Key Loss Drivers</b>
<b>Availability</b>	Line running time	Downtime, furnace access
<b>Performance</b>	Actual vs ideal speed	Micro-stops, slow cycles
<b>Quality</b>	Good units' ratio	Defects, rework, scrap

#### 4.5 Multi-Objective Optimisation.

The optimisation is formulated as a bi-objective problem seeking to maximise OEE while minimising specific energy consumption, and the resulting Pareto set is interpreted as non-dominated operating alternatives [32,33]. Pareto-based multi-objective evolutionary optimisation is widely adopted for industrial scheduling and energy-aware manufacturing problems because it provides a transparent representation of trade-offs rather than a single aggregated optimum [31]. This is consistent with energy-aware optimisation practice in manufacturing systems where productivity and energy objectives conflict under real operational constraints [29].

### 5. Proposed Global Energy-Centric Tpm Framework.

The suggested global framework combines the energy cues, TPM mechanisms, OEE behavior, and optimization into a single structure to produce glass continuously. It is based on five layers, which are: (1) data acquisition, (2) the Energy Maintenance Control Loop (EMCL), (3) dynamic interaction modelling, (4) multi-objective optimization, and (5) governance and decision support.

The data collection layer consolidates data from SCADA systems, programmable logic controllers, IIoT sensors, and energy meters. Some of its key variables are furnace temperatures, line speeds, downtime events, number of defects, and energy consumption metrics [2].

The framework is anchored on the EMCL. Continuous monitoring of energy and process signals is used to identify anomalies, classifying them relative to availability, performance, or quality losses, and takes suitable TPM measures. As an illustration, abnormal energy spikes during steady-state working can be an indication of imminent failures or inefficient control parameters, which can result in the interventions of the FIs and PM. Targeted AM and FI activities can be induced by micro-stop clusters on the cold-end. EEM aids in long-term design and accessibility enhancements, which creates Mean Time to Repair (MTTR) and thermal disturbances reduction. Dynamic modelling layer the temporal coupling between OEE and energy intensity. It reflects the impact of unexpected downtime on the generation of reheating penalties, the effect of speed changes on the amount of energy per ton of glass, and how the loss of quality results in the effective use of more energy per good unit. This layer will offer the granularity that static before-and-after studies do not have [35].

The optimization layer has devised OEE and specific energy consumption as conflicting goals. They are created as Pareto fronts, for example, to show trade-offs to decide whether to work on productivity, reduce energy usage, or settle on a compromise [34]. Lastly, the governance layer reports the results to the managers as dashboards and reports and incorporates KPIs of High- $\Delta$ OEE, energy per good unit, and sustainability measures and the proposed energy-centric TPM framework for continuous glass production is illustrated in

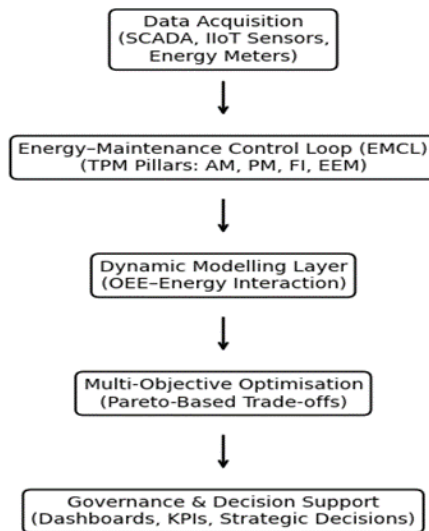


Figure 3. Global energy-centric TPM framework for continuous glass production[2]

The relationship between equipment effectiveness and energy performance can be formally expressed using the OEE formulation and specific energy consumption metrics.

$$OEE=A \times P \times Q \dots \dots \dots \text{ISO 22400 [40]}$$

Where:

A = Availability

P = Performance

Q = Quality

And ,  $E_s = E_t / G \dots \dots \dots$  Energy consumption  $\rightarrow$  Cantini et al. [23]

Where:

- $E_s$  = Specific Energy Consumption
- $E_t$  = Total Energy Consumption
- G = Number of Good Units

Productivity Region:  $OEE \geq 0.85$

Energy Efficient Region :  $E_s \leq E_{avg}$

Balanced Region :  $0.70 \leq OEE \leq 0.85$

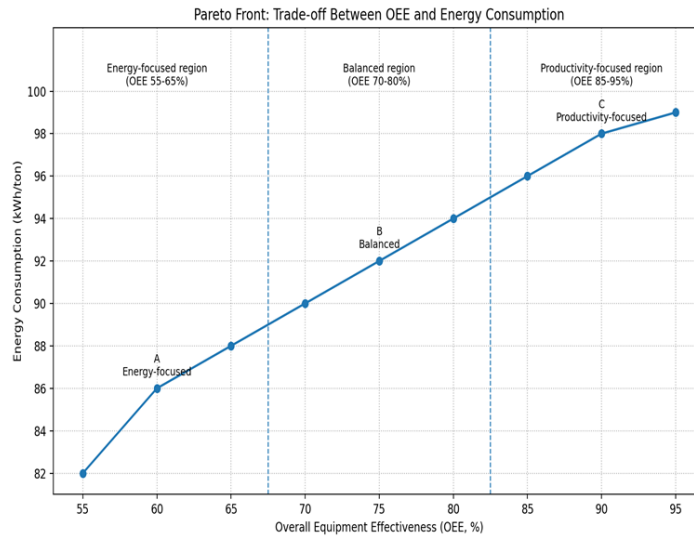
The Pareto front obtained from the optimisation model can therefore be interpreted using three operational regions: productivity-focused, energy-focused, and balanced operating regimes.

## 6. Results and Discussion.

The results of the proposed analytical framework provide insights into the relationship between operational performance and energy consumption in continuous glass manufacturing systems. The integration of configurational analysis, dynamic modelling, and multi-objective optimization enables the identification of operating regimes that balance productivity performance and energy efficiency.

The multi-objective optimization model produces a Pareto frontier representing non-dominated operating solutions balancing Overall Equipment Effectiveness (OEE) and specific energy consumption. Each point on the frontier represents a feasible operating regime where improvement in one objective cannot be achieved without

compromising the other. The optimization results are illustrated in Figure 3, which shows the Pareto frontier. The optimization results are represented by the Pareto frontier shown in Figure 4.



**Figure 4. Pareto front showing the trade-off between OEE and specific energy consumption with identified energy-focused, balanced, and productivity-focused operating regions.**

The Pareto front obtained from the optimization model can therefore be interpreted using three operational regions: productivity-focused, energy-focused, and balanced operating regimes.

These regions represent different operational regimes reflecting trade-offs between production effectiveness and energy performance. The energy-focused region corresponds to operating conditions where specific energy consumption is minimized, although OEE levels remain moderate. The productivity-focused region represents operating regimes with higher OEE values but relatively higher energy intensity due to increased throughput and thermal stabilisation requirements. Between these extremes lies the balanced region, where improvements in equipment effectiveness can be achieved without substantial increases in energy consumption. This balanced operating regime may represent the most practical option for glass manufacturers seeking simultaneous productivity and energy-efficiency improvements.

## 7. Management Implications

The results of this study provide practical insights for decision-makers in continuous glass manufacturing environments. Integrating energy performance indicators within TPM-based operational management enables plant managers to evaluate production effectiveness alongside energy efficiency. The Pareto analysis highlights the importance of balanced operating regimes where improvements in OEE can be achieved without substantial increases in specific energy consumption. This approach supports more informed decision-making by linking maintenance reliability, operational performance, and energy management within a unified analytical framework.

## 8. Validation of the Proposed Framework.

The proposed Global Energy-Centric TPM Framework is conceptually validated through the integration of configurational analysis, dynamic modelling, and multi-objective optimization results presented in this study. The fsQCA analysis identifies operational configurations associated with significant improvements in OEE, while the dynamic interaction model explains the relationship between downtime events, production stability, and specific energy consumption. Furthermore, the Pareto-based optimization results demonstrate the existence of feasible operating regimes balancing production effectiveness and energy efficiency. Together, these analytical components provide complementary evidence supporting the practical relevance of the proposed framework for continuous glass manufacturing environments.

Although the present study relies on literature-informed operational configurations rather than proprietary plant-level datasets, the analytical results demonstrate that the proposed framework provides a structured decision-

support approach for integrating maintenance governance and energy performance management in glass manufacturing systems.

## 9. Study Limitations.

This study has several limitations that should be acknowledged. First, the analysis relies primarily on literature-informed operational configurations rather than proprietary plant-level datasets from a specific glass manufacturing facility. While this approach enables the development of a generalizable conceptual framework, future research could validate the proposed model using real industrial production data. Second, the optimisation model is presented in a conceptual form to illustrate trade-offs between OEE and specific energy consumption; subsequent studies may extend this work by implementing computational optimisation algorithms using plant-level operational data. Despite these limitations, the proposed framework provides a structured analytical approach for integrating maintenance reliability and energy performance considerations in continuous glass manufacturing systems.

## 10. Conclusion.

This study proposed a Global Energy-Centric TPM framework aimed at integrating maintenance reliability, operational performance, and energy efficiency considerations in continuous glass manufacturing systems. By combining configurational analysis, dynamic modelling, and multi-objective optimisation, the study provides a structured analytical approach for understanding the relationship between production effectiveness and energy consumption.

The results highlight the importance of balancing productivity performance and energy efficiency when evaluating operational strategies. The Pareto analysis demonstrates that improvements in OEE may be associated with increased energy intensity under certain operating regimes, while energy-focused strategies may reduce achievable productivity levels. The identification of balanced operating regions therefore provides valuable guidance for decision-makers seeking to optimise both production performance and energy management. Overall, the proposed framework contributes to the development of more integrated decision-support approaches for energy-aware maintenance and operational management in continuous glass manufacturing environments. These findings are consistent with prior research highlighting the role of OEE as a comprehensive performance metric in manufacturing systems [43].

Future research may extend the present study by applying the proposed framework to real industrial datasets obtained from glass manufacturing plants. Empirical validation using plant-level operational data could further refine the optimisation model and improve the accuracy of energy-performance relationships. Additionally, future studies may explore the integration of advanced predictive maintenance techniques and digital monitoring systems to enhance the effectiveness of energy-centric TPM strategies in continuous manufacturing environments.

### Data Availability Statement.

The manuscript contains all the data supporting the findings of this study. Additional information may be available from the corresponding author upon reasonable request.

### Conflict of Interest.

The authors declare that there is no conflict of interest regarding the publication of this paper.

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