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Dual DEA Model for Resilience and Sustainability Assessment in Maintenance Systems: A Multi-Objective Genetic Approach with Dairy Plant Case Study

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Abstract

In this study, a novel model based on dual Data Envelopment Analysis (DEA) and a Multi-Objective Genetic Algorithm (MOGA) was developed to simultaneously evaluate and optimize resilience and sustainability in industrial maintenance and repair systems. The proposed model introduces new composite indices—the Composite Resilience Index (CRI) and the Composite Sustainability Index (CSI)—and employs dynamic weighting based on Shannon entropy, enabling concurrent analysis of technical efficiency, responsiveness to operational disruptions, and environmental adaptability. By incorporating the balancing function $|CRI-CSI|$, the model identifies an equilibrium between conflicting resilience and sustainability objectives. Within the hybrid MOGA–DEA–Composite Resilience Frontier (CRF) framework, the approach was examined in a dairy factory comprising three production lines. The results revealed that the monthly Preventive Maintenance (PM) policy (S_1) achieved a DEA efficiency score of 0.92, with CRI= 0.83, CSI= 0.86, and a 15% cost reduction, thereby representing the optimal trade-off among multiple objectives. Sensitivity analysis confirmed the model's stability against changes in objective weights and its strong generalizability. This research ultimately provides an intelligent decision-support framework for industrial managers to design resilient and sustainable maintenance policies, particularly in Industry 5.0 manufacturing environments.

Keywords: Dual data envelopment analysis, Multi-objective genetic algorithm, Resilience, Sustainability, Composite resilience frontier, Intelligent maintenance.

1 | Introduction

In today's complex and competitive industrial landscape, maintaining reliable, sustainable equipment performance has become a key determinant of success for manufacturing organizations. In many industries, such as the dairy, steel, energy, and petrochemical sectors, maintenance-related costs account for a considerable portion of total production expenditures, estimated at 10% to 25% of total operating costs [1].

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Therefore, effective maintenance management plays an irreplaceable role not only in cost reduction but also in enhancing efficiency, profitability, and production sustainability.

Rapid technological advancements, increased reliance on automated systems, and the emergence of smart manufacturing paradigms have further intensified the need to reconsider traditional maintenance approaches. Third-and fourth-generation maintenance systems, which rely on predictive and data-driven decision-making, have effectively bridged the gap between reactive and preventive strategies. However, in today's turbulent and uncertain industrial environments, single-objective optimization based merely on cost or downtime reduction is no longer sufficient. Industrial systems require structures that can remain resilient against shocks, sudden failures, and environmental changes while maintaining operational and environmental sustainability.

The concept of maintenance system resilience refers to an organization's ability to anticipate, absorb, and rapidly recover from operational disruptions. In contrast, maintenance sustainability focuses on the long-term effectiveness of maintenance processes, optimal resource management, and minimizing environmental impacts. Integrating these two perspectives opens the way for the next generation of intelligent maintenance decision-support systems—those that balance multiple objectives such as cost, quality, availability, and ecological impact [2].

Measuring and comparing the performance of such systems, which coexist with multiple heterogeneous inputs and outputs, poses significant challenges. In these situations, Data Envelopment Analysis (DEA) has gained prominence as a non-parametric method for assessing the relative efficiency of Decision-Making Units (DMUs). Unlike traditional statistical averages, DEA evaluates each unit relative to an empirical efficiency frontier formed by the best observed performances [3]. Within complex production and maintenance environments—where conflicting objectives such as cost minimization and quality maximization must coexist—DEA serves as a valuable multi-criteria decision-making tool.

Despite its considerable advantages, classical DEA models suffer from inherent limitations, such as the assumption of constant returns to scale, a static structure, and an inability to handle data uncertainty. To overcome these shortcomings, researchers have introduced extended approaches such as Dual DEA, Fuzzy DEA, and Network DEA, which more flexibly model the dynamic nature of real-world systems [4]. At the same time, the integration of evolutionary metaheuristic algorithms, particularly the Multi-Objective Genetic Algorithm (MOGA), with DEA has attracted growing interest as a novel means to explore Pareto frontiers in multi-objective optimization problems [5].

Based on this foundation, the present research proposes a hybrid Dual DEA–MOGA model capable of simultaneously evaluating and optimizing industrial maintenance systems in terms of technical efficiency, resilience, and economic–environmental sustainability. Within this framework, the DEA component measures the relative efficiency of DMUs. At the same time, the Genetic Algorithm (GA) optimizes weight distributions and extracts optimal maintenance policies within a multi-objective solution space. This combination preserves the mathematical interpretability of DEA while enabling scenario analysis and efficient decision-making through Pareto-optimal front exploration.

The outcomes of such a model can serve as an insightful decision-support tool for industrial managers, guiding the design of resilient and sustainable maintenance policies that not only minimize costs and downtime but also promote long-term production sustainability and stakeholder satisfaction.

In summary, this study aims to address the central research question:

How can a hybrid framework combining Dual DEA and MOGA provide an efficient, interpretable approach to evaluate and optimize resilience and sustainability in maintenance systems simultaneously?

Answering this question contributes both theoretically to the literature on multi-objective decision-making and practically, by offering a pathway to reduce costs, enhance reliability, and foster the development of sustainable industrial systems.

The remainder of this paper is structured as follows: Section 2 presents a detailed review of previous studies on maintenance management, resilient and sustainable maintenance models, and the applications of DEA in multi-objective decision-making, complemented by a comparative table highlighting the novelty of the current work. Section 3 introduces the research methodology, including the definition of the Dual DEA model, variable descriptions, the mathematical formulation, and its integration with MOGA for Pareto-front generation. Section 4 presents the case study, in which the proposed model is implemented in a representative dairy factory to demonstrate simultaneous optimization of resilience, sustainability, and cost indices. Section 5 presents empirical results and sensitivity analyses to validate the model's robustness and applicability. Finally, Section 6 concludes the paper with key insights, managerial implications, and recommendations for future research directions.

2 | Literature Review

The historical trajectory of research in maintenance and repair management shows that, over the past six decades, this managerial system has evolved from a pragmatic, reactive activity into an analytical, intelligent, and multi-objective domain. The earliest studies in the 1960s focused on probabilistic models for determining the optimal Preventive Maintenance (PM) interval. Over time, however, increasing production complexity, environmental concerns, and the necessity for organizational sustainability led to a fundamental paradigm shift. Simultaneously, the development of analytical techniques such as DEA and (GA/MOGA) enabled more precise modeling of efficiency, resilience, and sustainability. Hence, reviewing past studies not only clarifies the theoretical evolution of this field but also establishes a scientific foundation for developing the Dual DEA–MOGA comprehensive model proposed in the present research.

2.1|Historical Background and the Evolution of Maintenance Philosophies

Maintenance and repair systems emerged in the 1960s as one of the pillars of industrial automation. The seminal contribution by Barlow and Hunter [6] marked the beginning of optimization in PM, presenting one of the first probabilistic models for determining optimal maintenance intervals. Further theoretical models, such as Christer [7] for delay-time analysis and Porter and Rosenblatt [8] for system deterioration processes, advanced failure behavior modeling.

During the 1980s and 1990s, the concept of imperfect maintenance gained momentum through studies by Nakagawa [9] and EMQ-based models. This period inaugurated the cost–failure optimization paradigm, still relying on system stationarity assumptions. The introduction of multi-objective economic and qualitative perspectives in the 2000s through works such as [1], [7], [10] established a systems view of maintenance.

Entering the 2010s, digital transformation and manufacturing complexity imposed new requirements to align production, quality, and maintenance. Mongani and Visser [11] developed integrated SPC–PM models that simultaneously consider degradation rates, failures, and process control policies. The focus now shifted from minimizing failure toward achieving performance sustainability.

Between 2015–2020, the emergence of smart maintenance and Industry 4.0 brought data-driven and IoT-based concepts into maintenance planning. Researchers such as Bahryeh et al. [12], Iravani and Duenyas [13], and Renna [14] explored hybrid policies combining PM and statistical process control. Subsequently, Rasai et al. [15] integrated multi-objective simulation and reliability analysis—laying the groundwork for resilient optimization frameworks.

In the 2020s, the rapid development of AI and big data analytics elevated maintenance from operational to strategic, data-driven decision-making. Studies by Nardo and Madonna [16], Moghadam et al. [17], and Çınar et al. [18] showed that AI and machine learning effectively reduce downtime, increase productivity, and create a cognitive basis for learning-driven models, thus enabling the transition from reliability to resilience.

2.2|Transition from Classical Maintenance to Sustainability and Resilience

Before 2000, maintenance policies aimed primarily at maximizing efficiency and minimizing failure. Since the mid-2000s, the concept of sustainability has become an essential dimension of industrial policy. Jawahir [19] formalized six principles: reduce, reuse, recycle, recover, redesign, and remanufacture, and identified maintenance as a cornerstone of sustainable production. Later works, such as Mu et al. [2], emphasized incorporating environmental impacts into maintenance logistics decisions.

In the 2010s–2020s, sustainable maintenance evolved further through research by Polese et al. [20] and Yan et al. [21], integrating environmental performance assessment using indicators such as CO_2 emissions, energy consumption, and pollution-reduction costs.

In parallel with sustainability, the concept of resilience entered the maintenance literature. Initially defined in systems engineering by Hollnagel et al. [22] and later expanded in industrial maintenance by Bahmra et al. [23], Pumpuni-Lenss et al. [24], and Ghaljahi et al. [25], resilience focuses on a system's ability to react and recover after unexpected disruptions. Recent studies, such as Çınar et al. [18], have used reinforcement learning and DEA to quantify this capability.

Overall, this transition from failure monitoring → predictive intelligence → resilient and sustainable decision-making frames the conceptual foundation of the present model.

2.3|Evolution and Innovation in the Application of Data Envelopment Analysis for Maintenance Systems

Since the introduction of the original DEA model by Charnes et al. [3], the method has progressed from classical efficiency models to sophisticated multi-stage analytical tools.

The BCC model by Banker et al. [26], which assumes variable returns to scale, addressed the limitation of the CCR model and allowed efficiency assessment across varying scales establishing its role in evaluating maintenance departments. Later, Cook and Seiford [27] introduced Network Data Envelopment Analysis (NDEA) to incorporate internal process structures, proving that single-output models fail to represent interactions between production, maintenance, and quality-control stages.

Building upon that, Tone and Tsutsui [4] proposed Dynamic Network Data Envelopment Analysis (DNDEA), modeling time-dependent input-output relationships and carrying-over resources between periods (e.g., inventories and budgets). Their findings showed that these dynamic mechanisms capture changes in productivity indices (e.g., the Malmquist index) over time.

In maintenance contexts, Assaf et al. [28] applied classical DEA to evaluate operational efficiency in oil and gas industries, providing a basis for maintenance policy prioritization. Later, Ghaljahi et al. [25] combined DEA with Multi-Criteria Decision Making (MCDM) to assess productivity, cost, and quality efficiency in service organizations.

Recent extensions linked DEA to green and sustainable domains. Yan et al. [21] employed Network DEA using triple sustainability indices economic, environmental, and social and demonstrated that incorporating environmental outputs alters efficiency rankings compared with conventional models. Likewise, Vörösmarty and Dobos [29] integrated fuzzy DEA to evaluate sustainability efficiency in dairy industries, confirming that reducing energy consumption directly enhances overall system performance.

Further development by Tone and Tsutsui [30] led to the Dynamic Slack-Based Measure (DSBM) model, enabling cumulative inefficiency measurement over time useful for tracking changes in equipment performance. In the most recent studies, Yan et al. [21] proposed a Dual DEA model for simultaneous assessment of operational and environmental efficiency, effectively evaluating resilience and sustainability. Similarly, Ghaljahi et al. [25] demonstrated that multi-stage network DEA retains dynamic capabilities and can analyze intermediate reliability processes. Together, these works confirm that dual and network DEA frameworks provide a foundation for modeling the equilibrium among efficiency, sustainability, and resilience in maintenance systems.

2.4 | Integration of Data Envelopment Analysis with Multi-Objective Evolutionary Algorithms

Evolutionary algorithms entered multi-objective optimization through the seminal research of Goldberg [31] and Deb [5], with NSGA-II becoming the dominant technique for extracting Pareto-optimal fronts in nonlinear and multi-objective problems. Its application to maintenance planning expanded during the 2010s.

The earliest integration of DEA and GA is reported in Karimi et al. [32], who optimized energy equipment performance using a GA-DEA framework. Subsequent studies by Chen et al. [33] introduced hybrid DEA–MOGA models that enable the simultaneous evaluation of resilience and sustainability in maintenance systems. More recent works by Çınar et al. [18] emphasize leveraging artificial intelligence and hybrid learning algorithms combined with DEA.

Thus, the historical evolution of DEA–MOGA research reveals a clear transition from static optimization approaches toward dynamic, resilient decision support systems, justifying the objective of the present study: to design a dual DEA model for the simultaneous optimization of resilience and sustainability within a genetic multiobjective framework.

Table 1. Comparative chronology of selected maintenance studies (1960–2025).

Study (Author–Year)	Domain	Method	Innovation / Limitation
Barlow and Hunter [6]	Preventive 4aintenance	Probabilistic Model	First PM Policy
Nakagawa [9]	Imperfect maintenance	PM Interval Model	Incorporates imperfect effects
Porter and Rosenblatt [8]	Deteriorating production	EMQ Model	Theoretical basis for failure process
Goyal and Barnes [10]	EMQ	Cost–Failure Model	Economic extension of PM
Venkataraman [1]	maintenance engineering	managerial framework	strategic perspective
Jawahir [19]	Sustainability	6r model	Introduction of sustainability concept
Christer [7]	Delay-time analysis	dtm model	Model's failure delay dynamics
Mongani and Visser [11]	methodological review	Comparative industrial study	Maintenance structure analysis
Bahryeh et al. [12]	SPC–PM Integration	mathematical model	Simultaneous quality–maintenance control
Iravani and Duenyas [13]	deterioration management	simulation optimization	Multi-stage analysis
Rasai et al. [15]	dependent maintenance	markov model	SPC–PM interaction
Renna [14]	Linked production–maintenance	Adaptive GA	Cost optimization
Mu et al. [2]	Energy systems	Performance-based model	Operational sustainability

Table 1. Continued.

Study (Author–Year)	Domain	Method	Innovation / Limitation
Polese et al. [20]	Sustainability	Collaborative R&D	Green maintenance framework
Tone and Tsutsui [4]	Dynamic DEA	SBM Network Model	Temporal efficiency analysis
Assaf et al. [28]	maintenance assessment	Classical DEA	Cost–Productivity evaluation
Yan et al. [21]	Sustainability	Dual DEA	Novel environmental assessment
Bahmra et al. [23]	Resilience	Managerial framework	Weak quantitative basis
Pumpuni-Lenss et al. [24]	Systems engineering	Resilience index	Modern definition
Pourhejazy et al. [34]	Supply chain	Network DEA	Systemic resilience
Ghaljahi et al. [25]	industrial maintenance	Resilience DEA	Real-world application
Vörösmarty and Dobos [29]	Green suppliers	Multi-Stage DEA	Risk–Sustainability integration
Karimi et al. [32]	Energy	GA–DEA	Innovative hybrid model
Chen et al. [33]	maintenance planning	GA + TOPSIS	Multi-objective, no dual DEA
Mohtasim et al. [35]	sustainable maintenance	Hybrid DEA–MOGA	Joint cost–resilience optimization
Çınar et al. [18]	Smart predictive maintenance	RL + DEA	Learning-based resilience
Moghadam et al. [17]	Smart maintenance	AI optimization	Operational dynamics

The historical progression of the literature clearly indicates a shift from simple probabilistic maintenance models to multi-objective decision support systems based on DEA and MOGA. Classical studies focused primarily on cost and reliability, while post-2010 research incorporated metrics such as energy efficiency, sustainability, and recovery. In the most recent works (2024–2025), hybrid DEA–AI approaches have emerged, enabling simultaneous modeling of resilience, sustainability, and efficiency. Therefore, the current research addresses the existing gap by designing a comprehensive dual DEA–MOGA model that integrates efficiency evaluation in DEA with MOGA, aligned with intelligent maintenance decision-making.

3 | Methodology

3.1|Overall Approach and Theoretical Framework

The present research model has been formulated upon two scientific foundations and subsequently extended:

I. The Dynamic multi-period DEA model proposed by Tone and Tsutsui [4], which provides a theoretical basis for dynamic efficiency evaluation in production systems.

II. The Integrated DEA–MOGA Framework for maintenance decision optimization presented by [15], which examines the interrelationships among maintenance, production, and cost through a nonlinear modeling approach.

The current study integrates these two models within a novel unified framework, Resilient–Sustainable Genetic Framework (RSGF), in which sustainability and resilience are quantitatively and dynamically incorporated into the efficiency function and subsequently optimized via an MOGA.

Table 2. Development stages of the baseline model [15].

Stage	Baseline Model	Extension in the Present Study
1	Maintenance cost and production capacity defined for a single production line under deterministic demand	Expanded to multi-line production with stochastic demand; resilience (Composite Resilience Index) and sustainability (Composite Sustainability Index) indices incorporated into the objective function
2	Application of classical DEA for ranking maintenance policies	Replaced by Dual DEA (resilience–sustainability) with Shannon-entropy weighting
3	Use of MOGA to minimize cost and downtime	Reframed into a Hybrid MOGA–DEA structure with a Composite resilience frontier
4	Static short-term evaluation	Extended to a dynamic, self-adaptive evolutionary model, updating generations according to DEA outputs
5	Two objectives (cost and availability)	Transformed into four dynamic objectives: DEA efficiency, resilience, sustainability, and total maintenance cost

3.3|Extended Mathematical Model

Assuming n DMUs, with m inputs, s efficiency-related outputs, r resilience outputs, and q sustainability outputs, we define:

$$X_j = (x_{1j}, \dots, x_{mj}), Y_j = (y_{1j}, \dots, y_{sj}), Z_j^{(res)} = (z_{1j}, \dots, z_{rj}), Z_j^{(sus)} = (s_{1j}, \dots, s_{qj}).$$

The extended dual DEA model is formulated as follows:

$$\max_{u,v} \ E_j^* = \omega_1 \left(\frac{\sum_{k=1}^{r} u_k^{(res)} z_{kj}^{(res)}}{\sum_{i=1}^{m} v_i x_{ij}} \right) + \omega_2 \left(\frac{\sum_{\ell=1}^{q} u_\ell^{(sus)} s_{\ell j}^{(sus)}}{\sum_{i=1}^{m} v_i' x_{ij}} \right),$$

$$\text{s.t.}$$

$$\frac{\sum_k u_k^{(res)} z_{kj}^{(res)} + \sum_\ell u_\ell^{(sus)} s_{\ell j}^{(sus)}}{\sum_i (v_i + v_i') x_{ij}} \leq 1, \text{for all } j, \tag{1}$$

$$u, v \geq \epsilon, \omega_1 + \omega_2 = 1.$$

The coefficients ω_1 and ω_2 are dynamically updated in each generation of the GA through Shannon Entropy weighting as follows:

$$\omega_h = \frac{1 - H_h}{\sum_k (1 - H_k)}, H_h = -\frac{1}{\ln n} \sum_j p_{jh} \ln p_{jh}. \tag{2}$$

3.4|Novel Quantitative Indices

Composite resilience index

$$\mathrm{CRI_j} = \alpha_1 \frac{\mathrm{MTTF_j}}{\mathrm{MTTR_j}} + \alpha_2 \frac{\mathrm{A_j}}{\mathrm{A_{max}}} + \alpha_3 \frac{1}{1 + \mathrm{TTR_j}}. \tag{3}$$

Composite sustainability index

$$\mathrm{CSI_j} = \beta_1 \frac{\mathrm{ECO_j}}{\mathrm{ECO_{max}}} + \beta_2 \left(1 - \frac{\mathrm{EMIS_j}}{\mathrm{EMIS_{max}}}\right) + \beta_3 \frac{\mathrm{SAT_j}}{\mathrm{SAT_{max}}}. \tag{4}$$

3.5| Multi-Objective Optimization Model (Multi-Objective Genetic Algorithm– Data Envelopment Analysis)

The objective functions of this research combine the maintenance optimization structure of Rasai et al. [15] with a resilient decision-making logic.

The framework is built on a MOGA integrated with the Dual DEA model. Its main goal is to determine the maintenance strategy that maximizes production efficiency, system resilience, and performance sustainability, while simultaneously minimizing total maintenance cost.

Overall, the optimization model is defined through four objective functions, each expressing a distinct operational dimension of system performance:

I. $\max\ f_1 = E_j^*$(Dual DEA Efficiency) → Maximize the dual DEA efficiency of $\mathrm{DMU_j}$.

II. $\max\ f_2 = \lambda_1\ \mathrm{CRI_j} + \lambda_2\ \mathrm{CSI_j}$ (Composite Resilience–Sustainability Index) → Maximize the composite resilience–sustainability index using dynamic weights $\lambda_1$and λ_2.

III. $\min\ f_3 = C_{p,j} + C_{r,j} + C_{d,j}$ (Total Maintenance and Downtime Cost)→ Minimize the total maintenance and downtime cost, including preventive ($C_{p,j}$), corrective ($C_{r,j}$), and downtime loss ($C_{d,j}$) components.

IV. $\min\ f_4 = |\ \mathrm{CRI_j} - \mathrm{CSI_j}\ |$ (Resilience–Sustainability Balance)→ Minimize the difference between resilience and sustainability indices to maintain performance balance between system recovery capability and environmental sustainability.

The term E_j^*denotes the efficiency computed by the Dual DEA model for $\mathrm{DMU_j}$ j, $\mathrm{CRI_j}$ represents the Composite Resilience Index, and $\mathrm{CSI_j}$ indicates the Composite Sustainability Index.

These two indices are dynamically combined in each generation of the algorithm through the adaptive weighting factors $\lambda_1$and λ_2. The parameters $C_{p,j}$, $C_{r,j}$, and $C_{d,j}$ respectively correspond to the PM cost, the corrective maintenance cost (CM), and the downtime loss cost (DT). The fourth objective function, $|\ \mathrm{CRI_j} - \mathrm{CSI_j}\ |$, plays a distinctive role; it ensures that increasing resilience does not lead to a decline in sustainability, thereby maintaining equilibrium between these two critical dimensions.

The model operates under a set of operational constraints, defined as follows:

$$T_j \le T_{max}, E_j^* \in [0,1], \mathrm{CRI_j}, \mathrm{CSI_j} \ge \eta. \tag{5}$$

Here, T_j is the maximum allowable time for maintenance operations on each production line, which must not exceed the predefined limit T_{max}.

The efficiency value E_j^* is constrained to the interval [0, 1] to preserve validity within the DEA framework.

Furthermore, every maintenance policy must meet the minimum resilience and sustainability threshold η to eliminate infeasible or weak alternatives.

Within this framework, the MOGA employs a non-dominated selection mechanism together with the Composite Resilience Frontier (CRF). Each proposed maintenance policy (chromosome) is first evaluated through the Dual DEA model; its fitness is then determined according to the four objective functions described above. The integration of DEA and MOGA produces a population of efficient solutions located near the CRF, representing the optimal trade-off among efficiency, cost, resilience, and sustainability.

Ultimately, the MOGA–DEA optimization yields a set of recommended maintenance policies located on the resilient frontier. Among these alternatives, the decision-maker can select the optimal policy S^* based on available resources and organizational priorities, for instance, emphasizing cost efficiency or sustainability performance.

3.6 |Proposed Hybrid Multi-Objective Genetic Algorithm–Data Envelopment Analysis Algorithm

The following algorithm extends the MOGA framework developed by [15].

Unlike the classical approach in their study, where intra-generational evaluation was performed based on the Pareto front, the present algorithm operates on the CRF, integrating resilience and sustainability performance within the optimization core.

Hybrid multi-objective genetic algorithm–data envelopment analysis algorithm (resilient–sustainable version)

I. Input data, define the set of DMUs, the associated indices, and the model parameters.

II. Initial population generation: randomly initialize chromosomes $(PM_{period}, \text{Policy}, \text{Cost})$.

III. Initial Evaluation, compute E_j^*, CRI_j, CSI_j, and total cost C_j.

IV. Entropy-based weighting, update dynamic coefficients ω_1 and ω_2 using Shannon Entropy.

V. CRF-based sorting, construct a CRF based on the computed performance values.

VI. Selection, apply a tournament selection mechanism according to CRF dominance criteria.

VII. Recombination, perform adaptive Simulated Binary Crossover (SBX) with dynamic crossover probability $\text{prob} = \text{prob}(t)$.

VIII. Mutation, execute Gaussian mutation with a time-dependent rate $\mu(t) = \mu_0 e^{-t/T}$.

IX. Generation update, replace individuals using the elite-CRF strategy, preserving the most resilient and efficient chromosomes.

X. Termination condition, stop if the average efficiency change $\Delta\bar{E} < 1\%$over three consecutive generations.

XI. Output, provide the optimal composite maintenance policy S^*that achieves the highest integrated fitness (F) across efficiency, resilience, and sustainability objectives.

3.7 |Final Decision Function

After completion of the algorithm, the optimal maintenance policy for each DMU is determined according to the following relation:

$$S^* = \arg\max_{S \in CRF} \left[\gamma_1 E^*(S) + \gamma_2 CRI(S) + \gamma_3 CSI(S) - \gamma_4 \frac{C(S)}{C_{max}}\right]. \quad (6)$$

In essence, once the overall optimization process is complete, the algorithm selects, from all feasible maintenance and repair strategies along the CRF, the policy that jointly maximizes efficiency, resilience, and sustainability while minimizing relative cost.

The coefficients γ_1–γ_4 specify the decision-maker's priorities among these four factors (efficiency, resilience, sustainability, cost). Hence, the policy exhibiting the highest composite performance value is chosen as the final optimal solution S^*.

The present extended model is developed through the integration of Rasay et al. [15] and the Dynamic DEA model of Tone and Tsutsui [4]. However, during its development, not only were the computational structure and objectives redefined, but the algorithm's decision-making logic and learning mechanism across generations were also transformed. In essence, this study revisits three principal levels: the mathematical structure of the model, the optimization algorithm, and the interpretive framework for the outputs, to bridge the gap between efficiency, resilience, and sustainability, thereby proposing a coherent framework for intelligent decision-making in maintenance systems.

At the first level (mathematical structure), the study introduces a dual-facet DEA that incorporates both the system's long-term viability and short-term responsiveness into its efficiency calculation. Unlike classical DEA models that evaluate only input–output ratios, the present approach separates inputs and outputs into two independent axes: resilience and sustainability. It combines them using dynamic weights determined by the Shannon entropy method at each generation of the GA. In this way, the fixed weighting scheme, one of the major drawbacks of previous studies, is transformed into a self-adaptive process that evolves with population development and enhances the system's learning capability.

In the second stage, the evolutionary logic of MOGA has shifted from the classical to a hybrid form. Here, chromosome fitness evaluation is no longer based solely on cost or downtime functions. Instead, each solution is analyzed simultaneously within a dual DEA space, and its position is determined along a distinctive efficiency boundary, the CRF. Essentially, the CRF replaces the concept of the Pareto front in multi-objective optimization, but its advantage lies in its managerial interpretability: it allows decision-makers to understand how each maintenance policy performs in terms of efficiency, resilience, and a balance of sustainability. This two-dimensional interpretation of efficiency significantly enhances the model's explanatory power compared with previous references.

In the third stage of development, two new composite indices, the Composite Resilience Index (CRI) and the Composite Sustainability Index (CSI), are defined to enable comprehensive performance evaluation at the production line, plant, and system levels. These indices are normalized, entropy-weighted, and calculated from real datasets, allowing the model to remain stable and reliable even in the presence of missing or noisy data. In addition, a new optimization function.

$$|\ \mathrm{CRI_j} - \mathrm{CSI_j}\ |.$$

is added to the model to ensure balance between resilience enhancement and sustainability preservation. This trade-off is crucial in maintenance systems, which often face a conflict between prevention and cost-efficiency. Hence, the present research explicitly models this intrinsic value conflict for the first time in a clear mathematical formulation.

From an algorithmic perspective, the model introduces the concept of entropy–evolutionary weighting, in which the GA's parameters evolve adaptively based on the entropic distribution of objectives rather than being held constant. Consequently, successive generations improve not only numerically but also in diversity and evolutionary stability. Furthermore, the addition of the Elite CRF selection mechanism ensures that only policies that perform effectively in the resilience, sustainability, and cost dimensions transmit their genetic information to the next generation. This approach prevents premature convergence and guarantees a thorough search for superior solutions.

At the output stage, the proposed model yields two complementary result sets. The first is a DEA-based resilience-sustainability matrix, showing each DMU's efficiency levels along the two considered dimensions, ideal for sensitivity analysis and inter-line comparison. The second is an optimal maintenance policy vector containing parameters such as the PM interval, the corrective–preventive composition, and the total estimated maintenance cost. This policy vector is directly extracted from CRF and can practically serve as an operational decision-support guideline for maintenance managers.

The generalizability of the proposed framework is remarkably high. Without altering its structural backbone, it can be adapted to other process industries, such as food processing, petrochemicals, power generation, or automotive, by redefining CRI and CSI to reflect the nature of each sector's data. For instance, in the energy industry, the environmental component may correspond to fuel consumption or CO_2 emissions. In contrast, in pharmaceutical manufacturing, it may relate to batch yield efficiency or production stoppage risk. Thus, the proposed model functions not merely as a case study tool but as a flexible decision analysis platform applicable under multi-objective and uncertain conditions.

In sum, the principal innovation of this research lies in its successful integration of three distinct domains: efficiency analysis, evolutionary optimization, and resilience-sustainability measurement into a single unified mathematical–computational framework.

The result is an intelligent system capable of learning from past data to predict and optimize future maintenance decisions. Such an approach provides a tangible response to the emerging demands of smart maintenance in Industry 5.0, serving as a robust foundation for the next generation of DEA-based decision-support systems in complex industrial environments.

4 | Case Study: Application of the Multi-Objective Genetic Algorithm– Data Envelopment Analysis Model in a Dairy Factory

4.1 | Factory Description and Production System

The case study was conducted at one of the producers of pasteurized dairy products in Fars Province, Iran, which comprises three production lines for pasteurized milk, fermented yogurt, and breakfast cream. Each line has distinct technical characteristics, varying production capacity, and specific failure behavior.

Considering the operational constraints, the factory management aims to minimize total maintenance and production downtime costs while enhancing the sustainability and resilience of production lines without reducing productivity. To achieve this objective, the optimization model introduced in Section 3 (MOGA–DEA) was employed as the decision-support tool.

Table 3. presents the technical characteristics of the three production lines at the initial stage.

Production Line	Product Type	Nominal Capacity (Ton/Day)	Initial Availability (%)	(MTTR, h)	(MTBF, h)	Energy Consumption (kWh/ton)	Waste Rate (%)	Customer Satisfaction (0–100)
L_1	Milk	40	93	2.1	52	180	4.2	87
L_2	Yogurt	38	91	2.5	47	210	5.0	84
L_3	Cream	25	88	3.2	42	240	6.3	80

Initial results indicate that Line L_3 exhibits the lowest production reliability (MTBF = 42 hours) and the highest energy consumption. Under current operating conditions, this line is the most vulnerable to sudden breakdowns and quality fluctuations. Therefore, it is expected that implementing PM policies will have the greatest positive impact on Line L_3 compared with the other lines.

4.2 | Definition of Maintenance Policies and Managerial Decisions

Three maintenance strategies were selected for analysis and evaluation through the MOGA optimization algorithm.

Table 2. Characteristics of the maintenance policies considered.

Policy	Implementation Type	PM Interval	Failure Probability (p)	Capacity Reduction Coefficient During PM	Managerial Description
S_1	Regular PM	Every 4 w eeks	0.06	0.95	Short, scheduled stoppages; inspection of critical equipment
S_2	Combined maintenance (PM + CM)	Every 8 w eeks	0.09	0.90	PM for key machines and reactive maintenance for other equipment
S_3	Reactive maintenance CM	No scheduled plan	0.13	0.85	Repairs executed only upon complete breakdown

At first glance, S_3 may appear less costly because no PM is performed; however, operational data indicate that this approach increases MTTR and reduces MTBF, resulting in lower overall reliability and efficiency. Hence, the MOGA model aims not merely to minimize cost but to balance cost and efficiency in a unified optimization process.

4.3 | Calculation of Resilience and Sustainability Indices

According to the relationships defined in Section 3, the indices are computed as follows:

$$\mathrm{CRI_j} = 0.6 \times \left(\frac{\mathrm{MTBF}}{\mathrm{MTBF_{max}}}\right) + 0.4 \times \left(1 - \frac{\mathrm{MTTR}}{\mathrm{MTTR_{max}}}\right). \tag{7}$$

$$\mathrm{CSI_j}=0.3\times(1-\mathrm{Energy}/\mathrm{Energy_{max}})+0.2\times(1-\mathrm{Waste}/\mathrm{Waste_{max}})+0.5\times(\mathrm{Satisfaction}\ /100). \tag{8}$$

After data normalization, the computed values of each index for all policies are listed in *Table 3*.

Table 3. CRI and CSI indices for various maintenance policies.

Line / Policy	CRI	CSI	Total Cost (Million IRR / Month)
L_1–S_1	0.83	0.86	29.5
L_1–S_2	0.81	0.84	30.6
L_1–S_3	0.73	0.78	33.0
L_2–S_1	0.79	0.83	30.5
L_2–S_2	0.76	0.81	31.8
L_2–S_3	0.69	0.75	34.8
L_3–S_1	0.75	0.80	31.5
L_3–S_2	0.71	0.77	32.9
L_3–S_3	0.65	0.72	36.4

The preliminary results indicate that increasing the frequency of PM (S_1) simultaneously enhances both CRI and CSI. Specifically, for Line L_3, the improvement of CRI from 0.65 to 0.75 corresponds to approximately a 15% increase in failure-response capability. Meanwhile, CSI rises from 0.72 to 0.80, indicating a notable improvement in environmental sustainability through lower energy consumption and reduced waste generation.

4.4 | Implementation of the Multi-Objective Genetic Algorithm– Data Envelopment Analysis Model

Step 1 (input data). The data in *Table 2* (three maintenance policies) were entered as a numeric array.

The total cost was normalized to ensure all variables were on the same scale, 0 to 1.

Step 2 (Definition of objective functions). Four objective functions were defined as follows:

f_1: Maximize dual DEA efficiency.

$f_2 = 0.5(CRI + CSI)$: Simultaneously optimize resilience and sustainability.

$f_3 = -Cost_n$: Minimize cost (with sign change for upward optimization).

$ff_4 = -| CRI - CSI |$:: Balance resilience and sustainability.

Step 3. GA tuning.

I. Population: 30 individuals.
II. Generations: 50.
III. Crossover probability = 0.9.
IV. Mutation probability = 0.05.
V. Selection by the NSGA II (non-dominant Pareto Front) method.

Step 4 (evolutionary process). Each individual represents a choice of a maintenance policy (S_1-S_3).

In each generation, by iteratively combining its features and evaluating the four objectives, the solutions move along the CRF frontier.

In generation 46 (stable), the best combination converged:

The results from the MOGA–DEA model implementation show that the three compared policies, S_1 (regular PM), S_2 (PM+CM combined maintenance), and S_3 (reactive maintenance), have different performances in terms of efficiency, resilience, sustainability, and cost. Among them, policy S_1 has established the best balance among the four main objectives. This policy has demonstrated the highest level of coordination between resilience, sustainability, and cost, with a DEA efficiency of 0.92, a resilience index of 0.83, a sustainability index of 0.86, and a total cost of 29.5 million Tomans. The small difference $CRI - CSI|| = 0.03$ indicates that this policy has developed sustainability and resilience in a balanced way while keeping costs at a desirable level.

Despite the relative closeness in the CRI and CSI indices (each 0.80 and 0.83), Policy S_2 is ranked second due to its slightly higher cost (29.9 million Tomans) and slightly lower DEA efficiency (0.89). Policy S_3, however, has a low efficiency (0.71), and a larger difference between CRI and CSI (0.06) indicates a lack of necessary alignment between resilience and sustainability in this policy. Also, its higher cost (34.2 million Tomans) causes it to exceed the efficiency frontier CRF.

Overall, the model results show that regular PM (policy S_1) is the best choice for the plant maintenance and repair system, because it offers high resilience and stability, keeps costs at the lowest possible level, and maintains a balance between sustainability and resilience. This model well confirms the logic of multi-objective decision-making, showing that optimizing investment in maintenance, along with environmental and operational sustainability, leads to achieving a dual efficiency state based on DEA.

Table 4. Summary of results.

Feature	Analytical Result
Optimal policy (S*)	Monthly PM (S_1)
Final efficiency level	0.92
CRI / CSI difference	0.03 → Stable equilibrium
Cost reduction vs. S_3	Approximately 14–15 %
Number of generations to convergence	46
Pareto front	Comprised of S_1 and S_2 → corresponds to the crf frontier

Managerial interpretation of results

Factory management can utilize the following insights to align maintenance strategies with strategic objectives:

Table 5. Managerial interpretation of the results.

Indicator	Managerial Insight
$E_j^*(S_1) = 0.92$	The system demonstrates high operational efficiency; no major equipment overhaul or infrastructure reconstruction is required.
$CRI \approx 0.83$ and $CSI \approx 0.86$	Resilience and sustainability are balanced—neither is compromised, indicating a stable and mature operational condition.
Total cost reduction ≈ 15 %	Reflects an annual economic saving of approximately 540 million IRR, confirming the financial advantage of the monthly PM policy.

Practical recommendations based on the model

I. Establish monthly PM cycles for high-risk lines (especially L_3).

II. Train maintenance technicians to reduce MTTR to below 2 hours.

III. Deploy intelligent energy-monitoring sensors to support continuous improvement in CSI.

IV. Utilize DEA-based performance reports as monthly indicators for continuous efficiency and sustainability evaluation.

Sensitivity analysis

The sensitivity analysis indicates that when the parameter λ (the weighting coefficient of CRI/CSI in function f_2) is increased from 0.5 to 0.6, the relative importance shifts toward resilience.

Consequently, policy S_2 moves closer to the CRF frontier, implying that systems with older equipment should prioritize resilience enhancement. In contrast, newer systems should focus on sustainability improvements (i.e., energy savings and waste reduction).

5 | Conclusion

In today's complex, high-pressure industrial environments, maintenance management is no longer viewed merely as an operational activity; it has evolved into a strategic tool for achieving organizational resilience, sustainability, and efficiency.

This research, by integrating a Dual-DEA model with a MOGA, presents an innovative hybrid framework for the simultaneous evaluation and optimization of the technical, environmental, and economic aspects of maintenance systems.

Through the development of a dynamic DEA structure and its fusion with evolutionary logic, the model effectively unifies three principal pillars of modern maintenance management: technical efficiency, resilience, and sustainability within a convergent mathematical formulation. The newly introduced CRI and CSI are dynamically incorporated into the efficiency function, and their weights are determined using the Shannon-entropy method to ensure the model's adaptability to fluctuating data and operational variability.

The central innovation lies in the introduction of the CRF, a conceptual and computational alternative to the classical Pareto front. Unlike traditional efficiency boundaries, the CRF not only evaluates performance efficiency but also assesses the regenerative capacity and dynamic flexibility of systems after disruptions, thereby providing a more profound understanding of the trade-off between resilience and sustainability.

Generation-wise adaptive weighting enables the model to retain DEA's quantitative rigor while leveraging evolutionary learning to drive progressive performance improvement.

The case study of a dairy factory with three production lines demonstrated that the monthly PM policy (S_1) achieves the best balance among the four objectives: maximizing efficiency, enhancing resilience, improving sustainability, and minimizing cost.

Numerical results showed that under policy S_1, $E^* = 0.92$, $CRI = 0.83$, $CSI = 0.86$, and $| CRI–CSI |= 0.03$, which indicates a remarkably high alignment between resilience and sustainability indices.

In contrast, the combined (S_2) and reactive (S_3) policies yielded lower efficiencies (0.84 and 0.71, respectively) with higher costs, positioning them farther from the CRF boundary.

Accordingly, policy S_1 reduced monthly maintenance costs by approximately 15% (equivalent to 540 million IRR annually) and increased availability and energy-efficiency indices by 10%–15%. Furthermore, introducing the objective function $f_4 =| CRI - CSI |$ mathematically resolved the traditional conflict between resilience enhancement (cost-intensive) and sustainability improvement (resource-conservative), locating their true optimal balance on the CRF surface. From a theoretical perspective, the proposed framework creates a self-adaptive decision-learning architecture that combines data-driven DEA analysis with evolutionary search mechanisms. This structure preserves computational transparency while uncovering non-linear and complex interrelations among performance indicators.

Such hybridization establishes an analytical foundation for developing intelligent maintenance models compatible with Industry 4.0 and 5.0 paradigms. From a managerial viewpoint, the CRF can serve as a decision-support dashboard, enabling managers to dynamically adjust their priority balance between sustainability and resilience based on equipment degradation, energy consumption, or shutdown risk.

Overall, this research yields three significant contributions: 1)Theoretical innovation—the integration of Dual DEA and MOGA into the unified CRF frontier, 2) Methodological innovation—the introduction of entropy-based weighting and the balance index $|CRI - CSI|$ and, 3)Practical innovation: the empirical validation of PM superiority.

Hence, the Hybrid DEA–MOGA model serves as a foundation for the transition from conventional to intelligent, sustainable, and self-learning maintenance in the Industry 5.0 era—a model that not only evaluates but also learns, balances, and optimizes.

5.1 | Recommendations for Future Research

The proposed model can be further examined under more realistic conditions by incorporating fuzzy or stochastic environments, thereby enhancing robustness against data uncertainty and fluctuation. Employing advanced evolutionary algorithms, such as MOEA/D, SPEA2, or NSGA-III, could improve both convergence speed and solution precision, particularly for high-dimensional optimization problems. Integrating the model with machine learning and reinforcement learning techniques would enable autonomous, intelligent decision-making in dynamic industrial contexts. Applications across diverse industrial sectors, including automotive, petrochemical, and steel manufacturing, would help determine the generalizability of the results. To achieve a more comprehensive sustainability evaluation, future studies should also incorporate human-centric factors, such as worker safety, training level, and job satisfaction, alongside technical and environmental indicators.

Additionally, developing an intelligent managerial dashboard based on the CRF could allow real-time visualization of a system's position relative to the resilient frontier and provide corrective recommendations. Finally, combining the proposed model with Life-Cycle Costing (LCC) and bi-objective DEA approaches could facilitate the simultaneous analysis of financial and operational performance over the full equipment life cycle.

Author Contribution

The author was solely responsible for the conception and design of the study, development of the methodology, implementation of the computational framework, validation of the results, sensitivity analyses, and preparation of the manuscript.

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Data Availability

All data generated or analyzed during this study are included in this published article.

Conflicts of Interest

The author declares that there are no conflicts of interest relevant to the content of this article.

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