MILP-Based Optimization of Maintenance Strategies for Hydroelectric Power Plant

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Abstract

This paper presents a hybrid decision-support framework for optimal maintenance strategy assignment in hydroelectric power plants, combining pre-computed equipment importance indices with Mixed-Integer Linear Programming (MILP). Equipment importance is determined through a multi-factor assessment that integrates reliability, production impact, and maintenance cost into a unified composite score. These scores feed into a MILP model that assigns one of three maintenance strategies — conditional maintenance (CM), predictive maintenance (PM), or systematic maintenance (SM) — to nine critical plant components under a total budget constraint of €300,000. A key feature of the model is the definition of two continuous importance thresholds that partition the equipment set into strategy zones, and whose optimal values are jointly determined by the solver. Two assignment scenarios are examined: exclusive single-strategy assignment and concurrent dual-strategy assignment. Results demonstrate that the framework consistently allocates more intensive strategies to higher-importance equipment, yielding total costs of €299,209 and €288,373 for Scenarios 1 and 2 respectively, both within budget. Validation against an equivalent Goal Programming benchmark confirms the superiority of the proposed approach in terms of budget adherence, assignment precision, and operational actionability.

Keywords: maintenance strategy selection; Mixed-Integer Linear Programming; equipment importance index; hydroelectric power plants; budget-constrained optimization; threshold-based assignment

1. Introduction

Industrial maintenance has evolved from a reactive, break-and-fix activity into a strategically managed function that directly determines asset availability, production continuity, and overall operational cost. In capital-intensive sectors — and particularly in energy infrastructure — the consequences of inadequate maintenance extend beyond equipment failure to encompass production losses, safety hazards, and regulatory non-compliance. As Dekker (1996) noted in a seminal review, maintenance consumes between 15% and 40% of total operating costs in manufacturing industries, making it one of the largest controllable expenditure categories in plant management. The imperative to optimize maintenance resource allocation is therefore both economically and operationally compelling.

Hydroelectric power plants represent a particularly demanding context for maintenance decision-making. These facilities combine a large number of heterogeneous components — rotating machinery, high-voltage electrical equipment, control systems — each subject to distinct failure modes and degradation mechanisms. At the same time, the uninterrupted generation of electricity is critical for grid stability and national energy security. Yang et al. (2018) highlighted that unplanned outages in hydroelectric systems generate substantial direct economic losses due to reduced energy production and ancillary service revenues, while also affecting power system reliability by limiting the capability of hydropower units to provide load balancing and frequency regulation services. Growing electricity demand, driven by population growth, industrialization, and the electrification of transport and heating, further amplifies the need for robust, cost-effective maintenance planning (International Energy Agency, 2023).

Three principal maintenance strategies are in widespread industrial use. Conditional maintenance (CM) — also referred to as condition-based maintenance — relies on real-time monitoring and triggers interventions only upon detection of anomalous equipment behavior (Jardine et al., 2006). Predictive maintenance (PM) uses historical data and degradation models to schedule interventions before failure occurs, minimizing unplanned downtime while avoiding unnecessary service (Lee et al., 2014). Systematic maintenance (SM) operates on fixed time or usage intervals regardless of actual condition, ensuring high coverage at the cost of potentially excessive intervention frequency. Each strategy offers a distinct trade-off between resource intensity and failure prevention effectiveness, and the choice among them for any given asset is a non-trivial decision that depends on equipment importance, failure consequences, monitoring feasibility, and available budget (Alsyouf, 2007). Formalizing this selection process has motivated a substantial body of research. Mixed-Integer Linear Programming (MILP) has emerged as a dominant paradigm for maintenance strategy optimization because it can simultaneously handle discrete strategy choices, continuous cost variables, and multiple operational constraints within a single coherent formulation (van Horenbeek et al., 2010). MILP models allow maintenance managers to incorporate budget limits, reliability targets, and scheduling constraints, and to evaluate large sets of equipment simultaneously — capabilities that informal or purely expert-driven methods cannot match. Despite these advances, the explicit integration of continuous equipment importance scores into MILP-based maintenance strategy assignment remains limited in the literature. Most existing frameworks treat equipment priority as a binary or qualitative pre-filter, applying optimization only to a subset of assets without embedding importance as a continuous driver of strategy thresholds. This paper addresses that gap by proposing a hybrid framework in which pre-computed equipment importance indices (denoted Ψ_i) are embedded directly into a MILP model that governs strategy assignments through two endogenously optimized importance thresholds. The framework is applied to a real case study involving nine high-priority components of a hydroelectric power plant, enabling direct comparison with a Goal Programming benchmark drawn from the literature.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature across three streams: MILP-based maintenance optimization, structured equipment prioritization, and maintenance applications in the hydroelectric sector. Section 3 presents the case study, equipment data, and importance index values. Section 4 develops the full MILP model formulation, including the threshold-based assignment mechanism. Section 5 reports results for both assignment scenarios. Section 6 validates results against a reference benchmark. Section 7 concludes with perspectives for future research.

2. Literature Review

2.1. Maintenance Strategy Optimization

Maintenance strategy selection has progressively evolved toward structured decision-support approaches capable of balancing reliability, maintenance effectiveness, and economic constraints. Contemporary maintenance planning increasingly relies on quantitative models that transform heterogeneous operational information into optimized maintenance actions. A particularly relevant contribution was proposed by Houria et al. (2016), who developed an integrated maintenance optimization framework for medical equipment management combining Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Mixed-Integer Linear Programming (MILP). Their methodology followed a three-stage structure. First, AHP was used to derive criteria weights and compute equipment criticality scores from expert evaluations. Second, TOPSIS ranked alternative maintenance strategies according to their operational utility. Finally, an MILP optimization model established threshold values that partitioned equipment into Time-Based Maintenance (TBM), Condition-Based Maintenance (CBM), and Corrective Maintenance (CM) categories while satisfying a predefined budget constraint. Applied to approximately 2,000 medical devices in a real hospital environment, the framework demonstrated strong computational scalability and showed that maintenance strategy assignment can be formulated as an optimization problem driven by equipment importance indicators and constrained resource allocation. Recent developments have further expanded maintenance optimization beyond isolated scheduling problems toward integrated decision architectures. Pinciroli et al. (2023) highlighted that Industry 4.0 maintenance increasingly combines optimization models, asset prioritization, and operational constraints into unified decision-support systems capable of improving maintenance effectiveness at system scale.

These developments confirm the growing maturity of optimization-based maintenance planning. However, existing frameworks remain strongly domain dependent and frequently assume exclusive maintenance assignment structures, limiting their applicability in operational contexts where multiple maintenance actions may coexist.

2.2. Equipment Importance Assessment and Prioritization

Maintenance optimization requires mechanisms capable of distinguishing assets according to their operational significance because uniform maintenance allocation rarely leads to efficient use of resources. Equipment importance assessment therefore constitutes a fundamental stage in maintenance decision-making. Multi-criteria approaches have become widely adopted for maintenance prioritization because they allow simultaneous consideration of technical, operational, economic, and reliability dimensions. Bouchaala and Noureddine (2020) proposed an AHP-based methodology for identifying priority equipment for maintenance actions and demonstrated that structured evaluation improves consistency and transparency compared with conventional approaches. Similarly, Lopes et al. (2020) developed a criticality evaluation framework for maintenance management in manufacturing systems. Their work showed that integrating multiple operational indicators into a unified criticality index enables more rational allocation of maintenance resources and improves decision quality. Further developments focused on strengthening analytical rigor through optimized prioritization methods. Bouchaala et al. (2024) proposed a multicriteria framework for improving criticality assessment and enhancing maintenance decision support in industrial environments, emphasizing the value of structured quantitative prioritization. More recently, intelligent maintenance support approaches have incorporated semantic technologies and ontology-based reasoning to improve equipment evaluation and maintenance decision-making. Studies by Titah and Bouchaala (2022, 2024) and Titah et al. (2023) demonstrated that knowledge-driven maintenance frameworks can improve consistency, automate asset assessment, and reduce subjectivity in maintenance prioritization.

Despite these advances, most equipment importance approaches remain disconnected from optimization stages. Importance indicators are generally calculated independently and later used as qualitative guidance rather than being embedded directly as continuous drivers within optimization formulations.

2.3. Maintenance Optimization in Hydroelectric Power Plants

Hydroelectric power plants present specific maintenance challenges because equipment reliability directly affects electricity production, operational flexibility, and power system stability. Maintenance decisions must therefore balance technical reliability, production continuity, and financial feasibility. As hydropower increasingly supports renewable energy integration and grid balancing, maintenance planning has become progressively more critical. Yang et al. (2018) showed that hydropower units are exposed to increasingly dynamic operating conditions associated with balancing renewable generation, increasing equipment stress and maintenance requirements. Within this context, Özcan et al. (2017) proposed an integrated operations research framework for maintenance strategy selection in hydroelectric power plants combining TOPSIS, AHP, and Goal Programming (GP). Their methodology consisted of three sequential stages. First, TOPSIS was applied to evaluate plant equipment and identify nine critical equipment groups from a large inventory according to multiple operational criteria. Second, AHP was used to determine maintenance strategy priorities based on expert judgment. Finally, Goal Programming optimized maintenance planning while accounting for operational constraints associated with maintenance duration and available technical personnel. Applied in a real hydroelectric facility, the framework achieved approximately a 77% reduction in equipment downtime compared with historical operation periods, demonstrating the effectiveness of combining prioritization and optimization for maintenance decision-making. Building on this direction, Özcan et al. (2019) introduced a risk-based maintenance framework for hydroelectric power plants in which maintenance decisions were explicitly linked to equipment risk levels and operational consequences. Their work reinforced the importance of integrating equipment criticality into maintenance planning and highlighted the value of structured optimization support for improving asset reliability.

Collectively, these studies demonstrate the growing role of optimization in hydroelectric maintenance management. Nevertheless, existing approaches primarily address prioritization, scheduling, or risk evaluation independently and provide limited support for directly embedding continuous equipment importance indicators into maintenance assignment optimization.

2.4. Research Gaps and Positioning

Existing maintenance optimization studies and equipment prioritization approaches remain only partially integrated. Houria et al. (2016) demonstrated that threshold-based MILP models can optimize maintenance strategy allocation under budget constraints, but their framework was developed for hospital equipment and assumed exclusive strategy assignment. In contrast, Özcan et al. (2017) applied integrated prioritization and optimization to hydroelectric maintenance planning but did not embed continuous equipment importance indicators directly into the optimization process. The present study combines and extends these research directions by transferring threshold-based maintenance optimization to hydroelectric power plants and integrating pre-computed equipment importance indices directly into a MILP formulation through endogenously optimized thresholds. The proposed framework further supports both exclusive and concurrent maintenance assignments under explicit budget constraints, enabling more differentiated and operationally actionable maintenance planning.

3. Case Study and Data

3.1. Plant Context and Equipment Selection

Hydroelectric power plants occupy a critical position in national energy infrastructure. Their continuous operation is essential for grid frequency regulation, peak load management, and long-term energy security. As electricity demand grows — driven by population expansion, industrial growth, and energy transition initiatives — the consequences of unplanned outages become increasingly severe. In this context, maintenance planning must be both strategically sound and financially sustainable, motivating the need for structured optimization-based decision support.

This study is grounded in the hydroelectric power plant case examined by Özcan et al. (2017). The original study applied a structured prioritization process to identify nine high-importance equipment items from a fleet of over 1,400 components, and subsequently optimized their maintenance strategies using a Goal Programming model. The present work adopts the same equipment set, enabling direct comparison and cross-validation of results. The nine target components are drawn from the plant's high-voltage substation and generation system. They include circuit breakers, instrument transformers, generator rotor and stator assemblies, power transformers, and auxiliary electrical components. Each component is identified by a standardized code.

3.2. Equipment Importance Indices

Equipment importance indices (denoted Ψ_i) serve as the primary input linking equipment operational significance to maintenance strategy intensity. Each index is computed through a structured multi-factor assessment that integrates three fundamental evaluation metrics:

- The annualized failure rate was expressed as a percentage of expected annual breakdowns. In the absence of plant-specific failure records, reference values were adopted from established reliability and engineering databases and standards (IEEE, 2007; U.S. Department of Energy, 2010). This approach is considered appropriate given the strong operational and design similarities of high-voltage electrical equipment across different installations worldwide, which ensures reasonable transferability of reliability parameters. Furthermore, the primary objective of this study is the optimization of maintenance strategy assignment under operational and resource constraints, rather than the estimation of equipment importance indices themselves. Accordingly, these indices may be derived using any validated multicriteria or reliability-based method, provided that they yield consistent and crisp numerical scores suitable for integration into the optimization framework.
- Percentage of annual production loss attributable to each component, sourced directly from Özcan et al. (2017).
- Annual maintenance expenditure associated with each component, excluding production loss costs, sourced from Özcan et al. (2017) and converted from Turkish Lira to Euros for practical relevance.

The resulting normalized Ψ_i values from aggregating the 3 previous dimensions range from 0 to 1, with higher values indicating greater operational significance. The complete dataset — including importance indices and per-strategy implementation costs — is presented in the next sub-section.

3.3. Maintenance Cost Data and Strategy Overview

Three maintenance strategies are considered in this study, corresponding to increasing levels of intervention intensity:

- Conditional maintenance (CM): interventions triggered by condition monitoring signals. Generally, the least costly strategy among the three considered, which makes suitable for low to moderate-importance equipment with adequate monitoring infrastructure.
- Predictive maintenance (PM): interventions scheduled based on failure prediction models, targeting incipient faults before service disruption. Intermediate cost and effectiveness.
- Systematic maintenance (SM): fixed-interval interventions regardless of equipment condition. Highest reliability coverage, typically at highest cost.

The maintenance strategy implementation costs associated with each component, expressed in Euros and adapted from Özcan et al. (2017), are presented in Table 1 together with the corresponding importance indices. For proper integration into the MILP optimization framework, the components are arranged in ascending order of importance indices, along with their associated strategy costs. This structured representation is mandatory to enable the model to perform a consistent and effective maintenance strategy allocation while ensuring compliance with the imposed budgetary constraints.

Table 1. Equipment importance indices and unit maintenance strategy costs

Code	Component	Ψ_i	CM Cost (€)	PM Cost (€)	SM Cost (€)
GEN-STA	Generator stator	**0.161**	42.60	14526.11	87424.41
GEN-ROT	Generator rotor	**0.163**	42.60	14526.11	87424.41
CT-380	Current transformer (380 kV)	**0.164**	1825.01	0.00	7299.57
VT-380	Voltage transformer (380 kV)	**0.164**	1825.01	0.00	7299.57
TR-EXC	Excitation transformer	**0.176**	3661.95	7263.06	29064.39
SR-CB	Slip ring and carbon brushes	**0.281**	0.00	1812.84	29064.39
CB-SS-380	Substation circuit breaker (380 kV)	**0.375**	3649.78	10906.75	29173.92
CB-BB-380	Busbar circuit breaker (380 kV)	**0.498**	7263.06	10876.33	29514.68
TR-MAIN	Main power transformer	**0.606**	3661.95	16335.79	146040.00

CM: conditional maintenance; PM: predictive maintenance; SM: systematic maintenance. Ψ_i: importance index.

4. MILP Model Formulation

4.1. Model Overview and Threshold-Based Assignment Rationale

The core objective of the MILP model is to determine optimal maintenance strategy assignments for the nine target components, respecting the available budget while maximizing overall maintenance effectiveness. The model is formulated following the framework proposed by Houria et al. (2016) and adapted to the hydroelectric context.

A key conceptual feature of the proposed model is the use of two continuous importance thresholds — S_1 and S_2 — to partition the equipment set into three strategy zones. This translates into the following:

- Equipment with an importance index $\Psi_i < S_1$ is assigned conditional maintenance.
- Equipment with $S_1 \leq \Psi_i < S_2$ receives predictive maintenance.
- Equipment with $\Psi_i \geq S_2$ is assigned systematic maintenance.

This threshold mechanism directly encodes the intuition that maintenance intensity should increase with equipment operational significance.

Critically, S_1 and S_2 are not fixed a priori but are decision variables of the model, jointly optimized with strategy assignments. The objective function favors more intensive strategies — predictive and systematic maintenance — by assigning them higher effectiveness weights. Minimizing S_1 and S_2 therefore maximizes the share of equipment subjected to intensive strategies, subject to the budget constraint. The trade-off between maintenance effectiveness and cost is thus managed endogenously: the solver identifies the threshold pair (S_1, S_2) that maximizes the weighted strategy score without exceeding the available budget. This approach generalizes naturally to both single-strategy and multiple-strategy assignment scenarios by adjusting the per-equipment strategy count constraint.

4.2. Indices, Parameters, and Decision Variables

Indices

i: Equipment index, $i = 1, \ldots, 9$, ordered in ascending importance (GEN-STA through TR-MAIN).

j: Maintenance strategy index: $j = 1$ (CM), $j = 2$ (PM), $j = 3$ (SM).

Parameters

Ψ_i: Importance index of component i (listed in Table 1).

C_{ij}: Unit implementation cost (€) of strategy j for component i (listed in Table 1).

B: Total available maintenance budget: B = 300,000 €.

w_j: Effectiveness weight of strategy j: $w_1 = 0.23$ (CM), $w_2 = 0.66$ (PM), $w_3 = 0.77$ (SM), as derived by Houria et al. (2016).

The effectiveness weights reflect the relative maintenance value of each strategy: systematic maintenance ($w_3 = 0.77$) is rated highest for its comprehensive failure prevention coverage, followed by predictive maintenance ($w_2 = 0.66$), while conditional maintenance ($w_1 = 0.23$) receives the lowest weight as the least proactive approach. Overall, the adopted weighting scheme is coherent with the operational requirements of the power plant systems considered in this study and provides a reasonable representation of the relative effectiveness of the evaluated maintenance strategies.

Decision Variables

$X_{ij} \in \{0, 1\}$: Binary assignment variable; equals 1 if strategy j is assigned to component i, 0 otherwise.

S_1: Lower importance threshold: components with $\Psi_i < S_1$ are assigned CM.

S_2: Upper importance threshold: components with $S_1 \leq \Psi_i < S_2$ are assigned PM; those with $\Psi_i \geq S_2$ are assigned SM.

4.3. Objective Function

The model maximizes the weighted sum of strategy assignments across all components, with higher weights assigned to more intensive strategies to drive the optimizer toward comprehensive maintenance coverage:

$$Maximize\ Z = 0.23 \cdot \Sigma_i X_i^1 + 0.66 \cdot \Sigma_i X_i^2 + 0.77 \cdot \Sigma_i X_i^3 \tag{1}$$

By attributing weights of 0.77 and 0.66 to SM and PM respectively — against 0.23 for CM — Equation (1) drives the model to assign systematic or predictive maintenance to as many components as the budget permits. The result is an implicit minimization of the thresholds S_1 and S_2: lowering these thresholds moves more components into higher-strategy zones, increasing the objective value, until the budget constraint becomes binding.

4.4. Constraints

Budget Constraint

The total implementation cost of all assigned strategies must not exceed the available budget B:

$$\Sigma_i \Sigma_j C_{ij} \cdot X_{ij} \leq B \qquad (B = 300{,}000\ €, in\ our\ case) \tag{2}$$

Strategy Assignment Constraint

Each component must receive exactly k maintenance strategies, where k = 1 for Scenario 1 (exclusive single-strategy) and k = 2 for Scenario 2 (dual-strategy):

$$\Sigma_j X_{ij} = k\ , \quad \forall i = 1, \dots, 9 \quad (k \in \{1, 2, 3\}) \tag{3}$$

Importance-Ordered Assignment Constraint

Strategy assignments must respect the importance ordering of components: a component with a higher importance index must receive a strategy of equal or greater intensity than any component with a lower importance index. This constraint enforces the threshold-based logic mathematically:

$$X_{i,}^{1} + 2 \cdot X_{i,}^{2} + 3 \cdot X_{i,}^{3} \leq X_{i}^{+1,1} + 2 \cdot X_{i}^{+1,2} + 3 \cdot X_{i}^{+1,3}, \quad \forall i = 1, \dots, 8 \tag{4}$$

Threshold Definition Constraints

The thresholds S_1 and S_2 are defined relative to the importance index values at assignment transitions between strategy zones. These constraints link the continuous threshold variables to the binary assignment decisions:

$$S^1 \geq \Sigma_{i}^{=18} \Psi_{i} \cdot (X_{i,}^{1} - X_{i}^{+1,1}) \tag{5}$$

$$S^2 \geq \Sigma_{i}^{=18} \Psi_{i} \cdot (X_{i,}^{1} + X_{i,}^{2} - X_{i}^{+1,1} - X_{i}^{+1,2}) \tag{6}$$

Equations (5) and (6) ensure that S_1 captures the importance value at the CM-to-PM transition boundary, and that S_2 captures the PM-to-SM transition boundary, as determined by the binary assignment variables.

Threshold Bounds

Both thresholds must lie within the observed range of importance index values from table 1 and maintain strict ordering to ensure the three-zone partition is non-degenerate:

$$0.161 \leq S^1 < S^2 \leq 0.606 \tag{7}$$

4.5. Computational Implementation

The MILP model was implemented and solved using LINGO v21, which employs a Branch and Bound algorithm for mixed-integer optimization. The model involves 9 components, 3 strategies per component, and 27 binary assignment variables (X_{ij}), together with the two continuous threshold variables S_1 and S_2. The solver converged to a proven optimal solution in 0.26 seconds on a standard workstation with no constraint violations or infeasibility detected, confirming the consistency and correctness of the model formulation.

5. Results

5.1. Strategy Assignment Overview

Two assignment scenarios are evaluated. In Scenario 1, each component receives exactly one maintenance strategy (k = 1 in Equation (3)). In Scenario 2, each component receives exactly two strategies simultaneously (k = 2), enabling the application of a primary strategy supplemented by a secondary one. Results for both scenarios are presented in Table 2.

Table 2. MILP maintenance strategy assignments under both scenarios

Code	Component	Scenario 1			Scenario 2		
		CM	PM	SM	CM	PM	SM
GEN-STA	Generator stator	–	✓	–	✓	✓	–
GEN-ROT	Generator rotor	–	✓	–	✓	✓	–
CT-380	Current transformer (380 kV)	–	✓	–	✓	✓	–
VT-380	Voltage transformer (380 kV)	–	–	✓	✓	✓	–
TR-EXC	Excitation transformer	–	–	✓	✓	✓	–
SR-CB	Slip ring and carbon brushes	–	–	✓	–	✓	–
CB-SS-380	Substation circuit breaker (380 kV)	–	–	✓	–	✓	✓
CB-BB-380	Busbar circuit breaker (380 kV)	–	–	✓	–	✓	✓
TR-MAIN	Main power transformer	–	–	✓	–	✓	✓

5.2. Scenario 1: Single-Strategy Assignment

Under the single-strategy constraint, the MILP model assigns predictive maintenance (PM) to the three lowest-importance components — GEN-STA (Ψ_i = 0.161), GEN-ROT (Ψ_i = 0.163), and CT-380 (Ψ_i = 0.164) — and systematic maintenance (SM) to the remaining six components, whose importance indices range from 0.164 (VT-380) to 0.606 (TR-MAIN). No component is assigned conditional maintenance under this scenario.

This result reflects the interaction between the objective function weights and the budget constraint. Despite their low importance ranking, GEN-STA and GEN-ROT are assigned PM rather than SM because their SM implementation cost (87,424 € each) would exhaust the budget before all higher-importance components could be covered. The optimizer therefore assigns PM to these components — whose PM cost is also very low (14,526 € each) — and reallocates the saved budget to the more important assets. This illustrates the model's ability to identify non-obvious but cost-effective assignment combinations that purely rule-based approaches would miss.

Budget verification (Scenario 1):

$$\Sigma Costs_{CM} = 0 \text{ €}$$

$$\Sigma Costs_{PM} = 29052.22 \text{ €}$$

$$\Sigma Costs_{SM} = 270156.95 \text{ €}$$

$\Sigma Costs_{Total} = 299209.17$ € => Budget constraint satisfied.

5.3. Scenario 2: Dual-Strategy Assignment

Under the dual-strategy constraint, the model assigns PM to all nine components as a universal baseline strategy. This is supplemented by CM for the six lowest-importance components (GEN-STA, GEN-ROT, CT-380, VT-380, TR-EXC, SR-CB) and by SM for the three highest-importance components (CB-SS-380, CB-BB-380, TR-MAIN). SR-CB receives PM only, without a second strategy, reflecting the optimizer's budget management at that importance level.

The Scenario 2 assignment illustrates a progressive escalation of maintenance intensity with importance: low-importance components receive a conservative CM+PM combination; the highest-importance components receive the most comprehensive PM+SM pairing. This graduated structure is directly enforced by the importance-ordered assignment constraint (Equation (4)) and reflects the threshold-based logic of the model.

Budget verification (Scenario 2):

$$\Sigma Costs_{CM} = 7397.17 \text{ €}$$

$$\Sigma Costs_{PM} = 76246.997 \text{ €}$$

$$\Sigma Costs_{SM} = 204728.60 \text{ €}$$

$\Sigma Costs_{Total} = 288372.77$ € => Budget constraint satisfied.

Although the second scenario assigns two strategies per item, it results in lower overall costs, demonstrating the efficient and judicious utilization of maintenance resources by the model.

6. Comparison and Validation

6.1. Reference Benchmark

Validation is performed by comparing the MILP results against the strategy assignments produced by Özcan et al. (2017) using a hybrid Goal Programming (GP) model applied to the same nine components. The reference model considered four strategies — CM, PM, SM, and corrective maintenance (Corr.) — and produced the assignments summarized in Table 3.

Table 3. Maintenance strategy assignments from the reference GP model (Özcan et al., 2017)

Code	Component	CM	PM	SM	Corrective
GEN-STA	Generator stator	✓	✓	✓	–
GEN-ROT	Generator rotor	✓	✓	✓	–
CT-380	Current transformer (380 kV)	✓	✓	✓	–
VT-380	Voltage transformer (380 kV)	✓	✓	✓	–
TR-EXC	Excitation transformer	✓	✓	✓	–
SR-CB	Slip ring and carbon brushes	✓	✓	✓	–
CB-SS-380	Substation circuit breaker (380 kV)	✓	✓	✓	✓
CB-BB-380	Busbar circuit breaker (380 kV)	✓	✓	✓	✓
TR-MAIN	Main power transformer	✓	✓	✓	✓

The GP model assigns three or four strategies to each component simultaneously. Components GEN-STA through SR-CB receive CM, PM, and SM concurrently, while CB-SS-380, CB-BB-380, and TR-MAIN receive all four strategies including corrective maintenance. This near-exhaustive assignment pattern arises because the reference formulation incorporates neither a budget constraint nor a continuous importance score that differentiates strategy intensity across components.

6.2. Comparative Analysis

Figure 1 provides a visual synthesis of these differences. Each panel displays, for every component, which maintenance strategies are assigned (solid bars) versus not assigned (faded bars), across Scenario 1, Scenario 2, and the reference GP model. The contrast is immediately apparent: the two MILP scenarios present a sparse, differentiated assignment structure, with strategy intensity increasing from left to right as component importance rises, while the reference GP panel shows near-uniform assignment of all strategies to all components. The dashed vertical separator highlights the boundary between the proposed model outputs and the reference benchmark.

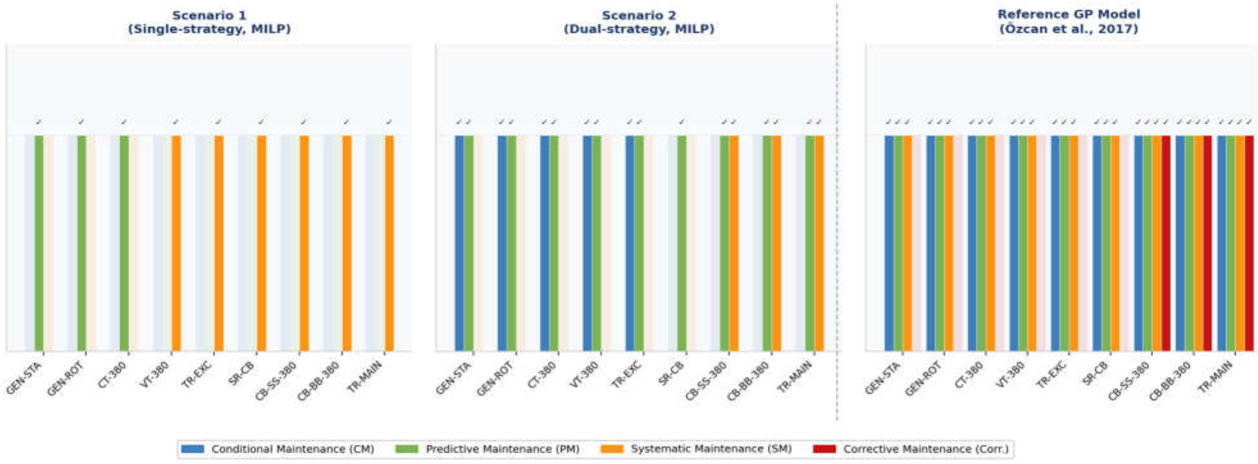

Figure 1. Comparative maintenance strategy assignments

The proposed MILP framework produces substantially more discriminating and operationally actionable assignments than the reference GP model. Four distinctions are noteworthy:

- Assignment precision: The MILP model assigns one or two targeted strategies per component, providing a clear and implementable maintenance plan. The GP model assigns three to four strategies to all components, offering limited discriminating guidance for operational planning.
- Budget adherence: The MILP model explicitly enforces a budget ceiling of €300,000, yielding financially feasible assignments verified in Section 5. The GP formulation omits cost constraints, potentially generating recommendations that exceed available resources.
- Importance-driven differentiation: Embedding importance indices directly into the MILP model ensures that higher-importance components systematically receive more intensive strategies. The GP model assigns similar strategy sets to all components regardless of their operational significance.
- Strategy scope: The proposed model excludes corrective maintenance from the assignable strategy set, consistent with industrial practice in which corrective intervention is an implicit baseline available for any component at any time. Including it as an explicit assignment option — as in the GP model — conflates a reactive fallback with a proactive planning decision.

Overall, the MILP assignments are not only valid but more informative and operationally actionable than the reference results. The model's outputs reflect genuine equipment prioritization, respect financial constraints, and provide clear strategic differentiation — making them directly deployable within operational maintenance management systems.

7. Conclusion

This paper presented a budget-constrained MILP framework for maintenance strategy optimization in hydroelectric power plants, in which pre-computed equipment importance indices are embedded as continuous parameters governing endogenously optimized strategy assignment thresholds. Applied to nine high-priority plant components under a €300,000 budget, the model produced clear and validated assignments across single-strategy and dual-strategy scenarios, with total costs of €299,209 and €288,373 respectively — both within budget.

Three principal advantages distinguish the MILP framework from existing approaches. First, equipment importance indices are embedded directly into the optimization model rather than serving merely as a pre-selection filter, enabling importance-driven differentiation of maintenance intensity across the full equipment set. Second, the threshold-based assignment mechanism provides a transparent and mathematically consistent link between importance scores and strategy assignments, with threshold values jointly optimized by the solver. Third, the dual-scenario formulation accommodates both exclusive and concurrent strategy assignment, offering flexibility for different operational planning contexts.

Validation against the Goal Programming benchmark of Özcan et al. (2017) confirmed the consistency of results and demonstrated the precision and operational actionability of the proposed framework, particularly through its explicit budget enforcement and importance-ordered assignment structure.

Several directions merit investigation in future work. Integrating maintenance crew availability, equipment interdependency, and time-windowing constraints would bring the model closer to real operational conditions. Stochastic or robust optimization extensions would improve resilience to uncertainty in failure rates and cost estimates.

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