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Risk-Based Optimization of Building Maintenance Sequencing in Multi-Plant Factories Using Genetic Algorithm

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ABSTRACT

Building maintenance management in multi-plant factory environments is a complex and challenging task due to the geographical distribution of facilities, limited maintenance resources, and varying levels of operational risk across plants. In practice, maintenance sequencing decisions are often based on expert judgement, which may lead to subjective and suboptimal outcomes. This study proposes a risk-informed optimization framework to determine the optimal sequence of building maintenance activities in a multi-plant factory by modeling the problem as a travel network optimization task. The objective of the proposed model is to minimize total travel cost associated with mobilizing maintenance equipment and materials, while incorporating risk-based maintenance priorities into the sequencing decision.

The proposed approach is demonstrated through a case study of a multi-plant factory located in Kudus, Central Java, Indonesia, consisting of eight plants. Each plant is represented as a node in the travel network, and inter-plant movements are associated with travel costs expressed under 2025 cost conditions. Risk values are assigned to each plant based on expert judgement, considering routine maintenance importance, audit compliance requirements, production impact, and safety and product quality risks. A single-objective optimization model is formulated and solved using a Genetic Algorithm (GA).

The results show that the proposed risk-informed GA produces a stable and efficient maintenance sequence that balances travel cost efficiency and risk prioritization. Compared to the initial maintenance plan proposed by the building administrator, the GA-based solution achieves a travel cost reduction of approximately 2.74%, while providing a more systematic and transparent prioritization of high-risk plants. Although the no-risk baseline scenario yields a slightly lower travel cost, it fails to adequately prioritize plants with higher risk levels. These findings indicate that the proposed approach offers a practical decision-support tool for maintenance planning in multi-plant industrial facilities, where modest cost savings combined with improved risk awareness can lead to more defensible and effective maintenance decisions. Future research may extend the model to larger-scale systems, multiple maintenance teams, and dynamic risk conditions.

Key Words: Building Maintenance, Multi-Plant Factory, Genetic Algorithm, Risk-Based Maintenance, Travel Network Optimization

INTRODUCTION

Managing building maintenance in multi-plant factory systems is a complex and challenging task, since it involves multiple buildings with different conditions, operational functions, and levels of risk (Cahyono et al., 2025; Shahzad et al., 2025). Each plant plays a distinct role in ensuring occupational safety, product quality, audit compliance, and the continuity of production processes. This complexity requires maintenance decisions that are not only technically effective but also economically and operationally efficient. In general, the operation and maintenance phase dominates the building lifecycle in both duration and cost, contributing approximately 80% of total lifecycle expenditure and extending far beyond the design and construction phases in terms of time (Zhao et al., 2022). This substantial cost proportion places significant pressure on building maintenance divisions to optimize budgets while maintaining safety standards, audit compliance, and production continuity. Consequently, decisions regarding the sequencing of maintenance activities become critical and must be supported by rational and scientifically defensible approaches (Asa, M. F., & Alfaritzi, F. 2025; Firdausi & Ansusanto 2025; Shiue et al., 2019).

In industrial practice, the determination of building maintenance sequences in multi-plant factories is still largely based on expert judgment and established operational routines (Al-Najjar, 2007). While this approach is practical and allows for quick decision-making, the resulting decisions tend to be subjective, difficult to replicate, and potentially suboptimal when faced with limited resources and budget constraints (O'Hagan, 2019). Moreover, experience-based approaches often fail to explicitly incorporate multiple risk factors with varying levels of severity and impact (Cooke & Goossens, 2004). From an academic perspective, several studies have explored maintenance optimization and route planning using travel network approaches and metaheuristic methods (Aljohani, 2023; Pasha et al., 2022). However, most of these studies focus on logistics (Bányai et al., 2019; Wu et al., 2023), distribution (Čamaj et al., 2025), or equipment maintenance (An et al., 2022), and only limited attention has been given to building maintenance in multi-plant factory environments that explicitly integrate diverse risk factors, such as routine maintenance requirements, audit compliance, production impacts, and risks related to occupational safety and product quality. As a result, a clear research gap exists in developing optimization models for building maintenance sequencing that not only minimize travel and maintenance costs but also systematically incorporate risk-based priorities.

To address this gap, this study aims to develop a risk-based optimization approach for sequencing building maintenance activities in multi-plant factories by modeling the problem as a travel network problem. The considered risk factors include the importance of routine maintenance, audit standards, production impacts, and occupational safety and product quality considerations. To solve the resulting combinatorial and complex optimization problem, this study employs Genetic Algorithm (GA) as metaheuristic methods (Holland, 1992) and compares their performance in generating efficient maintenance sequences.

Specifically, this study seeks to examine how building maintenance sequencing problems in multi-plant factories can be quantitatively modeled, how the integration of risk factors influences optimization outcomes, and to what extent GA can produce more efficient and objective solutions compared to traditional expert judgment–based approaches. The main contribution of this research lies in providing a more systematic and risk-informed decision-making framework for building maintenance, extending the application of metaheuristic methods to multi-plant building maintenance contexts, and offering a scientific basis for more transparent and accountable maintenance decisions in industrial practice.

LITERATURE REVIEW

Building Maintenance in Industrial Facilities

In multi-plant factory systems, maintenance activities become increasingly complex because they involve multiple buildings that are geographically distributed and serve different operational functions. Thus, building maintenance is a critical component of industrial facility management, aimed at ensuring the reliability, safety, and operational sustainability of factory environments. Previous studies have examined various building and industrial facility maintenance strategies, including preventive maintenance (Ebrahimi et al., 2020; Rodhi 2023), corrective maintenance (Sheut & Krajewski, 1994), and condition-based maintenance (Ahmad & Kamaruddin, 2012).

However, most of these studies focus on single facilities or individual buildings, without considering interactions among multiple plants or the travel-related costs arising from sequential maintenance activities.

In the context of multi-plant factories, the determination of maintenance sequencing is influenced not only by the technical condition of buildings but also by resource constraints, inter-plant distances, and the operational impacts of maintenance delays. Consequently, this problem can naturally be modeled as a travel network problem (Lecluyse et al., 2013), in which each plant is represented as a node and the distances between plants are represented as network edges. Despite this, studies that integrate travel network modeling with building maintenance contexts remain relatively limited, particularly those that explicitly link building technical conditions with the efficiency of maintenance routing and sequencing. This limitation highlights the need for further research that bridges maintenance decision-making and network-based optimization approaches.

Risk-Based Maintenance Decision Making

Risk-based maintenance approaches have been increasingly adopted in industrial facility management in response to growing demands for occupational safety, compliance with audit standards, and product quality assurance (Darányi et al., 2026). This approach recognizes that not all components or buildings carry the same level of urgency, and therefore, maintenance priorities should be established based on the level of risk they pose. Risk factors in building maintenance may encompass various aspects, including the importance of routine maintenance, the likelihood of audit non-compliance, impacts on production processes, and risks to human safety and product quality. In practice, risk assessment remains largely qualitative and heavily dependent on expert judgement, which can lead to subjective decisions that are difficult to evaluate quantitatively and systematically.

Several studies have proposed quantitative approaches to incorporate risk factors into maintenance decision-making (Rosa et al., 2021). However, the integration of risk considerations has generally been limited to determining maintenance priorities, with relatively little attention given to optimizing the sequence of maintenance activities, particularly within the context of multi-plant travel networks. Based on this review, it can be concluded that a clear research gap remains in the development of optimization models for sequencing building maintenance in multi-plant factories that explicitly integrate risk factors within a travel network framework and are solved using metaheuristic methods.

Metaheuristic-Based Optimization

Metaheuristic approaches have been widely used to solve complex and large-scale combinatorial optimization problems, particularly when deterministic optimization methods become inefficient due to expansive solution spaces and multiple constraints. Metaheuristic techniques such as Genetic Algorithm (GA) are well known for their ability to generate near-optimal solutions with relatively efficient computational performance. GA operates by mimicking biological evolutionary mechanisms, including selection, crossover, and mutation, to progressively improve solution quality across successive generations (Holland, 1992).

Genetic Algorithm has been extensively applied to a wide range of optimization problems, including routing, scheduling, and resource allocation, as well as problems analogous to the traveling salesman problem and the vehicle routing problem. One of the main advantages of GA lies in its strong global search capability, which enables it to explore diverse solution regions and avoid entrapment in local optima (Jalalian & Defersha, 2019). Although GA has been widely adopted in logistics, distribution, and transportation contexts, its application to building maintenance problems, particularly within multi-plant factory environments, remains relatively limited. This gap highlights the potential for adapting metaheuristic-based optimization approaches to industrial facility management and maintenance decision-making.

RESEARCH METHODOLOGY

Research Design

This study adopts a quantitative, optimization-based research design to address the problem of determining an optimal building maintenance sequence in a multi-plant factory case. As illustrated in Figure 1, the study begins with problem definition to clarify the challenges associated with risk-based maintenance under limited resources. A case study is then defined to describe the characteristics of the multi-plant factory and the maintenance context. Relevant data are subsequently collected, including plant locations, travel costs, and expert judgement information. Based on these data, key risk factors are identified and quantified through a structured risk scoring process. The factory layout is then abstracted into a travel network model, where plants are represented as nodes and inter-plant connections as edges. An optimization model is formulated to minimize total travel and risk-weighted maintenance costs subject to operational constraints. Finally, the formulated model is solved using a Genetic Algorithm to obtain the optimal maintenance sequence, which represents the output of the proposed approach.

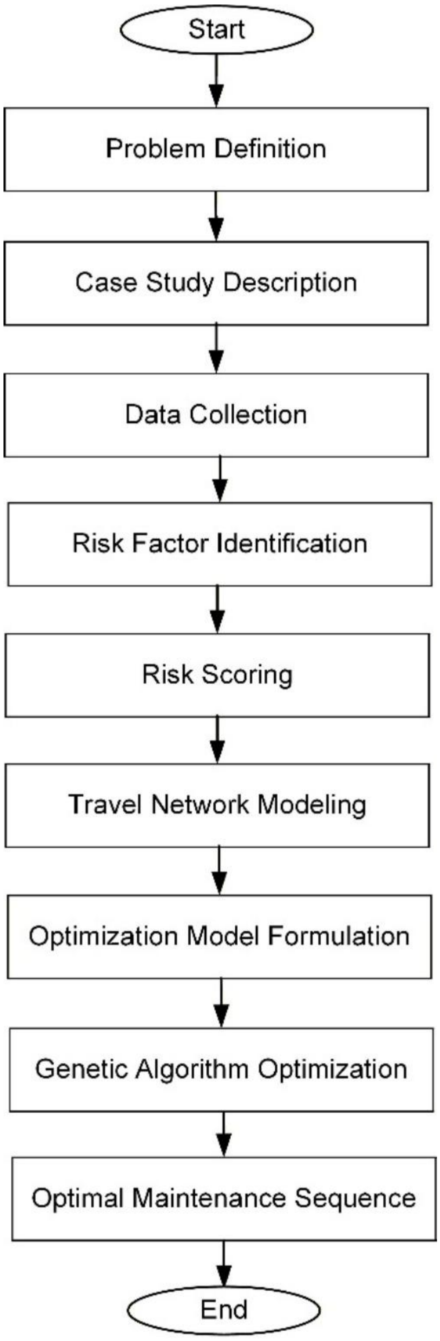

Figure 1. Flowchart of the proposed research methodology

Case Study Description and Modeling Assumptions

The research object of this study is a multi-plant factory located in Kudus, Central Java, Indonesia, consisting of eight geographically distributed plants, labeled Plant A to Plant H, that require periodic building maintenance. As illustrated in Figure 2, each plant is treated as an individual maintenance unit with distinct operational characteristics and risk levels. Plant A serves a dual function as both a production plant and the central warehouse and office for building maintenance activities, and therefore acts as the starting point of the maintenance sequence. To preserve data confidentiality, the case study is referred to as Company X. The scope of the study focuses on building maintenance activities and the sequencing of maintenance tasks across plants, while equipment-level maintenance and real-time operational disruptions are not considered.

Several assumptions are adopted to simplify the modeling and optimization process. It is assumed that a single maintenance team is mobilized from Plant A and performs all maintenance activities, visiting each plant exactly once during a maintenance cycle. Travel cost is defined as the cost associated with mobilizing maintenance equipment, materials, and supporting resources between plants, including transportation, handling, and related logistical expenses within the factory area in Kudus. All travel costs are expressed under 2025 cost conditions and are assumed to be known and constant during the analysis period. These costs are expressed in thousand Indonesian Rupiah (IDR) and are represented in the form of an inter-plant travel cost matrix (Table 1), which serves as an input to the optimization model. Maintenance costs for each plant are estimated prior to optimization based on planned maintenance activities and are also expressed in 2025 cost values. In addition, risk scores assigned to each plant are considered fixed during the optimization process and are derived from expert judgement. These assumptions allow the proposed optimization model to be formulated and solved effectively while maintaining practical relevance.

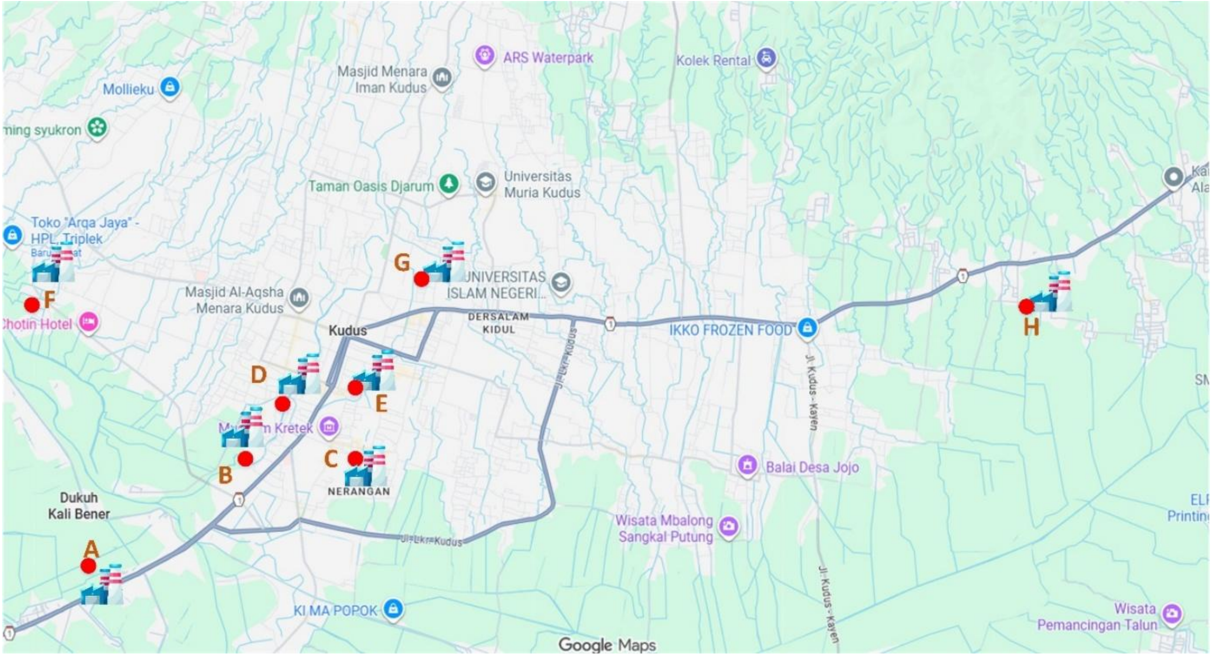

Figure 2. Location of multi-plant factory

Table 1. Travel Cost Matrix

From/To	A	B	C	D	E	F	G	H
A	0	1000	1200	1200	1200	1500	1600	2000
B	1000	0	700	700	700	1000	1000	1800
C	1200	700	0	700	700	1000	1000	1800
D	1200	700	700	0	700	1000	1000	1800
E	1200	700	700	700	0	1000	1000	1800
F	1500	1000	1000	1000	1000	0	1200	2000
G	1600	1000	1000	1000	1000	1200	0	1500
H	2000	1800	1800	1800	1800	2000	1500	0

Determination of Risk Factors and Risk Values

Determining risk factors and their corresponding values is a crucial step in establishing maintenance priorities across the multi-plant factory. In this study, a risk-based maintenance perspective is adopted to acknowledge that not all plants have the same level of urgency for maintenance intervention. The purpose of risk assessment in this context is not to predict failure probabilities but to provide a structured and transparent basis for prioritizing maintenance activities within the optimization process. Based on actual industrial maintenance practices, four key risk factors are considered in this study. These factors represent the most critical dimensions influencing building maintenance decisions in industrial facilities: (1) routine maintenance importance, (2) audit compliance requirements, (3) impact on production continuity, and (4) risks related to occupational safety and product quality. Together, these factors capture technical, operational, regulatory, and safety-related considerations that maintenance managers in industrial environments commonly evaluate.

Risk values for each plant are determined using expert judgement, which is widely accepted in maintenance and risk assessment studies when quantitative failure data are limited or unavailable. Experienced personnel from the maintenance and facility management divisions are consulted to assess the relative importance of each risk factor. To ensure consistency and transparency, a predefined ordinal scoring scale is adopted, where 5 indicates low risk, 6 medium risk, 7 high risk, 8 very high risk, and 9 critical risk. Based on this scale, routine maintenance importance is assigned a score of 5, audit compliance is assigned 7, production impact is assigned 8, and safety and product quality risk is assigned 9, reflecting their increasing levels of criticality. For each plant, the overall risk value is obtained by aggregating the scores of the relevant risk factors. As a result, each plant (Plant A to Plant H) is assigned a distinct overall risk value reflecting its specific maintenance and operational conditions, as summarized in Table 2. These risk values are treated as fixed parameters during the optimization process and are used to influence the prioritization of maintenance sequencing. Plants with higher risk values are therefore encouraged to be scheduled earlier in the maintenance sequence, while still maintaining the primary objective of minimizing travel cost.

Table 2. Aggregated risk values for each plant based on expert judgement

Plant	Value	Remark
A	5	low risk
B	5	low risk
C	7	high risk
D	9	critical risk
E	8	very high risk
F	8	very high risk
G	9	critical risk
H	7	high risk

Optimization Model Formulation

The maintenance sequencing problem in the multi-plant factory is formulated as a single-objective combinatorial optimization problem based on a travel network representation. Each plant is modeled as a node, and the travel cost associated with mobilizing maintenance equipment and materials between plants is represented by weighted edges. The objective of the model is to determine an optimal sequence of plant visits that minimizes total travel cost while incorporating risk-based maintenance priorities. Let $N = (1,2,\ldots,8)$ denote the set of plants, where Plant 1 (Plant A) represents the maintenance warehouse and starting point. Additionally, this study incorporates a penalty-based risk prioritization mechanism into the objective function. The proposed penalty term is intended to discourage maintenance sequences that place high-risk plants in lower maintenance priorities. In this formulation, plants with higher risk values contribute larger penalty values if they are not appropriately prioritized in the maintenance sequence. The weighting parameter (λ) is introduced to regulate the influence of the risk prioritization term relative to the travel cost component. Then, the optimization objective is defined as minimizing the total travel cost of the maintenance sequence while accounting for risk-based prioritization, as expressed in Equation (1) as follows:

$$\min Z = \sum_{i \in N} \sum_{j \in N, j \neq i} C_{ij}\, x_{ij} + \lambda \sum_{i \in N} R_i\, p_i \tag{1}$$

The formulation remains a single-objective optimization problem, as both travel cost and risk considerations are integrated into a single objective function. The model is subject to the following constraints, as expressed in Equations (2) and (3). Each plant must be visited exactly once during a maintenance cycle:

$$\sum_{j \in N, j \neq i} x_{ij} = 1 \ \forall_i \epsilon N \tag{2}$$

$$\sum_{i \in N, i \neq j} x_{ij} = 1 \ \forall_j \epsilon N \tag{3}$$

Further, Equation (4) defines the penalty component used to incorporate risk-based prioritization into the optimization process. The penalty term represents an additional artificial cost component introduced into the objective function to enforce risk-based maintenance prioritization. The penalty value is determined based on the risk priority of each plant, where higher-risk plants contribute larger penalty values if they are not appropriately prioritized in the maintenance sequence.

$$Penalty = \lambda \sum_{i \in N} R_i\, p_i \tag{4}$$

The notation used in the optimization model is summarized in Table 3.

Table 3. Notation used in the optimization model

Symbol	Description
Z	Total objective function value
C_{ij}	Travel cost from location i to location j
x_{ij}	Binary decision variable indicating whether travel occurs from location i to location j
R_i	Risk priority value associated with location i
p_i	Visitation position of plant i in the maintenance sequence
N	Set of maintenance locations
λ	Weighting parameter controlling the influence of risk prioritization

The optimization model has procedure that higher-risk plants assigned to later positions in the maintenance sequence will produce larger penalty values. These constraints ensure that the maintenance team departs from and arrives at each plant exactly once. In addition, the maintenance sequence is constrained to start from Plant A, which serves as the maintenance warehouse and office. Subtour elimination constraints are implicitly handled through the solution representation and search process of the Genetic Algorithm. In this formulation, maintenance costs at each plant are assumed to be fixed and independent of the visit sequence; therefore, they are not included in the optimization objective. Risk values are treated as fixed parameters derived from expert judgement and are incorporated into the objective function through the penalty mechanism to guide maintenance prioritization.

Solution Using Genetic Algorithm

In the proposed GA framework, each candidate solution is encoded as a chromosome representing a feasible maintenance sequence. The chromosome is modeled as a permutation of plant indices, starting from Plant A, which functions as both the maintenance warehouse and the initial node. This permutation-based representation inherently satisfies the constraint that each plant is visited exactly once during a maintenance cycle. The fitness function is derived from the optimization model formulated in the previous section. For each chromosome, the total travel cost is computed by summing the inter-plant travel costs along the sequence, while risk values are incorporated as priority weights to promote earlier scheduling of higher-risk plants. As a minimization problem, chromosomes with lower fitness values indicate better solutions.

An initial population of feasible chromosomes is generated randomly and iteratively improved through selection, crossover, and mutation operators. Selection favors chromosomes with lower fitness values, while a permutation-preserving crossover operator exchanges partial sequences between parent solutions. To maintain diversity and prevent premature convergence, a mutation operator is applied with a predefined mutation rate, randomly altering the order of selected plants within a chromosome. The population size, crossover rate, mutation rate, and maximum number of generations are defined as GA parameters and remain constant throughout the optimization process. The algorithm terminates when a predefined stopping criterion is met, either by reaching the maximum number of generations or when no significant improvement in the best fitness value is observed. The chromosome with the lowest fitness value at termination is selected as the optimal maintenance sequence. Overall, the GA-based approach provides a flexible and practical decision-support tool for identifying risk-informed maintenance sequences that minimize travel cost in multi-plant factory environments, where exact optimization methods are computationally impractical. Table 4 describes the parameters used in this study.

Table 4. Genetic Algorithm parameters used in the study

Parameter	Value	Justification
Population size	50	Commonly used size that balances exploration and computational efficiency for small-to-medium combinatorial problems
Crossover rate	0.8	Standard value in GA literature to promote effective recombination of good solutions
Mutation rate	0.1	Typical rate for permutation-based GA to maintain diversity and avoid premature convergence
Maximum generations	200	Sufficient to ensure convergence for an 8-node sequencing problem

ANALYSIS AND DISCUSSION

The proposed Genetic Algorithm was applied to determine the optimal maintenance sequence for the multi-plant factory using the travel cost matrix in Table 1 and the risk values in Table 2. The GA parameters were selected based on commonly adopted practices in routing and sequencing optimization and remained fixed throughout the analysis.

Optimization Results

The risk-informed Genetic Algorithm (GA) produced an optimal maintenance sequence starting from Plant A, followed by Plants D, E, C, B, F, G, and H. Under 2025 cost conditions, the resulting total travel cost was 7,000 thousand IDR. This sequence reflects a balanced integration of travel efficiency and risk-based maintenance priorities, in which plants with higher risk levels are scheduled earlier in the maintenance cycle. To evaluate the impact of risk integration, two comparative scenarios including administrator (expert judgement) and no-risk GA baseline were analyzed, as summarized in Table 5.

Table 5. Comparison results

Approach	⋋	Route	Travel cost (thousand IDR)	Interpretation
Administrator (expert judgement)	-	A–B–C–E–D–G–F–H	7,300	experience-based sequence
No-risk GA baseline	0	A–B–D–C–E–F–G–H	6,800	minimum travel cost
Risk-informed GA	25	A–D–E–C–B–F–G–H	7,000	balanced trade-off
Risk-informed GA	100	A–D–G–F–E–C–B–H	7,600	strong risk prioritization

In the no-risk baseline scenario, where the objective function considered travel cost only, the optimization yielded a lower total travel cost of 6,800 thousand IDR. However, this solution scheduled several high-risk plants later in the sequence, potentially increasing exposure to safety, production continuity, and audit compliance risks. In contrast, the initial maintenance sequence proposed by the building administrator (A–B–C–E–D–G–F–H) resulted in a total travel cost of 7,300 thousand IDR, which is higher than the travel costs obtained from both GA-based optimization scenarios with a weighting parameter value of (⋋= 25). This finding indicates that the proposed optimization approach can generate more travel-efficient maintenance sequences while simultaneously incorporating risk-based maintenance prioritization into the decision-making process. As shown in Table 5, the proposed risk-informed GA achieves a cost-efficient improvement over expert judgement, while deliberately accepting a modest increase in travel cost compared to the no-risk baseline in order to enhance risk prioritization. This comparison demonstrates that the integration of risk considerations enables more informed and defensible maintenance sequencing decisions, without imposing a substantial additional cost burden. Future studies may extend the proposed model by considering larger-scale multi-plant systems, multiple maintenance teams, and dynamic risk levels. Such extensions are expected to increase problem complexity and provide deeper insights into the convergence behavior and scalability of metaheuristic optimization approaches.

Convergence Analysis

Figure 3 illustrates the convergence behavior of the proposed Genetic Algorithm during the optimization process. The results show that the objective value decreases rapidly during the early generations, indicating effective exploration of potential maintenance sequencing solutions. As the number of generations increases, the improvement rate gradually stabilizes, suggesting that the algorithm converges toward a stable near-optimal solution. The convergence behavior demonstrates that the selected GA parameters are sufficient to ensure stable optimization performance for the maintenance sequencing problem under consideration. The convergence curve also indicates that significant improvements occur within the initial generations, while later generations mainly perform solution refinement with only minor improvements in the objective value.

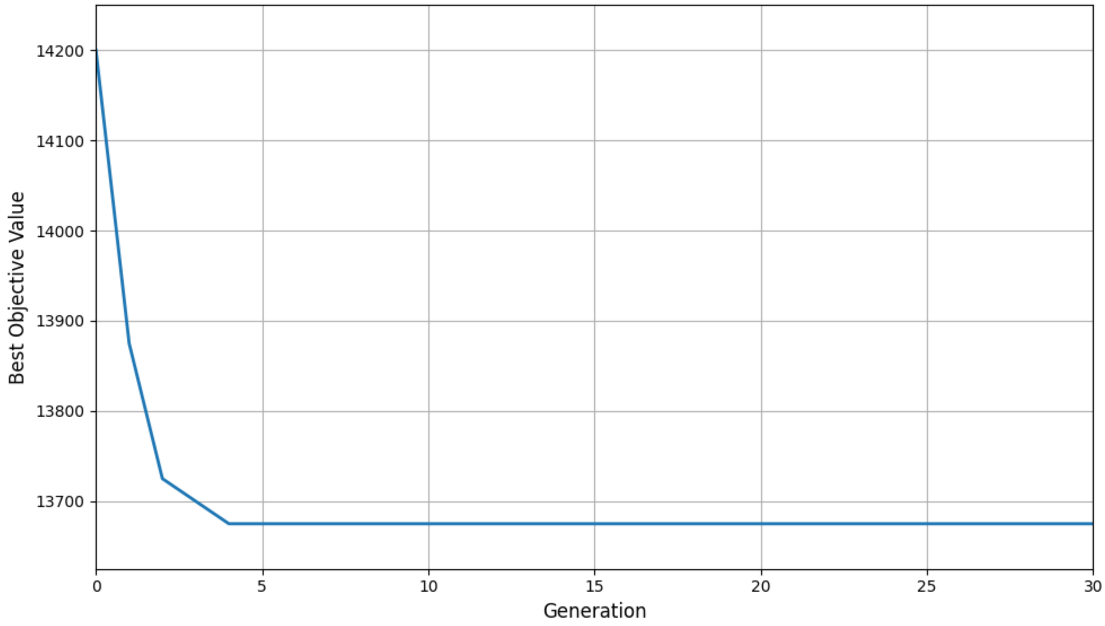

Figure 3. Convergence analysis

Sensitivity Analysis

A sensitivity analysis was conducted to assess the influence of Genetic Algorithm parameter settings on optimization performance. The analysis focused on population size and mutation rate, as these parameters strongly affect the exploration capability, convergence stability, and solution diversity of the GA. The analysis focused on population size and mutation rate, as these parameters strongly affect exploration capability and convergence stability in GA. Tables 6 and 7 present the results of the sensitivity analysis conducted to evaluate the influence of population size and mutation rate on the optimization performance of the proposed Genetic Algorithm. The analysis demonstrates how different parameter settings affect search exploration capability, convergence stability, and the quality of the resulting maintenance sequencing solutions. The sensitivity analysis results indicate that increasing population size does not always guarantee improved optimization performance. As shown in Table 6, a population size of 20 produced the best travel cost of 7,100 thousand IDR, indicating limited exploration capability during the optimization process. Increasing the population size to 50, improved the optimization performance and generated the lowest travel cost of 7,000 thousand IDR, suggesting a more balanced exploration and convergence behavior. However, further increasing the population size to 100 resulted in a higher travel cost of 7,100 thousand IDR. This finding suggests that although larger population sizes increase solution diversity, they may also introduce excessive exploration behavior that reduces convergence efficiency for relatively small-scale optimization problems such as the maintenance sequencing problem considered in this study.

Table 6. Sensitivity analysis of population size

Population size	Best travel cost (thousand IDR)	Observation
20	7,100	Limited exploration capability
50	7,000	Most stable optimization performance
100	7,100	Excessive exploration reduced convergence efficiency

In addition, the sensitivity analysis results for mutation rate demonstrate its significant influence on the exploration capability and convergence stability of the Genetic Algorithm. As presented in

Table 7, a mutation rate of 0.05 produced a higher travel cost of 7,100 thousand IDR, indicating limited solution diversity and a tendency toward premature convergence. Increasing the mutation rate to 0.10 improved the optimization performance and generated the lowest travel cost of 7,000 thousand IDR, suggesting a balanced exploration and convergence mechanism during the optimization process. However, further increasing the mutation rate to 0.30 resulted in a higher travel cost of 7,100 thousand IDR. This finding indicates that excessively high mutation rates may disrupt convergence stability by introducing excessive randomness into the search process. Overall, the results suggest that a mutation rate of 0.10 provides the most stable optimization performance for the proposed maintenance sequencing problem.

Table 7. Sensitivity analysis of mutation rate

Mutation rate	Best travel cost (thousand IDR)	Observation
0.05	7,100	Limited solution diversity and tendency toward premature convergence
0.1	7,000	Most stable optimization performance
0.3	7,100	Excessive mutation reduced convergence stability

Discussion

The comparison among the risk-informed Genetic Algorithm (GA), the no-risk GA baseline, and the administrator's initial maintenance sequence demonstrates the practical importance of incorporating risk considerations into maintenance sequencing decisions. As presented in Table 5, the no-risk GA baseline produced the lowest travel cost of 6,800 thousand IDR by focusing entirely on travel cost minimization without considering maintenance risk priorities. In contrast, the risk-informed GA scenario with (λ= 25) generated a slightly higher travel cost of 7,000 thousand IDR while prioritizing higher-risk plants earlier in the maintenance sequence. This result indicates that improved risk-based maintenance prioritization can be achieved with only a marginal increase in travel costs. However, when the weighting parameter was increased to (λ= 100), the optimization process strongly prioritized high-risk plants, resulting in a substantially higher travel cost of 7,600 thousand IDR. These findings demonstrate that the weighting parameter significantly influences the trade-off between operational efficiency and risk-based maintenance prioritization.

Compared to the administrator's experience-based maintenance sequence, the proposed optimization-based approach provides a more systematic and transparent prioritization mechanism. Although the administrator's sequence relied primarily on practical experience and operational intuition, the proposed model incorporates quantitative risk information directly into the optimization process. This highlights the limitation of relying solely on subjective judgement in maintenance planning and demonstrates the benefit of integrating optimization-based decision-support tools into industrial maintenance management. The convergence analysis further demonstrates the effectiveness of the proposed Genetic Algorithm in solving the maintenance sequencing problem. The convergence curve shows that the objective value decreases rapidly during the initial generations and stabilizes after approximately the fifth generation, indicating that the algorithm efficiently identifies a near-optimal maintenance sequence within a relatively short number of iterations. This rapid convergence behavior is likely influenced by the relatively small problem size considered in this study, which consists of eight maintenance locations.

In addition, the sensitivity analysis results indicate that the selected GA parameter configuration provides relatively stable optimization performance. The analysis of population size showed that a population size of 50 produced the best optimization performance compared to population sizes of 20 and 100. Similarly, the mutation rate analysis demonstrated that a mutation rate of 0.1

provided the most stable balance between exploration capability and convergence stability. These findings suggest that excessively small parameter values may limit search diversity, whereas excessively large parameter values may reduce convergence efficiency due to excessive exploration behavior.

Despite the promising results, this study has several limitations. First, the optimization problem considered in this study involves only eight maintenance locations, which may contribute to the rapid convergence behavior observed in the Genetic Algorithm. Larger-scale industrial maintenance networks may produce different optimization characteristics and computational challenges. Second, the risk values used in this study were derived from expert judgement, which may introduce subjectivity into the risk prioritization process. Third, the proposed model assumes fixed travel costs and static risk values, whereas real industrial environments may involve dynamic operational conditions, uncertain maintenance priorities, and fluctuating transportation costs. Future studies may extend the proposed framework by incorporating dynamic risk assessment, uncertainty modeling, and larger-scale maintenance scheduling scenarios to further improve the robustness and applicability of the optimization model in real-world industrial environments.

CONCLUSION

1. This study has demonstrated that the building maintenance sequencing problem in a multi-plant factory can be effectively modeled as a travel network optimization problem, where each plant is represented as a node and inter-plant movements are associated with travel costs.
2. A risk-informed single-objective optimization framework was successfully developed, in which total travel cost is minimized while risk-based maintenance priorities are incorporated to guide the sequencing of maintenance activities.
3. The application of the Genetic Algorithm proved to be an efficient and robust solution approach for the proposed problem, producing stable convergence and identifying an optimal maintenance sequence within a reasonable computational time.
4. The comparison results indicate that the proposed risk-informed GA approach outperforms expert-based maintenance planning by reducing total travel cost and providing a more systematic and transparent prioritization of high-risk plants.
5. Although the no-risk baseline scenario achieved a slightly lower travel cost, it failed to adequately prioritize plants with higher risk levels, highlighting the importance of integrating risk considerations into maintenance decision-making.
6. Overall, the proposed model offers a practical and implementable decision-support framework that balances operational efficiency and risk awareness, making it suitable for real-world application in multi-plant industrial maintenance management.
7. Future studies may extend the proposed model by considering larger-scale multi-plant systems, multiple maintenance teams, and dynamic risk levels. Such extensions are expected to increase problem complexity and provide deeper insights into the convergence behavior and scalability of metaheuristic optimization approaches.

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