Improving Heavy Maintenance Management Efficiency under Limited Depot Resources: A Case Study of MRT Pink Line

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Abstract

This research focuses on optimizing the heavy maintenance scheduling of the Pink Line MRT using two models: a non-flexible model (fixed at 120,000 km) and a flexible model, which allows a ±10% adjustment in the accumulated mileage (108,000 - 132,000 km). The study employs Mixed-Integer Linear Programming (MILP) and a two-year simulation to analyze the effects of key constraints, including depot capacity, repair duration, and flexibility levels. The results indicate that a 10% flexibility reduces unused accumulated mileage by 55.97% and increases utilized mileage by 10%, without requiring additional resources. However, increasing the flexibility to 15% yields diminishing returns, leading to higher operational costs and potential safety risks. Conversely, reducing flexibility to 5% helps control costs but increases maintenance frequency, affecting operational stability. Additionally, sensitivity analysis reveals that a depot capacity of C = 2 (2 maintenance tracks per day) with a 5-day repair duration is optimal, balancing efficiency and resource allocation. C = 1 leads to maintenance congestion and reduced operational efficiency, whereas C = 2 effectively distributes maintenance workload without delays. Although C = 3 shortens repair time, it offers only marginal benefits compared to the increased costs. The findings highlight the importance of strategic flexibility management and optimized depot capacity to reduce maintenance frequency, enhance resource utilization, and improve overall train operation management. This research provides valuable insights for railway maintenance planning, contributing to cost reduction and long-term operational efficiency.

Keywords: Heavy Maintenance, Maintenance Scheduling, Flexible Maintenance Planning, Mixed-Integer Linear Programming (MILP), Rail Fleet Management, Asset Utilization, Urban Rail System

1. Introduction

The increasing number of passengers in rail transit systems has made train scheduling and maintenance management crucial for ensuring operational efficiency. Effective maintenance planning plays a key role in sustaining train availability while minimizing operational costs and service disruptions. As rail networks expand and service frequencies increase, maintenance demands also rise, resulting in higher maintenance costs.

In particular, heavy maintenance (or overhaul) costs tend to escalate due to inefficient scheduling, depot capacity constraints, and limited resource allocation, all of which may lead to service delays and operational inefficiencies.

Beyond financial considerations, maintenance planning must also address train safety and reliability. Delayed maintenance can pose safety risks, while premature maintenance may cause unnecessary down-time and resource wastage. Moreover, simultaneous maintenance of multiple trainsets can strain depot capacity, leading to operational bottlenecks. Traditionally, maintenance planning relies on expert experience, but with increasing system complexity, mathematical optimization models have been introduced to enhance scheduling efficiency.

1.1 Principles of Railway Maintenance Planning

Railway maintenance can be categorized into three main types:

1) Preventive Maintenance

Scheduled inspections and component replacements to prevent failures.

2) Condition-Based Maintenance

Maintenance based on real-time monitoring of equipment conditions.

3) Corrective Maintenance

Repairs performed after faults or failures occur. (Sripraprutchai[1])

In recent years, Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) have gained attention in railway asset management. CBM involves real-time monitoring of asset conditions, such as vibration, temperature, or wear levels, to schedule maintenance only when needed. PdM further incorporates historical data and machine learning techniques to forecast failures and plan interventions proactively. While these approaches offer promising efficiency, their practical implementation requires advanced sensor infrastructure and data integration, which may not yet be fully developed across all urban rail systems. Therefore, this study focuses on preventive maintenance with accumulated mileage tracking, which remains the dominant method in current practice, especially in newly operated systems such as the MRT Pink Line.

Preventive maintenance is widely applied in rail systems as it helps prevent unexpected failures and enhances safety. However, improper maintenance scheduling may lead to suboptimal resource utilization, increased maintenance costs, and reduced train availability. For example, scheduling maintenance too early results in the loss of usable accumulated mileage, while excessive delays in maintenance can compromise system reliability (Lin et al.[2]).

1.2 Optimization Strategies for Heavy Maintenance

Heavy maintenance (or overhaul) is a periodic procedure that restores train functionality and extends service life. However, inefficient maintenance scheduling can lead to excessive train downtime, depot congestion, and increased operational costs. Previous studies have explored different scheduling strategies to mitigate these challenges.

One key approach is Flexible Maintenance Scheduling, which introduces tolerance windows for accumulated mileage to optimize maintenance timing. Studies have shown that improper scheduling can either lead to premature maintenance—resulting in lost usable accumulated mileage—or delayed maintenance, which can impact train safety and depot capacity utilization (Lin et al.[3]). To address this, mileage-based flexibility has been proposed as a strategy to balance maintenance efficiency and operational reliability:

- Early maintenance leads to the loss of usable accumulated mileage and unnecessary resource utilization.
- Delayed maintenance exceeds depot capacity limits and increases operational risks (Lin et al.[2]).
- Depot congestion occurs when multiple trainsets undergo maintenance simultaneously, reducing maintenance efficiency.

By defining a tolerance range for accumulated mileage before maintenance (flexibility range), the maintenance workload can be distributed more effectively. This approach helps reduce service disruptions, optimize maintenance re-sources, and lower overall maintenance costs.

1.3 Mixed-Integer Linear Programming (MILP) and Its Application in This Study

Mathematical optimization models have been widely applied in maintenance scheduling to enhance decision-making under various constraints. Mixed-Integer Linear Programming (MILP) is particularly suitable for complex maintenance scheduling problems, as it allows for the representation of both integer variables (e.g., train assignments) and continuous variables (e.g., allowable accumulated mileage).

While many studies have utilized 0-1 Integer Linear Programming (0-1 ILP) due to its binary nature for maintenance decisions (Lin et al.[2]), this study adopts MILP to provide a more flexible decision structure by incorporating both discrete and continuous constraints. The key advantages of using MILP in this study include:

- Depot capacity constraints
- Ensuring that maintenance workloads do not exceed facility limits.
- Accumulated mileage flexibility
- Allowing mileage-based adjustments to optimize maintenance timing.
- Train availability constraints

Maintaining sufficient trainsets for daily operation while scheduling maintenance efficiently.

Wang[4] utilized MILP to optimize workforce allocation in packet maintenance scheduling by considering crew skill compatibility, work shifts, and minimizing overtime costs. In contrast, this study extends the MILP approach to high-level heavy maintenance scheduling, focusing on optimizing depot capacity utilization and accumulated mileage allocation to improve long-term operational efficiency.

1.4 Related Research

Several studies have explored different optimization approaches to improve railway maintenance planning:

Wu et al.[5] optimized high-speed train maintenance scheduling to minimize operational disruptions during peak seasons while considering depot resource constraints.

Lin et al. [3] introduced accumulated mileage flexibility, reducing unused mileage by over 50% and improving depot resource utilization.

Lin et al.[2] applied an iterative algorithm with 0-1 ILP to refine maintenance schedules, ensuring all trainsets fully utilize their mileage before entering maintenance.

Wang[4] employed MILP to optimize crew scheduling for packet maintenance, balancing workforce allocation and reducing labor inefficiencies.

These studies collectively demonstrate the significance of optimization in railway maintenance scheduling. However, existing models often focus on either workforce management (Wang[4]) or mileage-based scheduling (Lin et al.[2]). This study integrates both aspects, introducing a holistic optimization framework that considers depot capacity, accumulated mileage flexibility, and long-term operational impacts.

1.5 Key Contributions of This Study

While prior research has examined maintenance scheduling and resource allocation, this study presents unique contributions, including:

1) Integrating depot capacity constraints with accumulated mileage flexibility

Optimizing maintenance scheduling to reduce operational bottlenecks.

2) Parameter analysis on flexibility range and depot capacity (C = 1, 2, 3; flexibility range = 5%, 10%, 15%)

Identifying optimal scheduling strategies based on different scenarios.

3) Long-term impact assessment through a two-year simulation (December 2023 - December 2025)

Evaluating how different scheduling strategies affect train operations over extended periods.

1.6 Summary of Related Research

Table 1 presents a summary of relevant studies and their approaches. It shows the evolution of maintenance planning techniques and highlights how this study builds upon previous work by integrating depot capacity constraints, mileage flexibility, and long-term operational considerations.

Table 1 Summary of Relevant studies and Approaches

Author	Mnt. Type	Optmz. Method	Key Focus	Notes
Wu et al.[5]	PM Heavy	ILP	Depot Congest Minim.	Focus on peak seasons
Lin et al.[3]	PM (flex)	ILP	Accumulate Mileage Efficiency	Introduced flexibility range
Lin et al.[2]	PM (flex)	Iterative 0-1 ILP	Full Mileage Utilization	5-round simulation
Wang [4]	PM Packet	MILP	Workforce Allocation	Crew skill compati-bility
This study	PM Heavy	MILP	depot capacity mileage flexibility	depot capacity mileage flexibility

For example, Lin et al. [2] validated their scheduling model through iterative simulations, adjusting train assignments until no trainset exceeded mileage thresholds. Similarly, Wu et al. [5] employed simulation to test scheduling strategies during peak seasons under depot capacity constraints.

This research aims to develop a comprehensive high-level maintenance planning model that enhances schedule flexibility, reduces unused accumulated mileage, and optimizes depot resource utilization. The proposed framework is expected to contribute to more sustainable railway operations and cost-effective asset management.

2. Materials and Methods

2.1 Materials and Equipment

2.1.1 Microsoft Office software for report preparation

Microsoft Office software, including Word and Excel, was used for preparing and organizing the final research report. Data analysis and visualization were also performed using Excel to interpret and present findings in a comprehensible manner.

2.1.2 Python Programming with PuLP Library for MILP Model Development

Python version 3.12.4, used via Anaconda Navigator, was employed to develop the Mixed-Integer Linear Programming (MILP) model using the PuLP library. This environment facilitated model formulation, data processing, and optimization execution efficiently.

2.2 Methods

2.2.1 Data Collection and Preparation

This study primarily relies on simulated data due to the unavailability of actual operational data from the Pink Line MRT, which is protected under commercial confidentiality agreements. To ensure realistic modeling, assumptions were developed based on:

- Publicly available data on train operation patterns
- Standard maintenance practices published by industry sources
- Expert interviews with maintenance personnel at the actual operating site

The interviews revealed that trainsets are frequently scheduled for maintenance prior to reaching the accumulated mileage threshold (120,000 km) in order to comply with warranty and service agreements. As a result, a significant portion of usable mileage is lost before maintenance, highlighting inefficiencies in current scheduling practices.

Given these constraints, the simulation was calibrated to reflect operational realities as closely as possible. This allowed the model to evaluate the potential benefits of flexible maintenance scheduling and its impact on mileage utilization, maintenance frequency, and depot resource allocation.

The data used in this study is based on assumptions derived from standard calculation models, general railway operation data, and interviews with industry personnel. Since actual operational data is commercially confidential, simulated data was used to replicate realistic conditions.

The following data parameters were considered:

Simulated train schedule data:

- Distance per trip: 69 kilometers (round trip)
- Minimum headway: 5 minutes during peak hours
- Travel time per round trip: 140 minutes
- Calculation of the required number of trainsets:

The total number of trainsets was calculated using the following Eq. (1):

$$N_{TU} = \frac{T}{h_{min}} \quad (1)$$

Where:

N_{TU} = Number of required trainsets (trainsets per cycle)

T = Total travel time per round trip (minutes)

h_{min} = Minimum headway (minutes per train)

Based on Eq. (1), the required number of trainsets is N_{TU} = 140 / 5 = 28 trainsets per cycle.

Additional parameters for operations:

- Travel time from depot to the origin station: approximately 4.8 minutes
- Travel speed: 20 kilometers per hour

The distance from the depot to the origin station was calculated based on practitioner interviews, which indicated that travel time is less than 5 minutes at a constant speed of 20 km/h. Since the exact layout and infrastructure data were not publicly available due to commercial confidentiality, a practical assumption was made using 4.8 minutes (i.e., 4 minutes 48 seconds), as Eq. (2):

$$T_d = \frac{L}{v_d} \quad (2)$$

Substituting the known values: 4.8 / 60 = L / 20→L = 1.6 km (per direction)

Where:

L = Distance per trip (kilometers)
v_d = Speed for travel from the depot to the origin station (km/h)
T_d = Travel time from depot per trip (minutes)

Thus, the depot distance is approximated as 1.6 kilometers per direction or 3.2 kilometers for a round trip and was used consistently throughout the simulation.

2.2.2 Train Operation Parameters

In addition to the primary maintenance scheduling considerations, several operational parameters were incorporated to further optimize the train operation planning. These factors play a crucial role in determining the efficiency and feasibility of the overall system while considering passenger demand, travel patterns, and time-of-day variations.

- Total Number of Trips Per Day:

The daily trip frequency was designed to accommodate both peak and non-peak hours, adjusting for varying demand patterns throughout the day and week. The operation is split into weekdays and weekends to reflect different traffic conditions (source: www.ebm.co.th/, October 2024).

1) Weekdays:
    - Peak Hours (06:30–08:30, 16:30–19:30): 5-minute intervals, resulting in 60 trips per direction during a 5-hour period.
    - Non-Peak Hours (06:00 - 06:30, 08:30 - 16:30, 19:30 - 24:00): 10-minute intervals, providing 78 trips per direction over 13 hours.
    - Total for Weekdays: 138 trips per direction.
2) Weekends and Holidays:
    - All-day Service (06:00 - 24:00): 10-minute intervals throughout the day, resulting in 108 trips per direction each day.

The operational setup was designed to maximize efficiency while ensuring that maintenance schedules did not interfere with the required trip frequencies. By balancing peak and off-peak hours and adjusting for weekends and holidays, the system maintained reliable service aligned with available resources and maintenance windows.

2.2.3 Simulated maintenance data:

- Accumulated mileage threshold for scheduled maintenance: 120,000 kilometers (as shown in **Table 2**)
- Average maintenance duration: 5 days per cycle, comprising:
    - 1 day for pre-maintenance preparation
    - 2 days for heavy maintenance (M1)
    - 1 day for light maintenance
    - 1 day for post-maintenance readiness testing
- Depot maintenance capacity:
    - 2 tracks currently in use
    - 1 additional track reserved for emergency maintenance

Table 2 Levels of Heavy Maintenance

Maintenance Level	Maintenance Threshold (km)
M1	120,000
M2	150,000

Source: Mass Rapid Transit Authority of Thailand (MRTA)

A literature review indicates that rail maintenance frameworks typically allow a 10% flexibility margin in accumulated mileage before maintenance (Giacco et al.[6]) . This flexibility was applied as a key parameter in model development.

This value reflects commonly accepted thresholds in both European and Asian railway systems, offering a balance between efficient mileage usage and safety compliance. The 10% range has also been validated in other studies (e.g., Lin et al.[2]) and was therefore chosen as the baseline for comparison against narrower (5%) and broader (15%) flexibility ranges.

2.2.4 Scenario Simulation

This study evaluates two maintenance planning models to assess operational efficiency and optimize resource utilization:

1) Non-Flexible Maintenance Model (Fixed Model)
    - This model represents the traditional maintenance approach currently used in railway operations. Trainsets are sent for maintenance immediately upon reaching the 120,000 km threshold, with no flexibility to adjust the maintenance schedule. While this approach ensures that trains are maintained before exceeding the mileage limit, it often results in unused accumulated mileage being discarded, leading to suboptimal resource utilization.
    - This model serves as the baseline for comparison in this study, representing the conventional approach to heavy maintenance planning without optimization techniques.
2) Flexible Maintenance Model:
    - This model introduces a new approach that allows trainsets to adjust the accumulated mileage within a ±10% range (108,000–132,000 km) before scheduling maintenance. By offering flexibility, this model aims to minimize unused mileage, reduce operational disruptions, and enhance overall system efficiency, making it a significant improvement over the Fixed Model.
    - The flexible model integrates optimization techniques using Mixed-Integer Linear Programming (MILP), allowing for dynamic adjustments based on operational constraints and available resources.

2.2.5 Model Development and Data Analysis

The MILP model was developed using Python with the PuLP library, focusing on minimizing unused accumulated mileage before maintenance while ensuring operational efficiency.

The data analysis compared the two models—non-flexible and flexible —in terms of:

- Maintenance frequency
- Operational downtime
- Overall system efficiency

To validate the proposed method, the study conducted a comparative analysis between the traditional fixed model and the optimized flexible model, highlighting improvements in mileage utilization and maintenance scheduling efficiency.

The results from the scenario simulation provided insights into the potential benefits of flexible maintenance scheduling for optimizing train operations. Furthermore, a sensitivity analysis was performed to assess the impact of key parameters such as depot capacity and repair duration, further validating the robustness of the proposed model.

Additionally, the simulation was repeated ten times to confirm the stability of the results, where the observed variance in remaining mileage was minimal. This repetition aligns with practices in related studies (e.g., Lin et al.[2]), which employed five simulation rounds to validate model convergence. Although real operational data could not be accessed, using the fixed model as a baseline allowed for reliable comparative validation of the proposed approach.

The model was solved using the PuLP library in Python, which utilizes commercial and open-source solvers (such as CBC). Given the MILP formulation and the problem scale (28 trainsets over a 760-day horizon), the solver was able to obtain the optimal solution for each scenario. Solver logs confirmed global optimality with zero integrality gap at the final node.

The simulation was executed 11 times (10 repeated trials plus one baseline run), with a total computation time of approximately 3 minutes. This corresponds to an average of 16–20 seconds per run on a standard workstation (Intel Core i5 processor, 16 GB RAM). This solving time demonstrates that the model is computationally efficient and practical for real-time or periodic rescheduling in railway operations.

2.3 Mathematical Model

The mathematical model in this study is designed to minimize unused accumulated mileage before maintenance, ensuring maximum utilization of train mileage. A smaller amount of unused mileage indicates higher operational efficiency, as trainsets are used closer to their full potential before undergoing maintenance. This objective is critical in demonstrating the improvement provided by the Flexible Model over the Fixed Model.

The proposed MILP-based framework ensures that the maintenance schedule is optimized by considering depot capacity, operational requirements, and mileage thresholds. Unlike traditional heuristic-based approaches commonly used in previous studies, which provide near-optimal solutions within a limited timeframe, this MILP model guarantees an exact optimal solution under complex constraints. This approach not only enhances operational efficiency but also offers a reliable and systematic method for maintenance scheduling, contributing to more effective resource utilization and long-term planning in railway operations.

Indices:

m : Index for trainsets where $m \in M$

t : Index for time (days) where $t \in T$

τ : Auxiliary index for summation over planning days, used in cumulative mileage calculations, where $\tau \in T$

Sets:

M = $\{1, 2, ..., R\}$: Set of trainsets, where R represents the number of trainsets required for daily operation

T = $\{1, 2, ..., H\}$: Set of planning days, where H represents the planning time horizon

$\mathcal{T}_{wd}$ = {set of planning days that fall on weekdays}

$\mathcal{T}_{we}$ = {set of planning days that fall on weekends}

Decision Variables:

$x_{m,t} \in \{0,1\}$: 1 if trainset m starts maintenance on day t, 0 otherwise.

$z_{m,t} \in \{0,1\}$: 1 if trainset m operates on day t, 0 otherwise.

$n_{m,t} \geq 0$: Number of trips for trainset m on day t

$y_{m,t} \geq 0$: Accumulated mileage of trainset m on day t (km)

Parameters:

d = 69 Distance per trip (km)

d_{depot} = 1.6 Distance between depot and main station (km)

d_{base} = 120,000 Maximum accumulated mileage before maintenance (km)

d_{lower} = 108,000 Minimum flexible accumulated mileage (km)

d_{upper} = 132,000 Maximum flexible accumulated mileage (km)

$T_{weekday}$ = 138 Total trips per system on weekdays

$T_{weekend}$ = 108 Total trips per system on weekends

k = 5: Number of consecutive days required to complete heavy maintenance

C = 2: Depot capacity (trains per day)

R = 28: Number of trains required for daily operations

Objective Function:

The objective of this model is to minimize the unused accumulated mileage before maintenance. This approach ensures efficient utilization of the trainsets' mileage, as formulated in Eq. (3)

$$Min \sum_{m \in M} \sum_{t \in T} (d_{base} - \sum_{\tau=1}^{t} y_{m,\tau}) \cdot x_{m,t} \quad (3)$$

The equation prioritizes scheduling maintenance for trainsets closer to their mileage threshold, reducing the cumulative unused distance before maintenance.

Constraints:

The following constraints ensure realistic and feasible maintenance and operational planning:

1) Operation or Maintenance Selection

Each trainset can either operate or undergo maintenance on any given day, but not both simultaneously, as formulated in Eq. (4)

$$x_{m,t} + z_{m,t} \leq 1, \forall m \in M, t \in T \quad (4)$$

2) Depot Capacity Constraint

The number of trainsets undergoing maintenance must not exceed the depot's daily capacity in Eq. (5)

$$\sum_{m \in M} x_{m,t} \leq C, \ \forall t \in T \quad (5)$$

3) Continuous Maintenance Constraint

Once a trainset begins maintenance, it must remain in maintenance for consecutive days, represented by Eq. (6)

$$\sum_{\tau=t}^{t+k-1} x_{m,\tau} \geq k \cdot x_{m,t}, \ \forall m \in M, t \in T \quad (6)$$

4) Daily Accumulated Mileage Calculation

The accumulated mileage for each trainset on a given day is calculated based on the number of trips and the distance between the depot and the main station, as shown in Eq. (7)

$$y_{m,t} = (n_{m,t} \times d + 2d_{depot}) \times z_{m,t}, \ \forall m \in M, t \in T \quad (7)$$

5) Daily Trip Requirement Constraint

The total number of trips from all trainsets must meet the daily service requirement, as defined in Eqs. (8)–(9)

- Weekday operation:

$$\sum_{m \in M} n_{m,t} = T_{weekday}, \ \forall t \in T_{weekday} \quad (8)$$

- Weekend operation:

$$\sum_{m \in M} n_{m,t} = T_{weekend}, \ \forall t \in T_{weekend} \quad (9)$$

6) Minimum Number of Operating Trainsets

A minimum of trainsets must operate each day, as constrained by Eq. (10)

$$\sum_{m \in M} z_{m,t} = R, \ \forall t \in T \quad (10)$$

7) Accumulated Mileage Constraints

Model I (Fixed Model): This is the traditional maintenance model where maintenance is triggered strictly at the 120,000 km threshold. While reliable, it lacks the flexibility to adjust to operational demands, often leading to unused mileage being discarded, as formulated in Eq. (11)

$$\sum_{\tau=1}^{t} y_{m,\tau} \leq d_{base}, \ \forall m \in M, \forall t \in T \quad (11)$$

Model II (Flexible Model): This enhanced model introduces a ±10% flexibility range for accumulated mileage (108,000–132,000 km). By allowing adjustments, it reduces unused mileage and improves resource allocation, addressing the limitations of the Fixed Model, as defined in Eq. (12)

$$d_{lower} \leq \sum_{\tau=1}^{t} y_{m,\tau} \leq d_{upper}, \ \forall m \in M, t \in T \quad (12)$$

2.4 Experimental Setup

The experimental setup was designed to simulate train operations and maintenance activities over a two-year period (December 2023 - December 2025). The simulation involved 42 trainsets with operations starting from December 1, 2023, under the following conditions:

1) Daily Train Operations

Each day, 28 trainsets were deployed to meet daily passenger demand. The remaining trainsets were either undergoing maintenance or were reserved as backups to maintain service reliability.

2) Operational Schedule

- Weekdays: 138 trips per direction
- Weekends & Holidays: 108 trips per direction

3) Maintenance Models

The study compared two maintenance scheduling models:

Model I (Non-Flexible Maintenance Model): Maintenance is scheduled strictly when a trainset reaches 120,000 km of accumulated mileage.

Model II (Flexible Maintenance Model): Maintenance is scheduled when a trainset's mileage falls within a ±10% flexibility range (i.e., between 108,000 km and 132,000 km).

4) Simulation Assumptions

- All trains start with 0 km of accumulated mileage on December 1, 2023.
- Maintenance lasts 5 consecutive days per trainset.
- Maintenance is performed at a depot with 2 available tracks, each accommodating 1 trainset per day.

5) Implementation Tools

The model was implemented in Python 3.12.4 using the PuLP library to solve the MILP optimization problem. Data input and result analysis were managed using Pandas and Matplotlib libraries for better visualization and interpretation.

6) Data Source and Integrity

The dataset used in this study is simulated for research purposes and does not represent actual operational data from the Pink Line Monorail. Simulated data ensures repeatability and allows for controlled scenario testing without compromising commercially sensitive information

The simulation process was implemented using Python and Mixed-Integer Linear Programming (MILP) to optimize maintenance scheduling while considering constraints such as depot capacity and maintenance flexibility levels. The execution of the Python code for train operation and maintenance planning is illustrated in **Figure 1**.

```python
model = pulp.LpProblem("Maintenance_Scheduling", pulp.LpMinimize)

days_horizon = 14
days = range(days_horizon)
trains = trains_needing_maintenance

x = pulp.LpVariable.dicts("maintenance",
                          ((t,d) for t in trains for d in days),
                          cat='Binary')

daily_distance = self.distance * (self.round_schedules[current_date.year][DayType.WEEKDAY] / self.daily_active_trains)

# Objective Function
model += pulp.lpSum((120000 - (self.cumulative_distance[t] + d * daily_distance)) * x[t,d]
                    for t in trains for d in days)

# Depot Capacity Constraint
for d in days:
    model += pulp.lpSum(x[t,k]
                        for t in trains
                        for k in range(max(0, d-4), d+1)) <= 2

# Operation or Maintenance
for t in trains:
    model += pulp.lpSum(x[t,d] for d in days) == 1

# Model I: Each trainset must not exceed 120,000 km before maintenance
for t in trains:
    for d in days:
        estimated_distance = self.cumulative_distance[t] + (d * daily_distance)
```

Figure 1 Python Code Execution for Train Operation and Maintenance Planning

Clarification of Variable Mapping between the Mathematical Model and Python Implementation

To ensure transparency and consistency, the following **Table 3** illustrates how the variables in the mathematical formulation correspond to the actual Python implementation used in this study:

Table 3 Correspondence between Mathematical Notation and Python Code Implementation

Math. Notation	Python Variable Syntax	Description
$x_{m,t}$	x[t,d]	Binary decision variable: 1 if train t enters maintenance on day d, 0 otherwise
$y_{m,t}$	estimated_ distance	Estimated cumulative mileage for train t on day d.
C (Depot capacity)	<= 2 (in constraint)	Maximize number of trains allowed in maintenance per day
Objective Function	lpSum((120000 - ...) * x[t,d])	Min. discarded mileage (maximize mileage utilization before maintenance).

Note: In the code, t refers to the trainset index, and d refers to the number of days from the current date. This index scheme differs from the mathematical notation $x_{m,t}$, but the logic and constraints remain functionally equivalent.

Figure 1 presents the implementation of the MILP model in Python, highlighting key components including the objective function, operational and maintenance constraints, and the use of cumulative mileage to ensure compliance with maintenance thresholds. This demonstrates how the mathematical model is translated into code to support systematic decision-making in scheduling.

Figure 2 presents a sample summary of the train operation and maintenance schedule generated from the model. This summary provides an overview of daily operations, maintenance activities, and accumulated mileage for each trainset across the two-year simulation period.

Summary of Train Operation and Maintenance

Apr-25

Train No.	Total Trips (km)	Distance (km)	Accumulated Mileage (km)	Remaining Mileage (km)	Maintenance Cycle	Maintenance Date
1	88	6,129.60	110,316.40	9,683.60		
2	84	5,847.20	116,526.40	3,473.60		
3	82	5,709.20	114,594.40	5,405.60		
4	114	7,942.80	114,318.40	5,681.60		
5	98	6,822.80	115,560.40	4,439.60		
6	58	4,043.60	119,976.40	23.6	1	2025-04-16-2025-04-20 (5Days)
6	42	2,926.80	2,901.20	117,098.80		
7	108	7,522.40	119,976.40	23.6		
8	88	6,129.60	119,976.40	23.6		
9	96	6,684.80	118,458.40	1,541.60		
10	98	6,829.20	117,630.40	2,369.60		
11	116	8,074.40	118,320.40	1,679.60		
12	118	8,212.40	114,732.40	5,267.60		
13	114	7,936.40	119,976.40	23.6		
14	90	6,270.80	119,976.40	23.6	1	2025-04-26-2025-04-30 (5Days)
14	0	0	0	120,000.00		
15	102	7,102.00	119,976.40	23.6		

Figure 2 Example of Summary of Train Operation and Maintenance

Figure 2 provides a snapshot of how each trainset's operational status, maintenance timing, and accumulated mileage were tracked throughout the simulation. This allows the model to assess when maintenance should occur and how closely the trains approach the upper or lower mileage thresholds under different scenarios.

3. Results and Analysis

3.1 Analysis of Optimization Results

The study compares two maintenance scheduling models for rail fleet management:

1) Fixed Model: Maintenance is scheduled strictly upon reaching the accumulated mileage threshold of 120,000 km.
2) Flexible Model: Maintenance can be deferred within a ±10% flexibility range, enabling scheduling between 108,000 km and 132,000 km.

Table 4 summarizes the remaining mileage before maintenance under the Fixed Model, while **Table 5** presents the distribution in the Flexible Model, highlighting the variability enabled by the flexible scheduling strategy. **Table 6** then compares the overall performance metrics between the two models, illustrating the effects of introducing flexibility in the maintenance scheduling process. The results align with previous studies by Lin et al.[2] and Wang[4], which demonstrated that scheduling flexibility could improve resource utilization and reduce operational disruptions.

3.1.1 Fixed Model

In the fixed model, maintenance is conducted immediately when the threshold of 120,000 km is reached. The following observations were made from 10 repeated simulations:

- The average remaining mileage before maintenance: 872.8 km, calculated by averaging the overall remaining mileage from each simulation run (i.e., the average remaining mileage across 42 trainsets per run, repeated 10 times).
- The minimum and maximum remaining mileage per trainset ranged between 17.2 km and 23.6 km, reflecting slight variability due to the fixed schedule that cannot adapt to real-time operational needs.
- The standard deviation (SD = 4.5 km) was computed from the 10 average values obtained from each run, indicating high consistency across repeated simulations despite the lack of flexibility in the fixed model.

Figure 3 further illustrates the variation in remaining mileage from repeated experiments, with recorded values ranging between 866.4 km and 879.2 km. This demonstrates that under the fixed model, trains generally undergo maintenance with only slight deviations from the 872.8 km average, reinforcing the model's predictability.

This finding aligns with Lin et al. [2], who noted that fixed maintenance scheduling results in trains being operated until the threshold is reached, with limited opportunities to optimize remaining mileage.

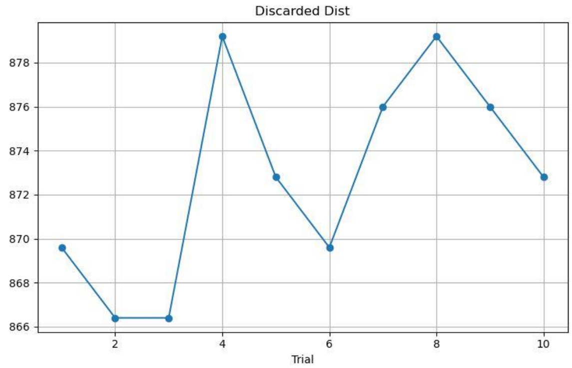

Figure 3 Graph Showing Results from Repeated Experiments of the Fixed Model

Figure 3 illustrates the discarded mileage values across ten trials under the fixed model. The narrow range, from approximately 866 km to 879 km, highlights the model's consistent scheduling behavior and limited adaptability, as maintenance timing follows fixed thresholds without opportunity for optimization.

To clarify, the 10 simulations were conducted using identical parameter settings and model structure. No variables were altered between runs. The purpose was to verify the model's robustness and consistency. Each run reached a global optimal solution, as confirmed by solver logs with zero integrality gap. The variation in outcomes was due solely to randomized initial train assignment sequences in the Python code, not differences in input conditions.

The distribution of remaining mileage before maintenance is summarized in **Table 4**.

Table 4 Remaining Mileage per Train—Fixed Model

Remaining Mileage (km)	Number of Trains (Fixed)
23.6	12
20.4	26
17.2	4
Total	42

Table 4 details the number of trains falling into each remaining mileage range before maintenance. It shows that a majority of trains enter maintenance with only a small remaining distance left, reinforcing the fixed model's lack of flexibility.

As shown in **Table 4**, 12 trains had 23.6 km remaining before maintenance, 26 trains had 20.4 km, and 4 trains had 17.2 km remaining. This distribution highlights the variability in the remaining mileage before maintenance, as some trains undergo maintenance with very little remaining mileage, while others can operate for a slightly longer distance before maintenance is required.

3.1.2 Flexible Model

The Flexible Model demonstrated significant improvements over the fixed Model:

- Average remaining mileage before maintenance was reduced to 384.3 km, a decrease of 55.97%, demonstrating that flexibility allows for more efficient use of train capacity before maintenance is required.
- The total mileage utilized increased by 504,488.5 km (+10%) compared to the Fixed model, demonstrating the efficiency gained from introducing scheduling flexibility. This increase accounts for the additional mileage accumulated before reaching the maintenance threshold.
- The minimum and maximum remaining mileage were observed at 4.8 km to 14.4 km, respectively. This range indicates that some trains are maintained when their remaining mileage is close to the model's lower bound, while others can operate until nearing the upper limit.
- The standard deviation (SD = 3.9 km) was calculated from the 10 average values of remaining mileage across repeated experiments, indicating a more uniform distribution of maintenance events compared to the Fixed Model, highlighting the effectiveness of the flexible scheduling strategy in reducing variability and maximizing resource utilization.

For example, the 10 average values of remaining mileage across runs ranged between 377.6 km and 387.2 km, with a mean of 384.3 km. This highlights the improved control over scheduling under the flexible model, ensuring that maintenance is performed efficiently while optimizing accumulated mileage usage as shown in **Figure 4**.

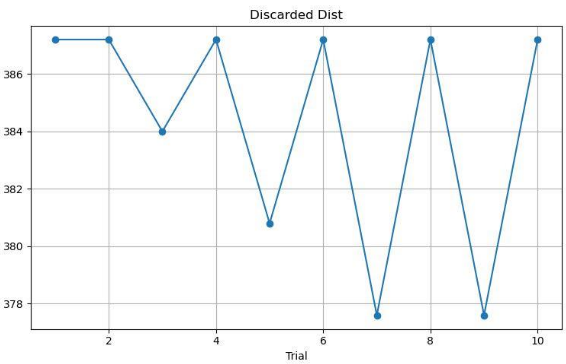

Figure 4 Graph Showing Results from Repeated Experiments of the Flexible Model

Figure 4 illustrates the variation in discarded mileage across ten simulation trials under the flexible model. The observed values range from 378.0 km to 386.4 km, indicating that while the model provides scheduling flexibility, it maintains consistent performance in optimizing mileage utilization across different scenarios.

The remaining mileage distribution under the flexible model is presented in **Table 5**.

Table 5 Remaining Mileage per Train—Flexible Model

Remaining Mileage (km)	Number of Trains (Flex)
14.4	1
11.2	19
8	20
4.8	2
Total	42

Table 5 presents the distribution of remaining mileage values across all trainsets. The diversity in values reflects the flexible model's ability to adjust maintenance timing dynamically, depending on how close a train is to its upper or lower mileage threshold.

As shown in **Table 5**, the distribution of remaining mileage in the Flexible Model is more spread out. One train has 14.4 km remaining, 19 trains have 11.2 km, 20 trains have 8 km, and 2 trains have 4.8 km remaining. This range indicates that some trains are scheduled for maintenance when their remaining mileage is very close to the minimum allowable, while others are scheduled for maintenance closer to the maximum allowable mileage.

The findings from both models are summarized in **Table 6** below, illustrating the effects of introducing flexibility in the maintenance scheduling process. The results align with previous studies by Lin et al.[2] and Wang [4], which demonstrated that scheduling flexibility could improve resource utilization and reduce operational disruptions.

Table 6 Overall Comparison of Maintenance Models

Accumulated Mileage (km)	Fixed Model	Flexible Model
Minimum Remaining per Train	17.2	4.8
Maximum Remaining per Train	23.6	14.4
Average Remaining	872.8	384.3
Total Mileage Utilized	5,039,127.2	5,543,615.7
Standard Deviation	4.5	3.9

Table 6 provides a direct comparison between the fixed and flexible maintenance models. It clearly shows that the flexible model significantly outperforms the fixed one in terms of reducing unused remaining mileage and increasing accumulated mileage utilization. Moreover, the reduced standard deviation in the flexible model suggests more uniform and efficient maintenance scheduling, minimizing idle resources and operational inefficiencies.

The 55.97% reduction in remaining mileage supports the findings from Lin et al.[3], who showed that a flexible approach to maintenance scheduling allows for longer operations before maintenance, thus optimizing the fleet's capacity.

3.1.3 Practical Implications

The introduction of a flexible maintenance model yielded notable practical advantages:

- The increase in utilized mileage (+ 504,488.5 km) allowed for an additional 7,311 round trips, equivalent to 8 weeks of additional operation without the need to increase fleet size. This efficiency directly contributes to cost savings and maximized utilization of existing resources. The increase in mileage can be broken down as follows:
- Round trip distance (round trip): 69 km
- Additional round trips: 504,488.5 km / 69 km ≈ 7,311 round trips
- Additional operation time:
- Weekdays: 690 round trips per week
- Weekends: 216 round trips per week
- Total weekly trips: 906 round trips
- Number of additional weeks: 7,311 / 906 ≈ 8 weeks
- The flexible model reduced simultaneous maintenance events, thus improving the distribution of maintenance workload across the depot. This not only optimized operational efficiency but also helped in better utilization of the depot's limited space and workforce.

These practical benefits are consistent with Wang[4], who found that optimizing scheduling can help balance workforce allocation, reduce inefficiencies, and ensure smooth operations.

Summary of Findings

The introduction of a flexible maintenance model brought significant practical advantages. The model increased the utilized mileage by 504,488.5 km, which allowed for an additional 7,311 round trips, equivalent to 8 weeks of extra operation without expanding the fleet. This efficiency directly contributes to cost savings by maximizing the use of existing resources. Additionally, the flexible maintenance approach reduced simultaneous maintenance events, optimizing the maintenance workload distribution across the depot, improving operational efficiency, and better utilizing depot space and workforce. These findings align with the study by Wang[4], which emphasized the benefits of optimizing maintenance schedules to balance workforce allocation, reduce inefficiencies, and enhance overall operational performance.

3.2 Maintenance Scheduling Analysis

3.2.1 Fixed Model

The maintenance scheduling under the fixed model demonstrated significant congestion in the depot:

- The first train's maintenance occurred on April 16, 2025 (Day 502) as depicted in **Figures 5–6**.

Key Observations:

- Several trains were scheduled for maintenance concurrently, leading to resource constraints in the depot.
- The high workload congestion necessitated efficient resource management to ensure minimal disruption during maintenance.

Lin et al.[2] observed similar congestion in their study, where the inability to adjust maintenance timing caused operational bottlenecks during peak periods.

Maintenance Notification and Repair History

Date: 2025-04-16
Number of Maintenance: 1 Train

Train No. 6 enters maintenance
Accumulated Mileage: 119,976.4 km.
Remaining Mileage: 23.6 km.

Date: 2025-04-21
Number of Maintenance: 2 Train

Train No. 19 enters maintenance
Accumulated Mileage: 119,976.4 km.
Remaining Mileage: 23.6 km.
Train No. 41 enters maintenance
Accumulated Mileage 119,976.4 km.
Remaining Mileage: 23.6 km.

Date: 2025-04-26
Number of Maintenance: 2 Train

Train No. 14 enters maintenance
Accumulated Mileage: 119,976.4 km.
Remaining Mileage: 23.6 km.
Train No. 25 enters maintenance
Accumulated Mileage: 119,976.4 km.
Remaining Mileage: 23.6 km.

Figure 5 Example of Maintenance Requests — Fixed Model

Figure 5 shows how the maintenance request was triggered based strictly on the fixed threshold.

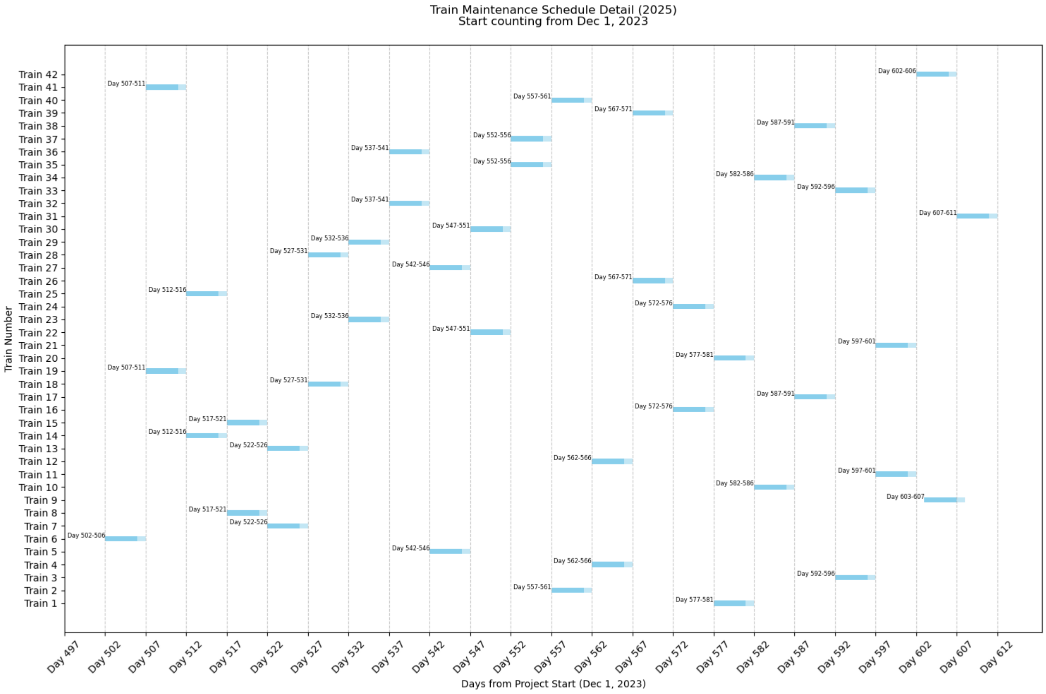

Figure 6 Maintenance schedule for all 42 trainsets under the Fixed Model.

Figures 6 show the maintenance schedule for all 42 trainsets under the Fixed Model. The schedule reveals limited flexibility in distributing maintenance tasks, leading to multiple overlapping repairs (up to two trainsets on the same day) during several periods, which may affect depot capacity utilization.

3.2.2 Flexible Model

In contrast, the flexible model allowed for the deferral of maintenance events:

- The first train's maintenance was delayed until May 30, 2025 (Day 546), a delay of 44 days compared to the fixed model. This is illustrated in **Figures 7–8**.

Key Observations:

- The deferral resulted in reduced simultaneous maintenance occurrences, improving overall scheduling efficiency.
- A more even workload distribution was achieved, thus optimizing depot resource allocation, with less strain on the maintenance personnel and equipment.

This improvement aligns with the work of Wu et al.[5], who noted that flexibility in scheduling helped reduce congestion and improve depot utilization during peak maintenance times.

Maintenance Notification and Repair History

Date: 2025-05-30
Number of Maintenance: 1 Train

Train No. 10 enters maintenance
Accumulated Mileage: 131,985.6 km.
Remaining Mileage: 14.4 km.

Date: 2025-06-03
Number of Maintenance: 1 Train

Train No. 31 enters maintenance
Accumulated Mileage: 131,988.8 km.
Remaining Mileage: 11.2 km.

Date: 2025-06-11
Number of Maintenance: 1 Train

Train No. 19 enters maintenance
Accumulated Mileage: 131,988.8 km.
Remaining Mileage: 11.2 km.

Figure 7 Example of Maintenance Requests — Flexible Model

Figure 7 presents the flexibility in triggering maintenance requests when trains reach anywhere between 108,000 and 132,000 km.

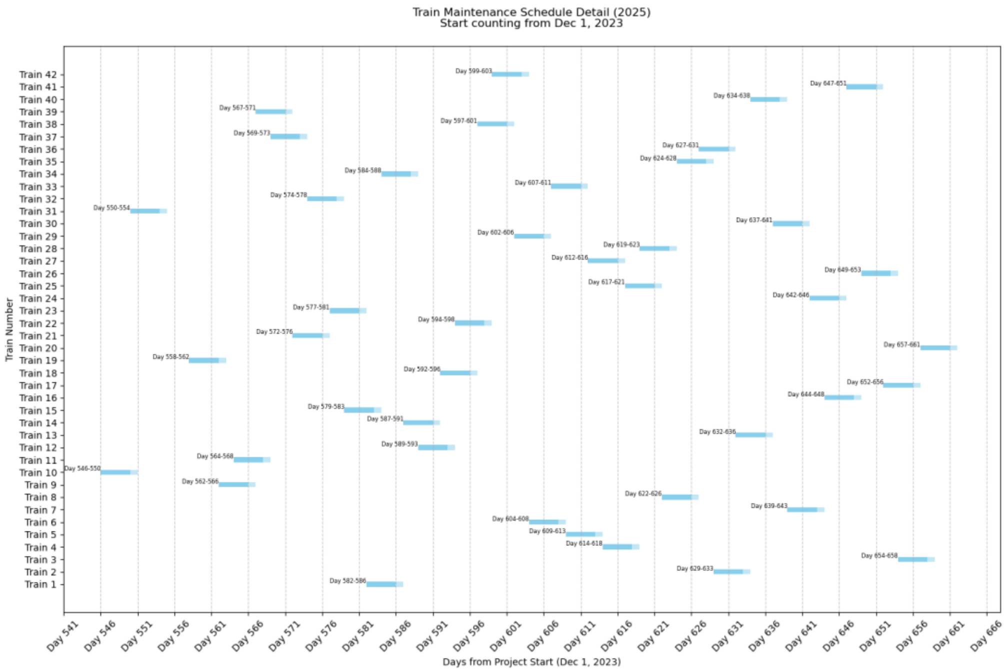

Figure 8 Maintenance schedule for all 42 trainsets under the Flexible Model

Figures 8 present the optimized maintenance schedule under the Flexible Model. The results demonstrate a more balanced allocation of maintenance tasks over time, effectively minimizing peak workloads and improving the overall utilization of maintenance resources.

3.3 Parameter Sensitivity Analysis

The sensitivity analysis in **Table 7** demonstrates how depot capacity and repair duration influence remaining mileage in the flexible maintenance model.

Key observations include:

In this study, sensitivity analysis was conducted on both the flexible model and the fixed model to provide a comprehensive understanding of the impact of key parameters. The flexible model's sensitivity analysis focuses on depot capacity, repair duration, and flexibility range, while the fixed model serves as the baseline for comparison.

3.3.1 Impact of Depot Capacity (C)

The sensitivity analysis reveals that depot capacity plays a crucial role in maintenance scheduling efficiency. In the Fixed Model (Baseline), depot capacity was set at C = 2 with a 5-day repair duration, ensuring that maintenance was scheduled in a controlled manner without excessive congestion or inefficiency. This configuration serves as the reference point for evaluating how different depot capacities impact the Flexible Model's performance.

The results show that adjusting depot capacity (C) in the Flexible Model leads to varying degrees of efficiency changes compared to the Fixed Model:

- C = 1 (1 track): This configuration shows the highest sensitivity to repair duration.

Reducing the repair time to 4 days (Scenario 4) maintains efficiency with only a 0.16% impact but extending it to 6 days (Scenario 6) causes a significant 12.83% increase in remaining mileage.

- This indicates that when depot capacity is too low, maintenance backlog can occur, leading to inefficiencies compared to the Fixed Model's baseline.
- C = 2 (2 tracks - Baseline Configuration):
- This configuration provides the most stable results across different repair durations.
- Scenarios 2 and 3 show minor deviations (1.25% and 0.65%), confirming that the baseline setup (5-day repairs) remains near-optimal under flexible scheduling.
- This suggests that increasing scheduling flexibility does not significantly disrupt the depot's ability to handle maintenance at C = 2.
- C = 3 (3 tracks):
- Increasing depot capacity to C = 3 allows for more simultaneous repairs, but the efficiency improvements are marginal.
- Scenario 7 (4 days) improves efficiency slightly by 0.75%, while Scenario 8 (5 days) offers a minor 0.16% reduction.
- These findings indicate that adding more depot capacity beyond C = 2 does not necessarily lead to proportional efficiency gains, particularly when the existing workload does not exceed the baseline demand.

Key Comparison with Fixed Model (Baseline – C = 2, 5 days)

- The Flexible Model at C = 2 performs similarly to the Fixed Model but allows greater mileage utilization before maintenance due to its flexibility range.

- Reducing C to 1 increases the risk of backlogs, leading to significantly higher remaining mileage in some cases.
- Increasing C to 3 does not yield substantial improvements, suggesting that the depot capacity in the Fixed Model (C = 2) is already well-matched to operational demands.

These findings align with Wu et al.[5], which emphasized that optimal depot capacity utilization is essential for efficient maintenance operations, particularly under high demand. However, this study also highlights that over-investing in depot capacity may not be cost-effective when current operational demands are adequately met.

3.3.2 Impact of Repair Duration:

The repair duration directly influences maintenance throughput and operational efficiency:

- Reducing repair duration to 4 days enhances mileage efficiency across all depot capacities, but it increases resource strain, requiring higher manpower and extended working hours, potentially raising operational costs.
- Extending repair duration to 6 days introduces variability, particularly in lower-capacity depots like C = 1, where it significantly reduces efficiency. This is due to longer maintenance periods per trainset, leading to fewer trainsets available for operation and a higher accumulation of remaining mileage.

This analysis demonstrates that shorter repair durations improve operational turnover but come with higher resource demands. Conversely, longer durations ease daily workload but may reduce overall efficiency, particularly in capacity-constrained environments.

These findings align with prior studies, such as Wu et al.[5], emphasizing that optimal depot capacity utilization is critical for maintaining operational efficiency in high-demand railway environments.

Table 7 Sensitivity Analysis of Depot Capacity and Repair Duration on Remaining Mileage

Scenario	D C (tracks)	R D (days)	R M (km)	impact (%)	SD
1	2	5	384.3	-	3.9
2	2	4	379.5	1.25	4.8
3	2	6	381.8	0.65	4.8
4	1	4	383.7	0.16	6.6
5	1	5	385.0	-0.18	7.9
6	1	6	335.0	12.83	8.6
7	3	4	382.1	0.75	5.8
8	3	5	383.7	0.16	5.2
9	3	6	385.9	-0.42	6.9

D C: Depot Capacity, R D: Repair Duration,
R M: Remaining Mileage

As shown in **Table 7**, when depot capacity is reduced to C = 1, the system becomes more sensitive to changes in repair duration. In Scenario 6 (C = 1, 6-day repair), remaining mileage spikes by 12.83%, indicating bottlenecks and inefficiencies. Conversely, increasing capacity to C = 3 results in marginal improvements; Scenario 7 (C = 3, 4-day repair) shows only a 0.75% improvement. These findings reinforce that C = 2 remains the most balanced and cost-effective option under current workload conditions.

3.3.3 Impact of Flexibility Range

The flexibility in maintenance scheduling is a key factor in optimizing resource utilization and operational efficiency. This analysis compares the effects of different flexibility levels (5%, 10%, and 15%):

- flexibility range = 10% provides the best balance between minimizing unused remaining mileage and maintaining cost efficiency. Compared to the fixed model, it reduces remaining mileage by 55.97% and increases accumulated mileage by 10%, demonstrating clear improvements in resource utilization without overburdening the maintenance schedule.
- flexibility range = 5% reduces operational costs due to fewer accumulated miles, but it results in higher remaining mileage, leading to more frequent maintenance. While this setting is cost-effective, it may disrupt operations due to increased downtime for maintenance activities.
- flexibility range = 15% slightly reduces remaining mileage but significantly increases accumulated mileage, raising operational costs and posing potential safety risks due to extended maintenance intervals. The diminishing returns at this level suggest that increased flexibility beyond 10% may not be practical for long-term operations.

With a 10% flexibility range, the accumulated mileage increased by 504,488.5 km, as shown in **Table 8**. This value represents the additional mileage gained before the maintenance threshold (120,000 km), reinforcing the efficiency improvement observed in the flexible model.

Table 8 illustrates that the 10% flexibility threshold yields the lowest remaining mileage and the highest accumulated mileage utilization. However, the analysis also highlights that further increasing flexibility (15%) leads to diminishing returns, making it less cost-effective and potentially risky.

Clarification on "Impact (km)"

The "Impact (km)" values in **Table 8** represent the reduction in remaining mileage when compared to the baseline Avg. Remaining Mileage (km) for the 10% flexibility threshold. For instance:

- At flexibility range = 5%, the Impact value of -3,144.7 km indicates a significant reduction in remaining mileage compared to the 10% flexibility model, but with increased maintenance frequency.

- At flexibility range = 15%, the Impact value of -2,658.7 km shows that higher flexibility leads to diminishing returns, with marginal reductions in remaining mileage at the cost of higher accumulated mileage and potential operational risks.

Table 8 Sensitivity Analysis Results of the Flexible Model

Flexibility (%)	Average Remaining Mileage (km)	Impact (km)	Increased Accumulated Mileage (km)
10	384.3	-	504,488.5
5	3,529.0	-3,144.7	249,343.8
15	3,043.0	-2,658.7	753,829.8

Table 8 highlights that a 10% flexibility threshold yields the lowest remaining mileage and highest accumulated mileage, proving most efficient. Reducing flexibility to 5% increases remaining mileage and decreases utilization, while increasing it to 15% yields minimal improvements but significantly increases the total accumulated mileage, leading to potential cost and safety concerns. This demonstrates the importance of selecting an optimal flexibility level—10% provides the best balance between cost and operational performance.

These results align with Lin et al.[3], who highlighted that managing flexibility effectively can enhance both cost and operational efficiency. This study expands on their findings by demonstrating that a 10% flexibility range provides the most balanced solution, especially when considering depot capacity and repair duration constraints.

Summary of Sensitivity Analysis:

The results highlight the robustness of the flexible maintenance model in optimizing resource allocation and operational efficiency:

- Depot capacity of C = 2 with a 5-day repair duration offers the most stable and efficient maintenance schedule.
- A 10% flexibility threshold optimizes resource utilization while ensuring balanced maintenance scheduling, making it the most effective configuration.
- Lower flexibility (5%) reduces costs but leads to increased maintenance frequency, potentially causing operational disruptions.
- Higher flexibility (15%) offers only marginal benefits in reducing remaining mileage but significantly increases accumulated mileage and operational costs, making it less practical.

Compared to the traditional Fixed Model, which strictly triggers maintenance at the 120,000 km threshold, the Flexible Model significantly improves mileage utilization while maintaining an efficient maintenance schedule. The ability to adjust accumulated mileage within a ±10% range leads to better fleet management and reduced maintenance congestion.

Validation and Limitations

To validate the proposed methodology, this study conducted scenario-based simulations and sensitivity analyses to compare the Fixed Model and Flexible Model under various operational constraints. The results consistently demonstrate the advantages of introducing flexibility in maintenance scheduling.

However, one limitation of this study is that the simulation scenarios were based on assumed operational conditions. Further studies using real-world operational data could enhance the reliability of these findings and provide additional insights into practical implementation challenges.

4. Discussion and Conclusion

4.1 Comparison of Experimental Results with Related Research

The experimental results demonstrate that increasing the accumulated mileage flexibility by 10% can significantly reduce the remaining mileage by 55.97% and increase the utilized mileage by 10% compared to the Fixed Model. This finding is consistent with Lin et al.[3], which emphasized that mileage flexibility improves depot resource utilization and reduces operational costs.

From an economic perspective, flexible maintenance allows each trainset to maximize its usage before undergoing costly overhauls, thereby improving cost-effectiveness in terms of cost per kilometer. Fewer maintenance events also lead to reduced downtime and better workforce scheduling, which collectively lower the indirect operational costs. In contrast, increasing flexibility to 15% leads to excessive accumulated mileage, which could elevate long-term maintenance costs and safety risks if maintenance is deferred too far — aligning with Wang[4]'s observation on over-deferred scheduling risks.

The simulation was conducted over a two-year period (December 2023 to December 2025) for both models to ensure consistency in comparison. Among the tested configurations, the most recommended condition for maintenance management was a flexible model with 10% mileage flexibility, 5-day repair duration, and a depot capacity of C = 2, which effectively balanced resource allocation and minimized maintenance congestion. Increasing depot capacity beyond C = 2 offered only marginal efficiency gains, while reducing it to C = 1 caused significant congestion and reduced fleet availability.

Although the simulation used operational patterns that mirror the MRT Pink Line's service schedule and maintenance cycles, actual accumulated mileage data was not accessible due to commercial restrictions. Therefore, the simulated data may differ slightly from real-world variations. Nonetheless, the results confirm that optimizing model parameters—especially flexibility level, depot capacity, and repair duration—substantially improves maintenance efficiency. This study reinforces the importance of adopting data-driven approaches to maintenance scheduling for both cost minimization and enhanced operational performance, with further model refinement needed for real-world implementation.

The ±10% flexibility threshold used in this study aligns with actual maintenance practices in European railways. For instance, Giacco et al.[6] presented a maintenance scheduling table for key train components used in Italy, showing a ±10% tolerance as a standard for accumulated mileage before maintenance. Similarly, Lin et al.[2] tested ranges between ±3% and ±10%, demonstrating that operational performance improved within this band. These studies reinforce that a 10% flexibility strikes a practical balance between efficient mileage use and safety compliance. On the other hand, extending the range to ±15% may result in certain components exceeding their safe operational limits, particularly when approaching the upper threshold. This could increase the risk of mechanical failure, service disruption, or reduced warranty coverage. Therefore, the selected flexibility range must consider not only model performance but also practical safety standards and industry regulations.

In conclusion, this study contributes to the advancement of maintenance planning in urban railway systems by proposing a MILP-based flexible scheduling model that reduces unnecessary mileage loss and enhances resource utilization. The findings recommend a 10% mileage flexibility as the most effective condition for optimizing maintenance intervals without compromising operational reliability. By analyzing depot capacity, repair duration, and mileage thresholds through a two-year simulation, the study provides practical guidelines for maintenance managers to achieve a balance between cost-efficiency and service quality. These contributions support the development of more adaptive, data-driven maintenance strategies that can be applied to real-world railway networks with varying resource constraints.

4.2 Recommendations for Practical Applications

The findings from this study provide valuable insights for improving maintenance planning in MRT systems and railway networks. The following key recommendations are proposed:

4.2.1 Use of 10% Mileage Flexibility as a Standard Value

Based on the experimental findings, a 10% mileage flexibility should be adopted as the standard for maintenance scheduling. This setting effectively reduces unused remaining mileage while keeping maintenance costs under control, offering a balanced trade-off between cost efficiency and operational reliability.

4.2.2 Optimizing Depot Capacity Based on Train-set Demand

Optimizing depot capacity based on the number of trainsets in service and expected maintenance frequency is essential to prevent maintenance delays and improve resource allocation.

- If depot capacity is too low (C = 1), maintenance congestion occurs, leading to inefficient scheduling.
- If depot capacity is too high (C = 3), there is minimal additional benefit, suggesting that C = 2 remains the optimal configuration under current operational conditions.

This result highlights the importance of strategic resource allocation to ensure that depot capacity is aligned with real operational demand, minimizing unnecessary infrastructure expansion while maintaining efficiency.

4.2.3 Enhancing the Mathematical Model for Real-World Implementation

While this study focuses on optimizing accumulated mileage and resource allocation, future research should integrate comprehensive cost factors to reflect real-world maintenance decision-making more accurately. These may include:

- Labor and technician wages
- Material and spare parts expenses
- Penalty costs due to downtime or missed service schedules

Incorporating cost-related variables into the objective function — either as single or multi-objective optimization — would allow stakeholders to evaluate maintenance strategies based not only on technical efficiency but also economic feasibility.

Additionally, factors such as the lifespan of replaceable components and real-time operational variations should be considered to enhance model realism.

Implementing Artificial Intelligence (AI) and Big Data Analytics could further improve planning through:

- Monitoring actual maintenance vs. planned outcomes
- Identifying deviations and optimizing future intervals dynamically
- Using machine learning to predict component degradation and support predictive maintenance strategies

4.2.4 Long-Term Development of Domestic Railway Maintenance Capabilities

In the long run, Thailand's railway industry may transition toward localized maintenance capabilities, reducing dependence on foreign manufacturers. As maintenance contracts with external providers expire, shifting toward local maintenance operations and domestic rolling stock manufacturing could become a strategic priority.

This transition would require:

- Adjustments to maintenance planning frameworks
- The integration of locally sourced components

- Workforce development programs to ensure that maintenance personnel possess the necessary skills
- Establishment of national railway standards to support long-term railway sustainability

4.2.5 Integrating Scheduling Constraints with Fleet Expansion Planning

As railway demand grows, fleet expansion must be carefully planned in conjunction with maintenance scheduling adjustments.

- A larger fleet means higher maintenance demand, which may necessitate adjustments to depot capacity and maintenance resource allocation.
- Future studies should explore how fleet expansion scenarios affect the long-term feasibility of different maintenance strategies.

Adopting an integrated maintenance planning approach that considers both accumulated mileage and scheduled time constraints is crucial for sustainable railway system development. This approach will:

- Enhance operational efficiency
- Reduce long-term maintenance costs
- Extend the lifespan of rolling stock assets
- Improve railway reliability for passengers

Ultimately, implementing these recommendations will contribute to a more cost-effective, efficient, and sustainable railway network in the long term.

4.2.6 Integrating Failure Rates and Long-Term Degradation

The current study did not incorporate failure rates or Mean Time Between Failures (MTBF) due to the unavailability of detailed component-level reliability data, which is often restricted by manufacturers or not publicly disclosed. However, integrating these reliability metrics into the optimization model would significantly enhance the accuracy of long-term maintenance planning.

In future research, incorporating MTBF and degradation profiles could enable the model to better estimate the trade-off between extended maintenance intervals and increased failure risk. This would also support a more comprehensive condition-based or predictive maintenance strategy, allowing operators to optimize both safety and cost-effectiveness over the asset lifecycle

5. Acknowledgment

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