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Optimizing Maintenance and Repair in a Railway Transportation Company in Southern Iran: A System Dynamics Modeling Approach

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A B S T R A C T

This study develops and evaluates a system dynamics (SD) model to optimize maintenance and repair processes for a railway transportation company in southern Iran. Recognizing the intricate feedback relationships among workforce skill, part quality, maintenance budget, failure rate, mean time between failures (MTBF), and mean time to repair (MTTR), the proposed model was constructed using operational data and expert insights, and implemented in Vensim. Five managerial scenarios were simulated to assess the impact of human, technical, and managerial policies on key performance indicators, including fleet availability, downtime costs, and rework rates. The simulation results reveal that traditional reactive maintenance approaches are inadequate to manage the system's complexity, resulting in higher failure rates, operational delays, and indirect costs. In contrast, preventive and integrated maintenance strategies—which simultaneously address human and technical factors—achieved substantial performance improvements. Among the scenarios, the integrated policy that combined workforce training with part-quality enhancement produced the most significant results, increasing fleet availability and reducing overall system costs. Conversely, short-term budget cuts, while appearing economical, led to long-term inefficiencies and reduced reliability. The study concludes by recommending continuous workforce development, comprehensive preventive maintenance, dynamic budget allocation, optimized spare-part inventory management, and a transition toward data-driven intelligent maintenance as critical policies to achieve operational and economic sustainability in railway systems.

Keywords

System dynamics; Railway maintenance; Preventive maintenance; Fleet availability; Vensim; Maintenance optimization.

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1. Introduction

Maintenance and repair activities are critical determinants of reliability, safety, cost efficiency, and service quality in railway transportation systems (Jafari, 2016). As railway operations become increasingly complex, traditional reactive and time-based maintenance approaches are no longer sufficient to ensure long-term system performance (Kaewunruen et al., 2023). Frequent equipment failures, resource misallocation, and delayed spare-part procurement often generate reinforcing feedback loops that progressively degrade fleet availability and increase life-cycle costs (Nota et al., 2024).

In complex socio-technical systems such as railway maintenance, performance outcomes emerge from dynamic interactions among human capabilities, technical reliability, and financial resource allocation (Smith et al., 2021). However, many existing maintenance strategies focus on isolated components—such as reliability-centered maintenance, cost optimization, or predictive analytics—without explicitly modeling the feedback structures linking workforce skill, repair quality, spare-part inventory, maintenance budget, and system reliability over time (Crespo Márquez et al., 2023).

System Dynamics (SD), originally developed by Forrester (1961) and further formalized by Sterman (2000), provides a powerful framework for modeling such feedback-driven systems. By representing reinforcing and balancing loops, delays, and nonlinear relationships, SD enables decision-makers to evaluate the long-term consequences of alternative maintenance policies before implementation (Farokhi and Jafarian-Moghadam, 2018).

A railway transportation company in southern Iran—one of the country's key regional freight operators—faces persistent challenges, including high failure rates, increasing downtime costs, aging rolling stock, and inefficient maintenance planning (Amiri, 2024). The company's predominant reliance on reactive maintenance practices has intensified operational instability (Davari et al., 2021). Short-term managerial decisions, such as budget reductions or delayed procurement of spare parts, may temporarily reduce expenditures but often generate adverse long-term consequences in terms of reliability and cost performance (Deylemipour, 2018; Mostofi-Nia et al., 2023).

Although prior research has applied system dynamics and predictive maintenance approaches in railway contexts, several important gaps remain. First, few studies explicitly integrate human resource development (e.g., workforce skills and repair quality) with technical reliability variables within a unified SD framework. Second, limited research has addressed maintenance optimization in developing-country railway systems, particularly under resource constraints and macroeconomic volatility. Third, the combined effects of preventive and corrective maintenance policies on long-term operational and financial performance have not been sufficiently explored in an integrated dynamic structure (Jessada and Kaewunruen, 2023).

To address these gaps, this study develops a data-informed system dynamics model to optimize maintenance and repair processes for a railway transportation company in southern Iran. In this study, the term data-informed (rather than purely data-driven) refers to the integration of historical operational data (2020–2023) with expert knowledge to calibrate parameters and validate system behavior. Furthermore, the concept of sustainable maintenance is used here to denote long-term operational and economic sustainability—namely, the ability of the maintenance system to maintain reliability and cost stability over time—rather than environmental sustainability.

The main objectives of the study are to:

- Identify and model the causal relationships among major human, technical, and financial factors influencing fleet performance.
- Simulate alternative maintenance policy scenarios (reactive, preventive, and integrated) and evaluate their long-term impacts on fleet availability, downtime cost, and rework rate.

Propose an integrated, long-term maintenance strategy grounded in system-level feedback analysis, where maintenance decisions are iteratively updated using quantitative operational and condition data to capture system-wide interactions and assess long-term performance impacts. This study contributes theoretically by extending the application of system dynamics to an integrated human–technical–financial maintenance structure in a developing-country railway context. Methodologically, it combines operational data with expert-based structural validation to enhance model credibility. Practically, it provides railway managers with a simulation-based decision-support tool to test "what-if" scenarios and avoid unintended long-term consequences of short-term policy decisions. Therefore, the conceptual framework of the research is based on Figure 1.

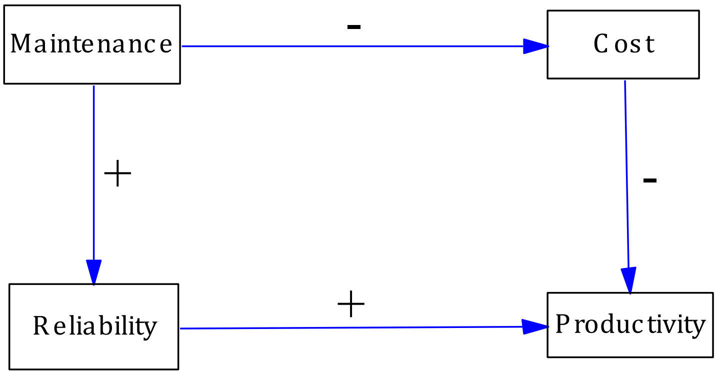

Figure 1. Conceptual framework of the research

2. Literature review

Maintenance of railway assets plays a central role in ensuring operational reliability, safety, and cost efficiency. Traditional maintenance strategies—corrective (reactive) and time-based preventive maintenance—have long been used in railway systems; however, these approaches often fail to capture the dynamic interdependencies among workforce capability, asset deterioration, spare-part logistics, and budget allocation (Davis and Andrews, 2022).

2.1. System dynamics in railway maintenance

System Dynamics (SD), introduced by Forrester (1961), provides a framework for analyzing complex feedback systems characterized by delays, nonlinear relationships, and policy resistance. In railway maintenance, SD has been used to model infrastructure deterioration, fleet availability, and maintenance budgeting under uncertainty (Mahmoudi, 2022).

Nazem et al. (2022) applied SD modeling to metro fleet management and demonstrated that dynamic budget allocation improves availability performance. Moradi et al. (2023) examined railway financial sustainability under inflationary pressures, showing that short-term budget reductions may generate reinforcing loops that increase long-term costs. Similarly, Sedighi et al. (2021) highlighted the importance of accounting for spare-part delay feedback effects in railway maintenance systems.

These studies confirm the usefulness of SD in capturing policy-driven dynamics. However, most models focus primarily on financial or technical variables, with limited integration of human resource capability into the feedback structure.

2.2. Predictive and data-oriented maintenance approaches

Recent international research has increasingly emphasized predictive and data-driven maintenance under the Industry 4.0 paradigm. Studies such as Zhang et al. (2023), García-Méndez et al. (2025), and Werbińska-Wojciechowska et al. (2024) explore machine learning, digital twins, and the prediction of remaining useful life (RUL) for railway assets. These approaches enhance fault detection accuracy and support condition-based maintenance scheduling (Sedighi et al., 2025).

While such methods improve short-term prediction accuracy, they often concentrate on component-level reliability rather than system-level policy feedback. Moreover, their implementation requires high-frequency sensor data and advanced digital infrastructure, which may not be fully available in developing-country railway contexts (Binder et al., 2023).

2.3. Integrated human–technical perspectives

A growing body of literature recognizes that maintenance performance depends not only on asset condition but also on workforce expertise, repair quality, and organizational learning. Nevertheless, explicit integration of workforce skill development, repair quality, and rework dynamics within SD-based railway models remains limited (Ghahremani et al., 2024).

Human factors influence Mean Time To Repair (MTTR), failure recurrence rates, and maintenance efficiency (Stamatakis et al., 2021). Ignoring these relationships may lead to incomplete policy evaluation, particularly when analyzing long-term maintenance strategies (Hojjati Astani, 2024).

2.4. Identified research gaps

Based on the reviewed literature such as Davis and Andrews (2022), Sedighi et al. (2025) and Ghahremani et al. (2024) three major gaps can be identified:

- Limited integration of human resource development variables into system dynamics models of railway maintenance.
- Insufficient modeling of the combined effects of preventive and corrective maintenance policies within a unified feedback structure.
- Scarcity of data-informed SD applications in developing-country railway systems operating under budget constraints and macroeconomic volatility.

2.5. Positioning of the present study

To address these gaps, the present research develops an integrated system dynamics model that simultaneously incorporates human, technical, and financial subsystems in a railway transportation company in southern Iran. Unlike purely predictive or component-level approaches, this study focuses on system-level feedback interactions and long-term policy evaluation.

By combining historical operational data with expert-based structural validation, the study offers a context-sensitive and practically implementable framework for maintenance optimization in resource-constrained railway environments.

3. Methodology

This research adopts a system dynamics (SD) modeling approach to analyze, simulate, and optimize the maintenance and repair processes of the fleet of a railway transportation company in southern Iran. SD is particularly effective for complex socio-technical systems characterized by interdependencies, feedback loops, and time delays (Sterman, 2000). The methodology enables the researcher to understand the system's causal structure, identify leverage points, and evaluate the long-term consequences of policy interventions before real-world implementation. The study follows a quantitative, model-based research design developed through five main stages (Sushil, 2000):

1. Problem identification and boundary definition
2. Development of the causal loop diagram (CLD)
3. Construction of the stock-and-flow model in Vensim
4. Model validation and behavior testing
5. Scenario simulation and policy analysis

Data for the model were collected from operational records of a railway transportation company in southern Iran (2020–2023) and supplemented by expert opinions from maintenance engineers and operational managers.

3.1. Model development process

3.1.1. Problem definition and boundary selection

The central research problem focuses on inefficiencies in maintenance planning, resource allocation, and reliability performance in the railway system of a transportation company in southern Iran. The model boundary includes three interrelated subsystems:

1. Human-resource subsystem – workforce skill, training rate, and quality of repair work
2. Technical subsystem – failure rate, spare-part quality, and mean time to repair
3. Financial subsystem – maintenance budget, cost of downtime, and spare-part inventory

The simulation time horizon spans 10 years (2020–2030), capturing both short- and long-term dynamic effects of maintenance policies.

3.1.2. Causal loop diagram (CLD)

According to Figure 2, the CLD represents the maintenance system's feedback structure. Positive (reinforcing) and negative (balancing) feedback loops were identified among major variables.

- Reinforcing loops illustrate how improved workforce skill increases repair quality, leading to higher availability and reduced rework, which further enhances system performance.
- Balancing loops capture how budget limitations constrain spare-part availability, causing delays and higher failure rates.

These feedback loops demonstrate the systemic interactions among human, technical, and financial dimensions of railway maintenance. The R1 loop shows the relationship between personnel workload and repair quality. The B1 loop shows the impact of spare parts inventory on repair speed. The more inventory is maintained at a suitable level, the faster repairs are completed and the number of operational wagons increases. The R2 loop shows the impact of workforce skill level and experience on repair quality. According to the R3 loop, the full implementation of preventive maintenance (PM) programs reduces breakdown rates and increases fleet reliability. Based on the R4 and B2 loops, the role of fiscal policies in supporting or weakening the entire rail fleet maintenance and repair system is determined.

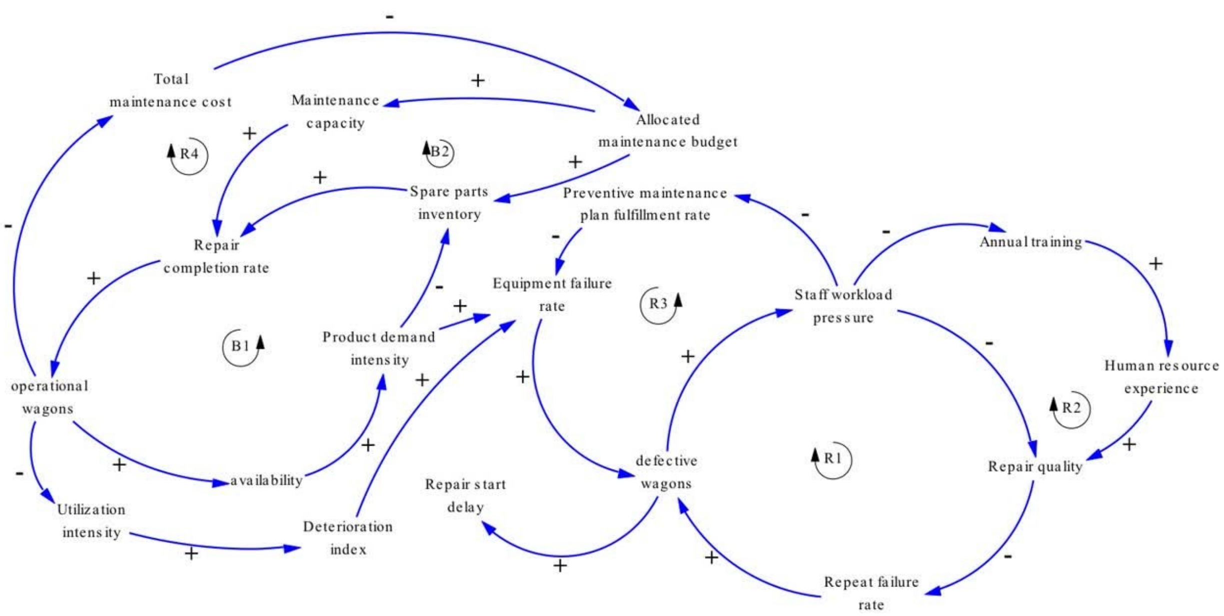

Figure 2. Causal diagram of the railway maintenance system

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3.1.3. Stock-and-flow model construction

Based on the CLD, a stock-and-flow structure (Figure 3) was developed in Vensim DSS. Stocks represent accumulations, such as the number of operational locomotives or trained employees, while flows capture changes over time, such as training rate, repair completion rate, and budget allocation.

Equations were formulated for each relationship using operational data, expert calibration, and literature benchmarks. For instance:

- Failure rate is modeled as a function of equipment aging and maintenance quality.
- Availability is computed as the ratio of operational locomotives to total fleet size.
- Maintenance cost includes preventive, corrective, and rework costs, dynamically adjusted based on budget feedback.

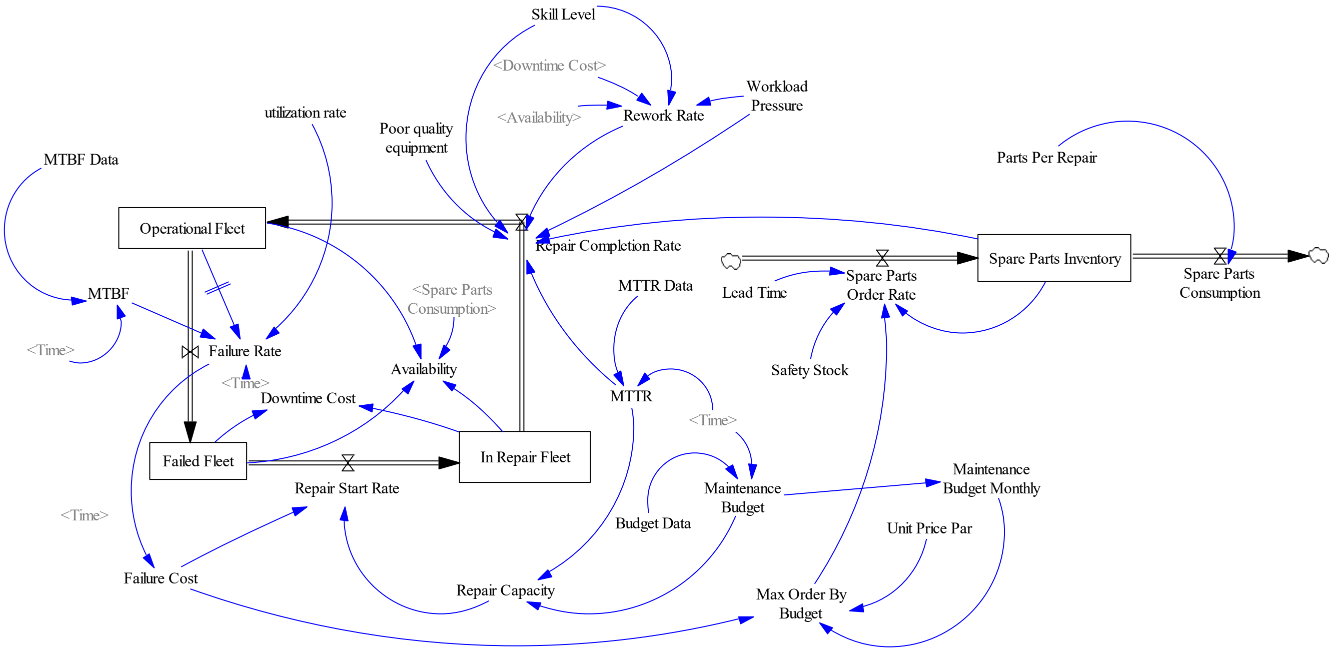

Figure 3. Stock and flow diagram of the system dynamics model

3.1.4. Representative model equations

To enhance model transparency, selected core equations governing critical system relationships are presented below:

$$\text{Failure Rate}(t) = \text{Base Failure Rate} \times \text{Deterioration Index}(t) \times \text{Utilization Intensity}(t) \times (1 - \text{Maintenance Quality}(t)) \quad (1)$$

Equation (1) reflects the increasing probability of failure as equipment deteriorates and utilization intensifies, while higher maintenance quality reduces failure likelihood.

$$\text{Mean Time To Repair (MTTR}(t)) = \text{Base Repair Time} / (1 + \text{Staff Skill Level}(t)) \times \quad (2)$$

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Spare-Part Availability Factor(t)

Equation (2) captures the influence of workforce capability and spare-part availability on repair duration.

$$\text{Fleet Availability}(t) = \text{Operational Wagons}(t) / \text{Total Fleet Size} \quad (3)$$

Availability is computed dynamically based on stock variations in operational and failed wagons (Equation 3).

$$\text{Rework Rate}(t) = \text{Failure Rate}(t) \times (1 - \text{Repair Quality}(t)) \quad (4)$$

Equation (4) represents the proportion of failures that recur due to inadequate repair quality.

$$\begin{aligned} &\text{Maintenance Cost}(t) = \text{Preventive Cost}(t) + \text{Corrective Cost}(t) + \text{Rework Cost}(t) \\ &\text{Corrective Cost}(t) = \text{Failure Rate}(t) \times \text{Cost per Failure} \quad (5) \\ &\text{Rework Cost}(t) = \text{Rework Rate}(t) \times \text{Rework Unit Cost} \end{aligned}$$

Equation (5) illustrate how human, technical, and financial subsystems interact dynamically within the model structure.

The key variables used in the model development, along with their definitions and variable types, are presented in Table 1.

Table 1. Key Variables and parameters of the model

No.	Variable	Definition	Type
1	Number of operational wagons	Main stock represents the fleet available for service	Endogenous
2	Number of defective wagons	Stock: main input to the repair process	Endogenous
3	Number of wagons under repair	Stock: intermediate stage in the repair cycle	Endogenous
4	Failure rate	Inflow to the failure section; it depends on deterioration and utilization intensity	Endogenous
5	MTBF (Mean Time Between Failures)	Performance indicator derived from the failure rate	Constant
6	MTTR (Mean Time To Repair)	Function of repair capacity, spare parts, and staff skills	Endogenous
7	Downtime	Duration of fleet unavailability	Endogenous
8	Maintenance capacity	Limits the speed and volume of repairs	Endogenous
9	Staff skill level	Influences repair quality and duration	Endogenous
10	Repair quality / Re-failure rate	Indicates the likelihood of failure recurrence after repair	Endogenous
11	Spare parts inventory	Determines the speed and quality of the repair process	Endogenous
12	Spare part supply delay	Slows down the repair process when inventory is insufficient	Endogenous
13	Maintenance and repair costs	Includes preventive, corrective, and predictive	Endogenous

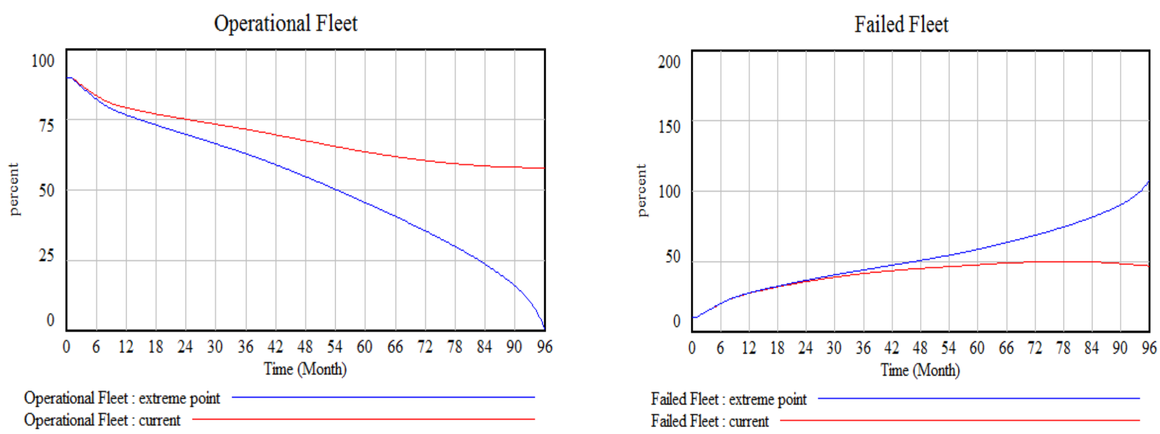
No.	Variable	Definition	Type
		maintenance expenses	
14	Deterioration index	Cumulative effect of time and usage intensity on the fleet	Endogenous
15	Utilization intensity	Fleet usage rate affects failure occurrence	Endogenous
16	Staff training and development	Control policy to enhance skills and reduce MTTR	Endogenous
17	Availability index	Key model output: ratio of operational fleet	Endogenous
18	Transport demand pressure	Determines fleet utilization level; external input	Exogenous
19	Macroeconomic conditions (inflation, exchange rate)	Affect costs and resource availability	Exogenous
20	Government transport policies	Define strategic constraints and priorities	Exogenous
21	Emerging technologies (BIM, Digital Twin, AI)	Potential future impact on repair quality and cost	Exogenous

4. Model validation

Dynamic validation tests are conducted to evaluate the model's ability to reproduce the dynamic behavior of the real system. These tests assess the model's accuracy and reliability by examining the system's response under different operating conditions. In the following, several dynamic validation tests used in this study are introduced and discussed.

4.1. Extreme condition test

In system dynamics, the Extreme Conditions Test is used to examine a model's behavior under very unusual or extreme conditions.In this method, some variables are set to extreme values (such as zero or very large values).If the model behaves logically under these conditions, its structural validity increases.



a:Operational fleet b:Failed fleet

Figure 4. Diagram of the model behavior validation test results – extreme condition test

By maximizing the values of the components that negatively affect the number of active wagons, such as workload pressure and poor equipment quality, the variables associated with

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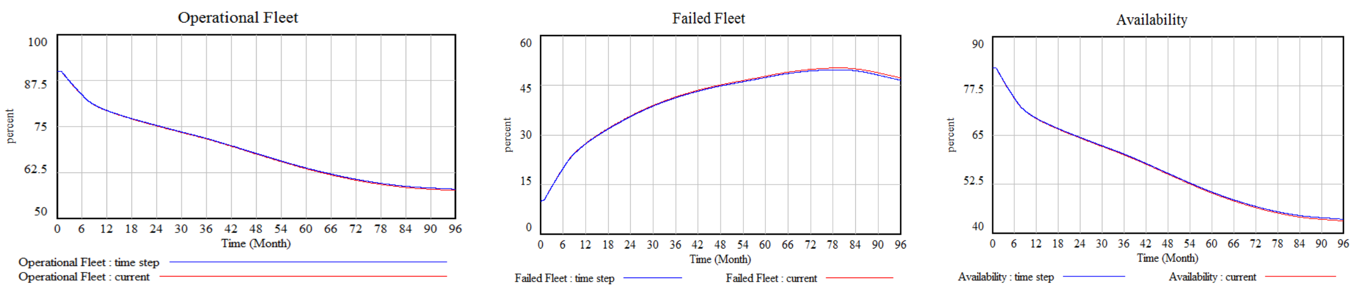
these components also change depending on the type of their relationship (direct or inverse). Under extreme conditions, the number of active wagons decreases to the minimum possible value zero (Figure 4.a), while the number of retired wagons reaches its maximum 100 (Figure 4.b).

4.2. Integration test

Integration Test checks whether different parts or sub-models of a system work correctly when connected together.Its purpose is to find errors in communication, data transfer, and coordination between components.In system dynamics, it is used to ensure consistency between different parts of the model.



a: Operational fleet b: Failed fleet c: Availability

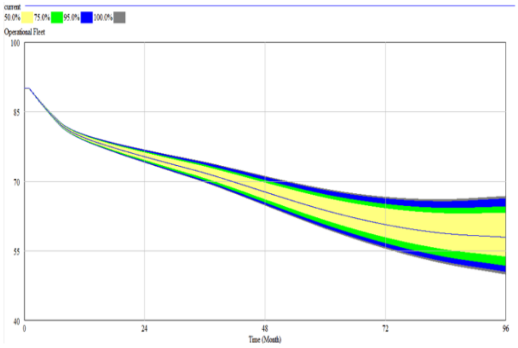
Figure 5. Test Results – Time step sensitivity (Integration Test)

As shown in the Figure 5, since reducing the time step does not change the behavior of the curves and no values fall outside the larger time-step range, the system is considered valid with respect to time interval selection. The result of this test is shown for the variables Operational fleet (Figure 5.a), Failed fleet (Figure 5.b) and Availability (Figure 5.c).

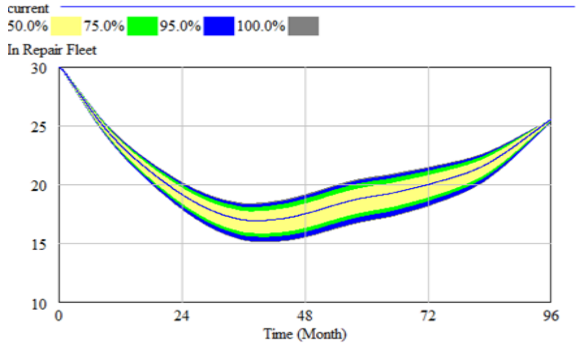
4.3. Sensitivity analysis

To evaluate model robustness, sensitivity tests were conducted by varying key parameters such as training rate, spare-part quality, and maintenance budget within ±20% of their base values. The results indicate that the system is most sensitive to workforce skill level and spare-part quality, while budget changes alone had a comparatively smaller impact on long-term performance.

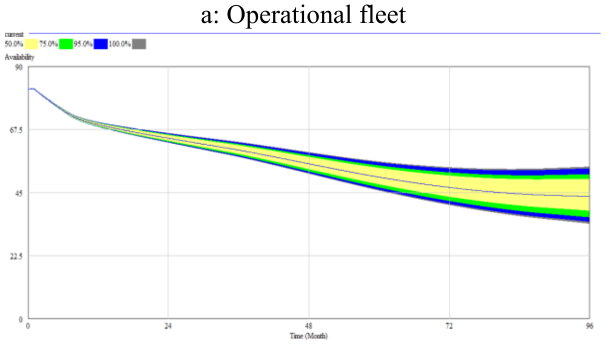
This finding suggests that management efforts should focus on reinforcing human-technical interactions rather than isolated budget increases.

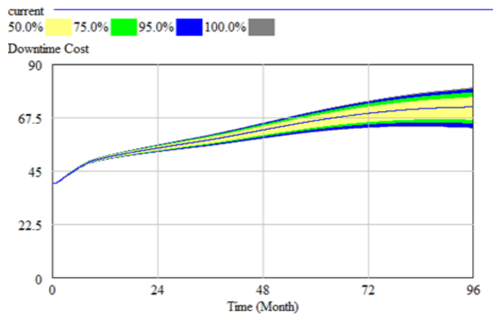


a: Operational fleet



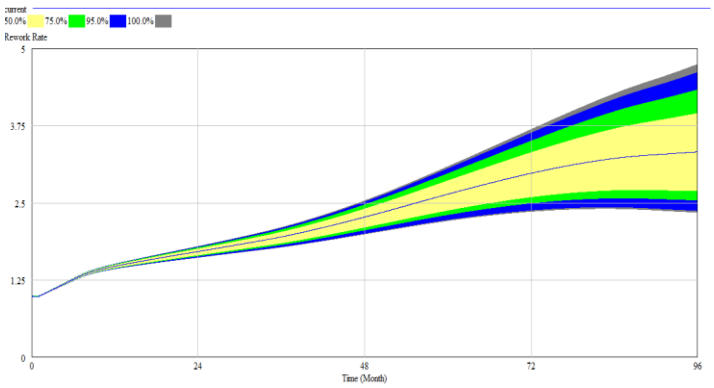
b: Failed fleet





c: Availability

d: Downtime cost



e: Rework rate

Figure 6. Results of the model sensitivity analysis

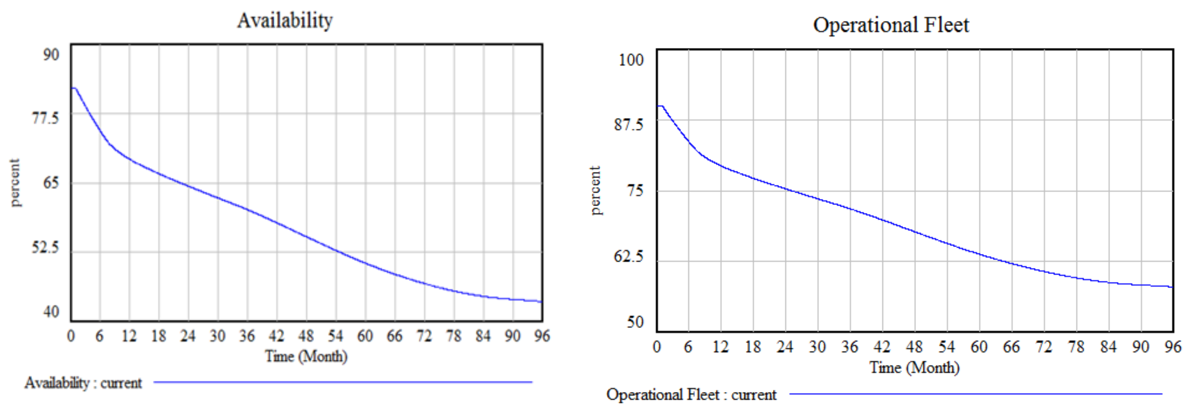
The overall simulation outcomes demonstrate that system dynamics modeling provides valuable insight into how maintenance policies interact over time. By revealing hidden feedback loops and time delays, the model helps decision-makers identify the most effective leverage points to enhance reliability and reduce costs in a railway transportation company in southern Iran. The result of this test is shown for the variables Operational fleet (Figure 6.a), Failed fleet (Figure 6.b), Availability (Figure 6.c), Downtime cost (Figure 6.d) and Rework rate (Figure 6.e)

5. Results

The developed system dynamics model was simulated in Vensim DSS to examine the behavior of a railway transportation company in southern Iran maintenance system under various policy scenarios over a ten-year period (2020–2030). The results are presented in three main parts: baseline behavior, policy scenario comparison, and sensitivity analysis.

5.1. Baseline behavior

The baseline scenario represents the continuation of current maintenance practices, which rely primarily on reactive maintenance and limited preventive actions. Simulation results show a gradual decline in fleet availability over time, accompanied by an increase in both maintenance costs and rework rate. The shortage of skilled workforce and the aging of spare parts create reinforcing feedback loops that worsen performance year by year. Specifically, fleet availability decreases by approximately 15% within the simulation period, while maintenance costs rise by nearly 25%. This degradation highlights the long-term inefficiency of the current maintenance strategy and demonstrates the need for systemic policy reform.



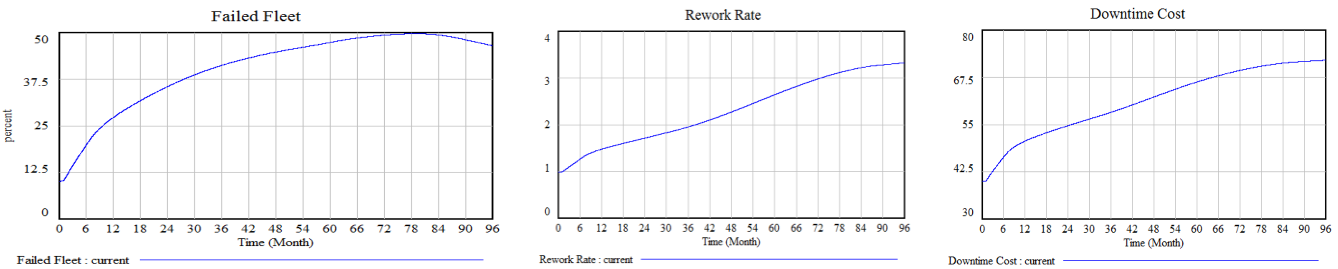
a: Wagon Availability

b: Active Fleet Percentage

Figure 7. Behavior of wagon availability and active fleet percentage over time in the baseline scenario

The baseline scenario reveals a steady decline in wagon availability over time. Initially around 80%, availability gradually decreases to nearly 40% by month 96. This trend indicates that if current conditions persist without corrective actions, fleet operational efficiency and overall productivity will significantly decline (Figure7.a).

The percentage of active wagons shows a downward trend throughout the simulation period. Starting at about 90%, it gradually declines to nearly 55% by month 96. This continuous decrease indicates gradual fleet degradation and rising failure rates due to the absence of effective maintenance programs (Figure7.b).



a: Failed Fleet b: Rework Rate c: Downtime Cost

Figure 8. Behavior of failed fleet, rework rate and downtime cost over time in the baseline scenario

The percentage of the failed fleet increases steadily over time, rising from less than 10% at the beginning to about 50% around month 80, and then stabilizing slightly. This trend shows that without preventive maintenance, a considerable portion of the fleet becomes non-operational, leading to reduced transport capacity and lower system performance (Figure8.a).

The rework rate shows an upward trend, increasing from below 1% to about 3.5% by month 96. This indicates rising errors or the need for reprocessing in maintenance and repair activities, which, if unaddressed, can lead to higher costs and lower efficiency (Figure8.b).

Downtime costs rise steadily during the simulation, increasing from about 35 units to nearly 75 units by month 80, and then stabilizing toward the end. This upward trend reflects the growing financial burden caused by equipment failures and downtime, emphasizing the need for effective maintenance strategies (Figure8.c).

5.2. Policy design framework

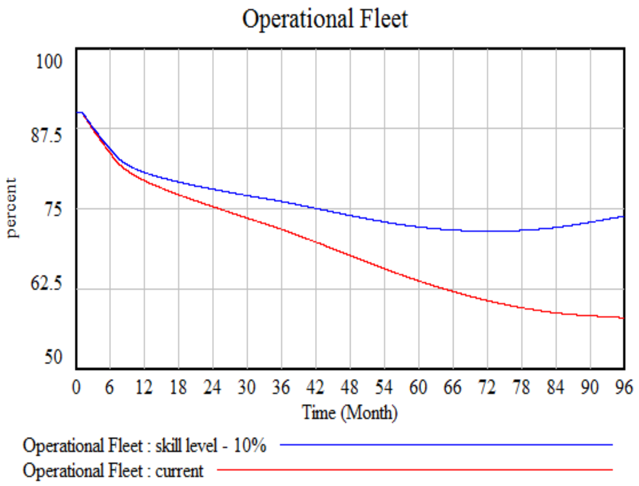
To systematically evaluate managerial decisions, policy scenarios were designed based on two guiding principles:

- Each scenario isolates a specific intervention variable.
- The integrated scenario combines complementary interventions to assess synergy effects.

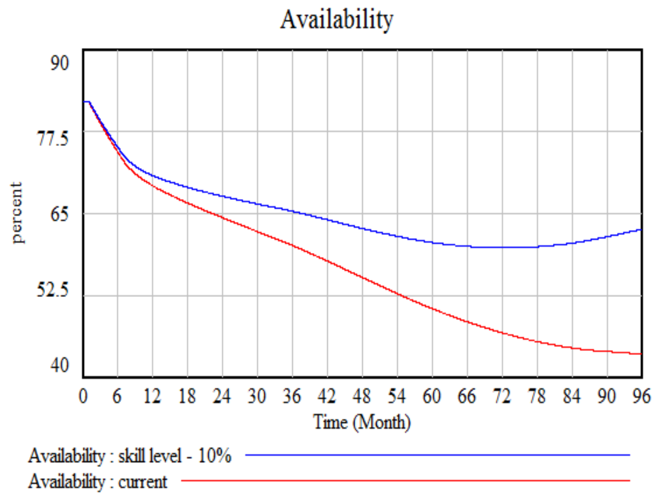
All scenarios were simulated over a 10-year horizon (2020–2030) under identical initial conditions to ensure comparability. The five scenarios are defined as follows:

5.2.1. Human-Resource development policy

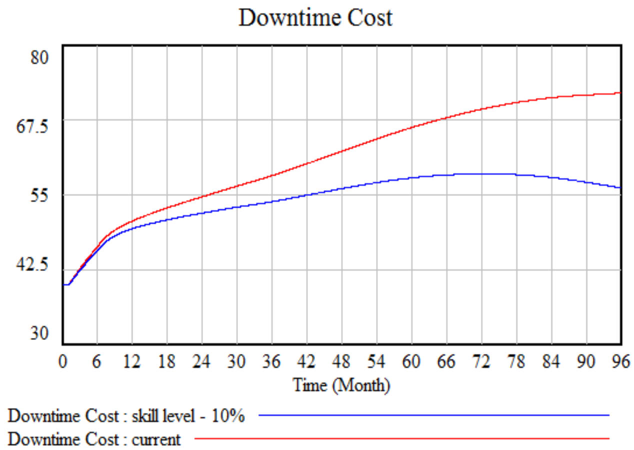
A 10% increase in workforce skill level through structured training programs, aimed at improving repair quality and reducing MTTR and rework rate.



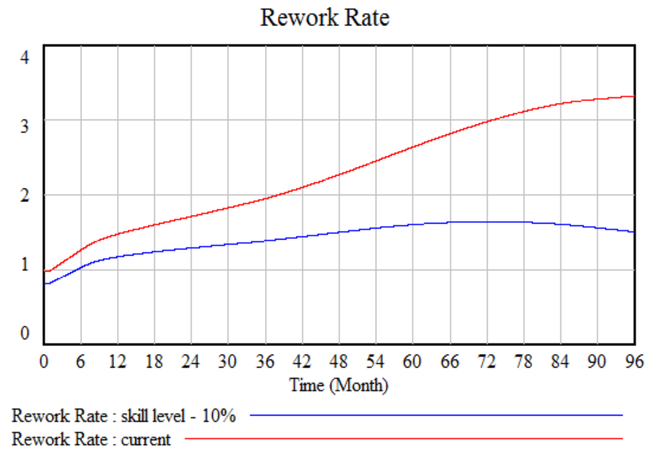
a: Operational fleet



b: Availability



c: Downtime cost



d: Rework rate

Figure 9. Human resource skill improvement

The 10% increase in maintenance personnel skill level led to a significant improvement in system performance, as the percentage of active wagons rose from 57% to 73% (Figure 9.a), fleet availability increased from 43% to 62% (Figure 9.b) and Downtime cost decreased from 70% to 55% (Figure 9.c). Additionally, the rework rate declined from 3% to 1.5% (Figure 9.d), indicating higher repair accuracy and reduced human errors.

5.2.2. Technical reliability policy

A 10% reduction in component failure rate through improved spare-part quality and enhanced inventory management.

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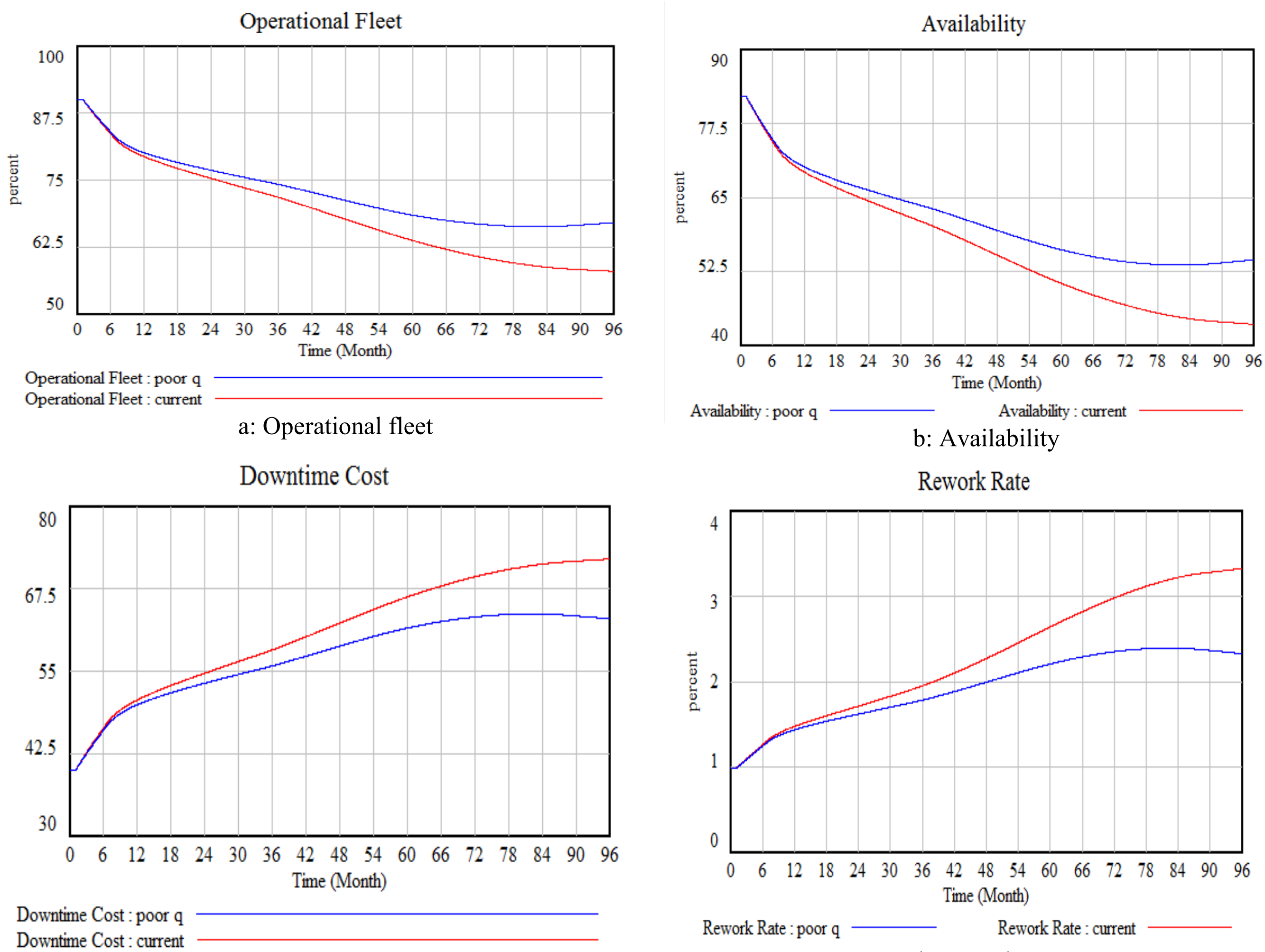


a: Operational fleet

b: Availability

c: Downtime cost

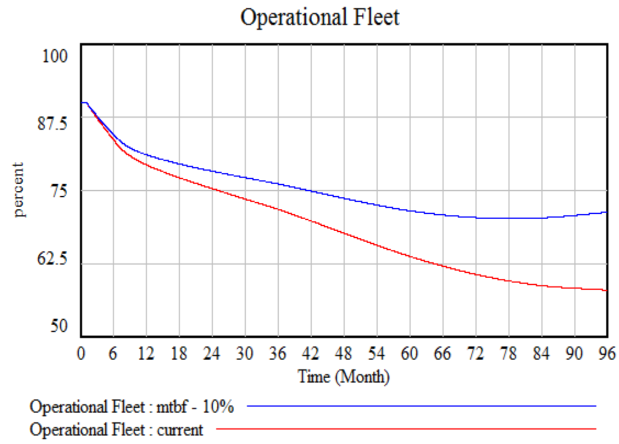
d: Rework rate

Figure 10. Improvement of equipment and spare part quality

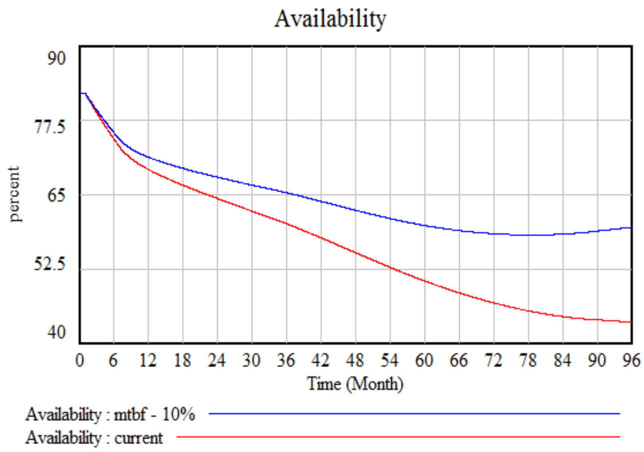
The 10% reduction in component failure rate led to a noticeable improvement in system performance. The percentage of active wagons increased from 57% to 67% (Figure 10.a), and fleet availability rose from 43% to 54% (Figure 10.b), indicating higher reliability and operational stability. Furthermore, downtime costs decreased from 72 to 62 units (Figure 10.c), and the rework rate dropped from 3.3% to 2.3% (Figure 10.d), confirming that higher-quality parts reduce both failures and the need for repeated maintenance.

5.2.3. Preventive reliability reinforcement (MTBF +10%)

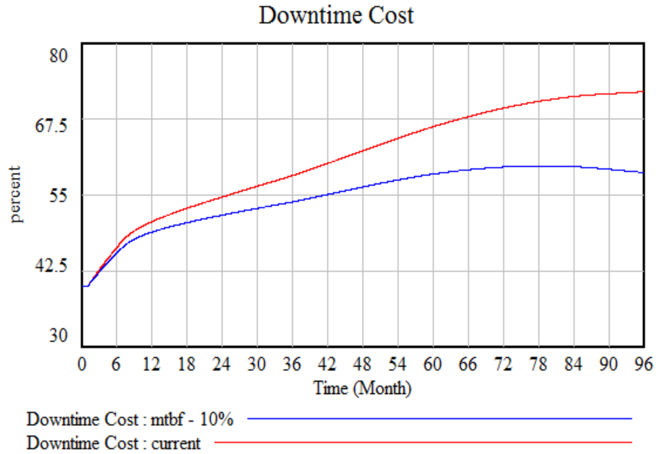
An increase of 10% in Mean Time Between Failures (MTBF), representing intensified preventive maintenance planning.



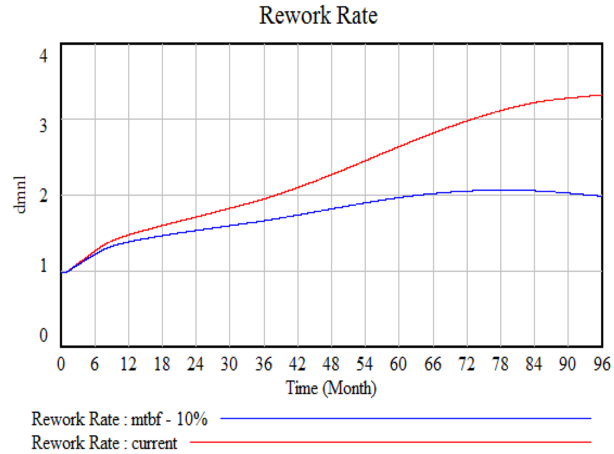
a: Operational fleet



b: Availability



c: Downtime cost



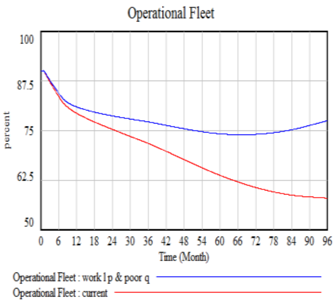
d: Rework rate

Figure 11. 10% Increase in mean time between failures (MTBF)

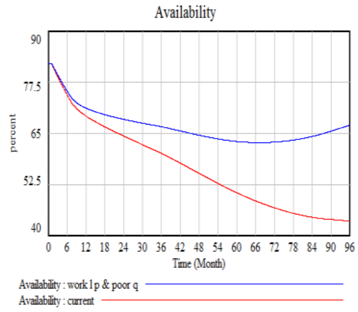
The 10% increase in MTBF indicates that equipment operates for longer periods without failure. As a result, the percentage of active wagons increased from 58% to 70% (Figure 11.a), and fleet availability rose from 45% to 60% (Figure 11.b). Moreover, downtime-related costs decreased from 70 to 60 units (Figure 11.c), while the rework rate declined from 3.2% to 2% (Figure 11.d), confirming improved reliability and maintenance accuracy.

5.2.4. Integrated human–technical policy

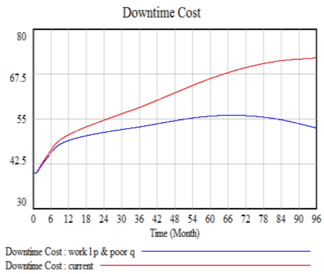
Simultaneous implementation of workforce skill enhancement and spare-part quality improvement, designed to activate reinforcing feedback loops between human and technical subsystems.



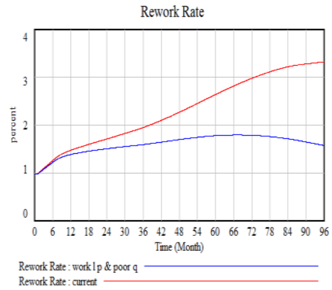
a: Operational fleet



b: Availability



c: Downtime cost



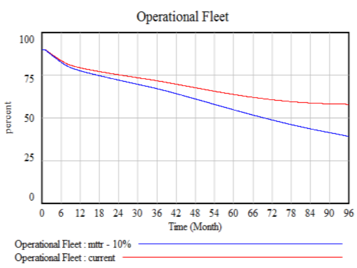
d: Rework rate

Figure 12. Workload reduction and equipment quality enhancement

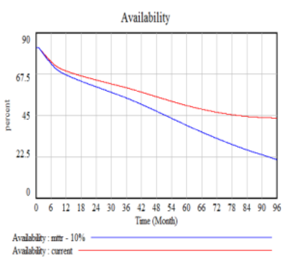
The simultaneous implementation of workload reduction and equipment quality improvement resulted in a remarkable rise in performance. The percentage of active wagons increased from 57% to 77% (Figure 12.a), while fleet availability rose from 43% to 67% (Figure 12.b). Additionally, downtime-related profit loss decreased from 72 to 52 units (Figure 12.c), and the rework rate dropped from 3.32% to 1.57% (Figure 12.d), demonstrating both operational and economic efficiency.

5.2.5. mean time to repair (MTTR) policy

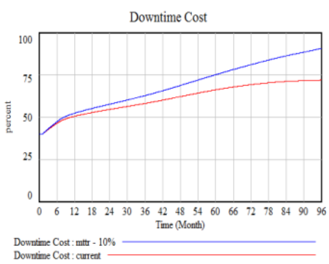
A 10% increase in MTTR means repairs take longer to complete, leading to a notable decline in performance. The share of active wagons drops from 58% to 39%, and fleet availability falls from 43% to 21%. Consequently, downtime costs rise from 72 to 90 units, indicating lower efficiency and higher opportunity loss. This scenario highlights the negative impact of prolonged maintenance time on operational and financial performance.



a: Operational fleet



b: Availability



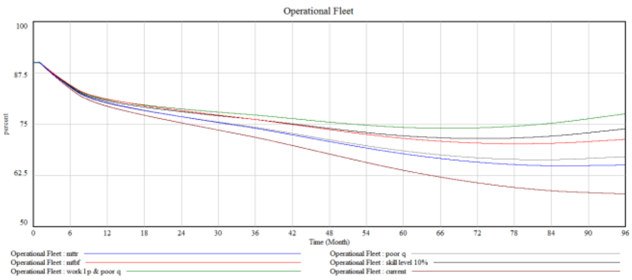
c: Downtime cost

Figure 13. 10% Increase in mean time to repair (MTTR)

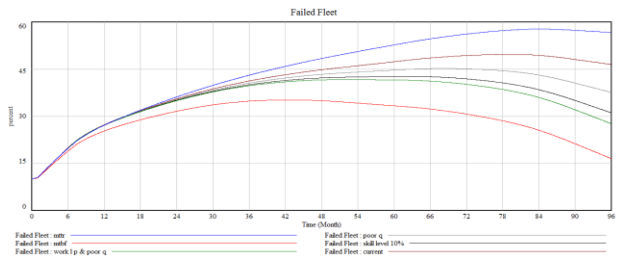
The result of this policy is shown for the variables Operational fleet (Figure 13.a), Availability (Figure 13.b) and Downtime cost (Figure 13.c).

5.3. Comparative policy evaluation

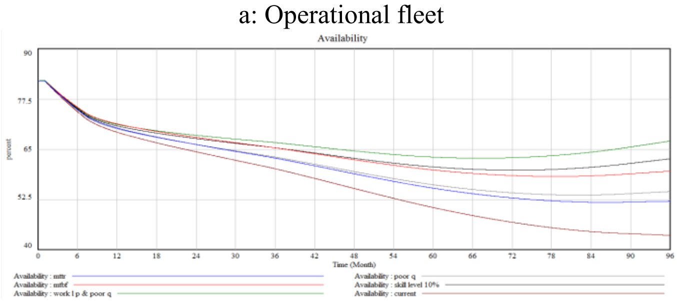
Combining human-resource and technical improvements yielded the strongest results. Availability increased by 22%, total maintenance cost decreased by 18%, and rework rate dropped significantly. The integrated scenario activated reinforcing feedbacks between skill improvement and equipment reliability, leading to self-sustaining performance growth. The result of this policy is shown for the variables Operational fleet (Figure 14.a), Failed fleet (Figure 14.b), Availability (Figure 14.c), Downtime cost (Figure 14.d) and Rework rate (Figure 14.e).



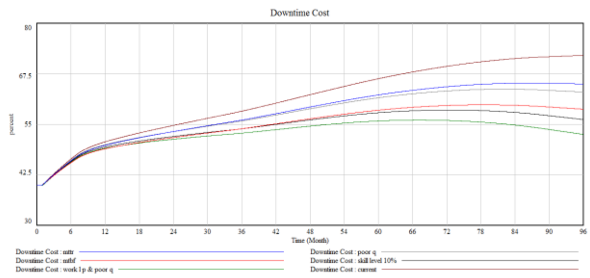
a: Operational fleet



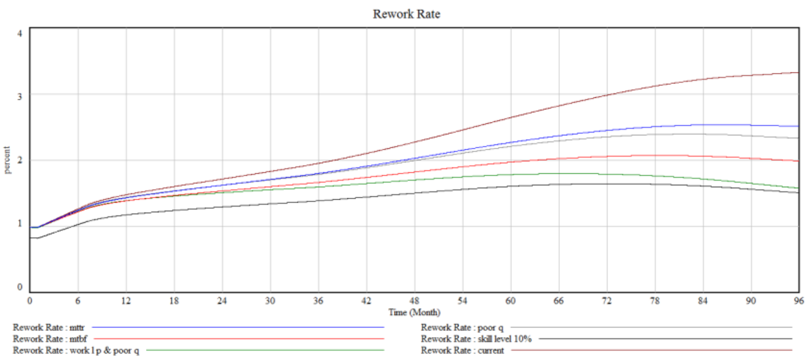
b: Failed fleet



c: Availability



d: Downtime cost



e: Rework rate

Figure 14. Comparison of scenario results

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Table 2 also shows a summary of the impact of the results of different scenarios on the key variables of the model. The analysis of the scenarios shows that different policies have different effects on key variables such as fleet availability, downtime cost, and rework rate. Increasing employee skills improves repair quality and reduces rework, while improving spare part quality increases equipment reliability and reduces downtime. The best result is achieved in the Integrated Human–Technical Policy scenario, which combines workforce training and spare part quality improvement, leading to the highest fleet availability (around 67%) and the lowest downtime cost. In addition, increasing MTBF through preventive maintenance improves performance, whereas increasing MTTR significantly reduces availability and increases costs. From a managerial perspective, achieving sustainable performance requires a combination of workforce development, spare part quality management, and effective maintenance planning.

Table 2. Summary of quantitative scenario results

Scenario	Main policy change	Effect on fleet availability	Effect on downtime cost	Effect on rework rate	Managerial insight
1. Workforce Skill Enhancement	Ten percent increase in employee skill level	Increased to about 62 percent	Significantly decreased	Reduced to 1.5 percent	Training and empowerment improve repair quality and reduce repeated failures.
2. Spare Part Quality Improvement	Ten percent reduction in part failure rate	Increased to around 54 percent	Decreased to 62 units	Reduced to 2.3 percent	Better part quality extends equipment lifespan but requires skilled staff for full effect.
3. Integrated Human–Technical Policy	Combination of skill improvement and part quality enhancement	Increased to about 67 percent	Decreased to 52 units	Reduced to 1.6 percent	Produces the best results through synergy between human and technical improvements.
4. Preventive Reliability Policy (MTBF +10%)	Ten percent increase in mean time between failures	Increased to 60 percent	Decreased to 60 units	Reduced to 2 percent	Preventive maintenance improves reliability and lowers long-term costs.
5. Delayed Repair Policy (MTTR +10%)	Ten percent increase in mean time to repair	Decreased to 21 percent	Increased to 90 units	Slightly increased	Represents the weakest scenario, showing the negative impact of delays and poor planning.

The SD model thus provides a comprehensive platform for analyzing policy effectiveness and identifying optimal strategies for improving maintenance performance in a railway transportation company in southern Iran. Overall, the integrated policy scenario outperformed all others, confirming that simultaneous improvement of human and technical factors is essential for sustainable maintenance optimization.

5. Discussion and conclusion

The findings of this study confirm that railway maintenance systems behave as feedback-driven socio-technical structures rather than as isolated technical processes. The baseline scenario illustrates a classic “fixes that fail” system archetype, in which corrective maintenance temporarily restores functionality but reinforces long-term degradation through accumulated failures and declining repair quality. This behavior aligns with foundational system dynamics theory (Forrester, 1961; Sterman, 2000).

Consistent with previous SD applications in railway systems (Nazem et al., 2022; Moradi et al., 2022), the results demonstrate that short-term budgetary or reactive interventions may appear beneficial initially but generate counterintuitive long-term consequences. However, unlike prior studies that primarily emphasized financial or infrastructure dimensions, the present study explicitly integrates human resource capability into the dynamic structure. The results show that workforce skill development significantly influences MTTR, rework rate, and long-term availability.

The comparative policy analysis further reveals that isolated interventions—whether technical or financial—produce limited and sometimes unstable improvements. While the technical policy reduces failure frequency and the preventive policy improves reliability indicators, neither fully activates reinforcing learning loops within the system. The integrated human–technical policy, by contrast, generates synergistic effects. Improved workforce skills enhance repair quality, reducing rework and failure recurrence, thereby freeing capacity and stabilizing availability. This self-reinforcing structure explains the superior long-term performance observed in the integrated scenario.

These findings extend existing predictive and data-oriented maintenance research (Zhang et al., 2023; García-Méndez et al., 2025) by shifting attention from component-level prediction accuracy to system-level policy interaction. While machine-learning-based maintenance improves failure detection, it does not inherently address organizational learning, budget feedback, or workforce capability. The present model complements such approaches by providing a macro-level policy simulation framework.

Based on the results of the scenario analysis, it is recommended that the organization adopt an integrated human–technical strategy as the main fleet management policy. This strategy should include continuous investment in employee training and skill development, improvement of spare part supply and quality control processes, and the implementation of preventive maintenance programs. In addition, focusing on reducing repair time (MTTR) and increasing the time between failures (MTBF) can help prevent unnecessary downtime. Overall, combining workforce capabilities with technical equipment reliability can improve fleet availability, reduce downtime costs, and enhance long-term operational sustainability.

6. Limitations and future suggestions

While the developed system dynamics model offers valuable insights into railway maintenance interdependencies, several limitations remain. First, it was calibrated using data from a single company in southern Iran, which may limit its generalizability. Future research should validate the model with multi-regional datasets. Second, the model assumes stable external conditions (e.g., inflation, spare-part supply, energy costs), whereas real-world variability could significantly affect outcomes. Incorporating stochastic variables and scenario-based uncertainty would strengthen robustness. Third, the model focuses on strategic and tactical decisions (budgeting, skill development, spare-part management), excluding operational elements like real-time scheduling, IoT monitoring, and predictive analytics due to data constraints. Future studies could integrate hybrid approaches—combining System Dynamics with Agent-Based or Discrete Event Simulation—to capture micro-level dynamics. Integrating machine learning with SD could also enable data-driven predictive maintenance and real-time parameter updates, aligning with smart maintenance and digital twin concepts. Overall, despite these limitations, the model establishes a strong foundation for understanding and optimizing feedback mechanisms in railway maintenance, paving the way for more adaptive and intelligent maintenance systems.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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