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Optimizing The Number Of Mechanic Crews And Heavy Equipment Replacement Rule Options To Reduce Heavy Equipment Unplanned Downtime, Enhance Heavy Equipment On Running, And Maximize Profit At Pt. Xyz's Construction Project: An Agent-Based Modelling Approach

Ami [1]; Manahan Siallagan [2]
[1] Students, Master of Business Administration Program, Institut Teknologi Bandung, Indonesia
[2] Lecturer, Master of Business Administration Program, Institut Teknologi Bandung, Indonesia
Email: [1] ami_mba69@sbm-itb.ac.id ;[2] manahan@sbm-itb.ac.id

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ABSTRACT

This research aims to reduce unplanned downtime, enhance the on-running time, and maximize profits from heavy equipment in PT. XYZ's construction projects through the application of Agent-Based Modeling (ABM). The study uses ABM to simulate the interaction between mechanical crews and heavy equipment units. It explores various optimization scenarios involving the number of crews and heavy equipment replacement rule options. Data was collected from field observations, and company internal reports, then implemented in AnyLogic software for simulation. The simulation results indicate that a combination of five mechanical crews and a heavy equipment replacement rule option after five preventive maintenance (PM) periods significantly reduces unplanned downtime by 6.13%, increases on-running time to 89.32%, and maximizes profit to Rp. 11,052.04 million. Model validation via a two-sample t-test shows no significant difference between real and simulated data (*P*-value = 0.3908). This research introduces an integrated ABM approach that combines equipment availability, maintenance crew availability, and profit optimization, bridging gaps left by prior studies that analyzed these factors separately. The findings provide practical insights into optimizing heavy equipment management, emphasizing the importance of proactive maintenance strategies and efficient resource allocation to reduce operational costs and improve sustainability in large-scale construction projects.

INTRODUCTION

The construction of power plant project and its associated facilities is highly complex work, of large scale, requiring the co-ordination of innumerable people from construction contractors, engineering firms and local and central governments. Delays in construction work, which leads to increased costs and reduced productivity. Material procurement issues, labour, weather and poor project management can all lead to construction delays. Delay in the project can result in considerable project performance effects, cost overrun, productivity loss, and stakeholders dissatisfied (Corio et al., 2020). Project delays (5% in March 2025) in the construction of coal fired power plants (CFSPP), are often caused by unplanned heavy equipment downtime. This issue is critical because every hour of heavy equipment downtime could result in significant financial losses, project delays, and potential contractual disputes. Equipment downtime not only affects the project schedule and costs but could also impact the quality of work and the overall integrity of the project. This heavy equipment unplanned downtime is different from planned downtime heavy equipment where planned downtime heavy equipment is caused by regularly planned maintenance activities to ensure equipment operates efficiently and safely.

While precise figures are difficult to ascertain without in-depth analysis, industry research suggests that downtime could inflate project costs by about 23.9% from the total manufacturing cost ratio, and 13.3 % from planned production time mechanism according to research conducted by (Deshmukh & Manoj Bharat, 2021), with some studies reporting even higher figures. Furthermore, delays in project completion could lead to penalties, lost profit from delayed electricity energy production, and reputational damage for the Engineering Procurement Construction (EPC) contractor. Therefore, an approach is needed that can optimize maintenance planning and the use of heavy equipment so that downtime could be minimized, and projects can be completed on time. Unplanned maintenance could contribute up to 70% of total downtime according to a study conducted by (Irman et al., 2019) so that optimizing Preventive Maintenance (PM) is one of the main focuses.

Previous research on Preventive Maintenance (PM) of equipment has been widely conducted as one of the determining factors in preventing unplanned downtime or equipment breakdown and how to optimize revenue, costs, and profits, mostly conducted separately and by empirically methods such as mathematical optimization model, cost function analysis, sensitivity analysis, performance evaluation through OEE, Weibull distribution, etc. However, research that integrates PM, equipment availability, maintenance crew availability, revenue, costs, and profits obtained empirically with the dynamic capabilities of Agent-Based Modelling (ABM) is still very lacking, especially in Indonesia. So, this limits the potential for more realistic and comprehensive simulation of PM, equipment availability, maintenance crew availability, revenue, costs, and profits. Thus, The purpose of this research is to create an ABM to optimize heavy equipment replacement rule, equipment availability, maintenance crew availability, revenue, costs, and profits. This method bridges the gap between several approaches carried out by previous studies research which are usually carried out separately by integrating all of them empirically verified into a dynamic ABM.

LITERATURE REVIEW

The Impact of Unplanned Downtime on Construction Project Costs

Unplanned downtime is one of the biggest contributors to cost overruns on construction projects. As stated by (Mabrouk & Chelbi, 2022), an unplanned downtime results in a chain of undesirable consequences, such as excessive maintenance costs, project delay penalties, and even revenue loss because of inoperative equipment. Furthermore, in the study of (Supriatna et al., 2020) explains that measuring finances due to unplanned downtime using overall equipment effectiveness (OEE) can be used as a basis for decision making. Optimizing maintenance service practices enables construction firms to reduce the likelihood of equipment failure, which ultimately aids in cost control and enables the maintenance of schedules.

Based on (Tlili et al., 2024) the average number of breakdowns in operational periods is directly related to both the utilization rate and involves the maintenance strategy of the equipment. Indeed, when repair equipment is often out of service, the costs associated with minor repairs, as well as the penalties for the lack of sale of consumables during unsold equipment downtime can quickly pile up. Such a scenario causes a chain reaction, that results in either project delays or higher labor costs due to entering the same equipment (Tlili et al., 2024).

Optimal Heavy Equipment, and Maintenance Crew Availability Utilization

The effective availability of heavy equipment and the availability of maintenance crews are the most important factors affecting the operational efficiency and cost-effectiveness of construction. Unavailability of equipment for maintenance issues often has a significant impact on the bottom line, as not only the expected income from the use of the equipment is lost but also costs for expedited repairs or interim solutions may arise.

Optimal Maintenance Service Considering PM, Repair, and Replacement Cost

The construction project is more challenged by optimizing maintenance services and heavy equipment availability—as well as their usage costs which vary with time. Poor maintenance planning can result in high operational costs, equipment downtime and delays in mining projects that are crucial issues of construction management. These problems are compounded by the stochastic nature of equipment failure and the uncertainty in repair costs, emphasizing the importance of developing a robust maintenance service that can handle these uncertainties.

Moreover, the (Ben Mabrouk et al., 2024) study highlights the need to tailor maintenance strategies to fit the anticipated utilization rates of equipment. Accordingly, by analyzing the number and timing of maintenance actions, their results show that adjusting these factors would considerably increase equipment availability, resulting in maximizing construction companies' revenue potential (Ben Mabrouk et al., 2024). Such captive maintenance windows during high demand periods for equipment can reduce the risk of equipment and critical project phase downtimes.

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Agent-Based Modelling Simulation

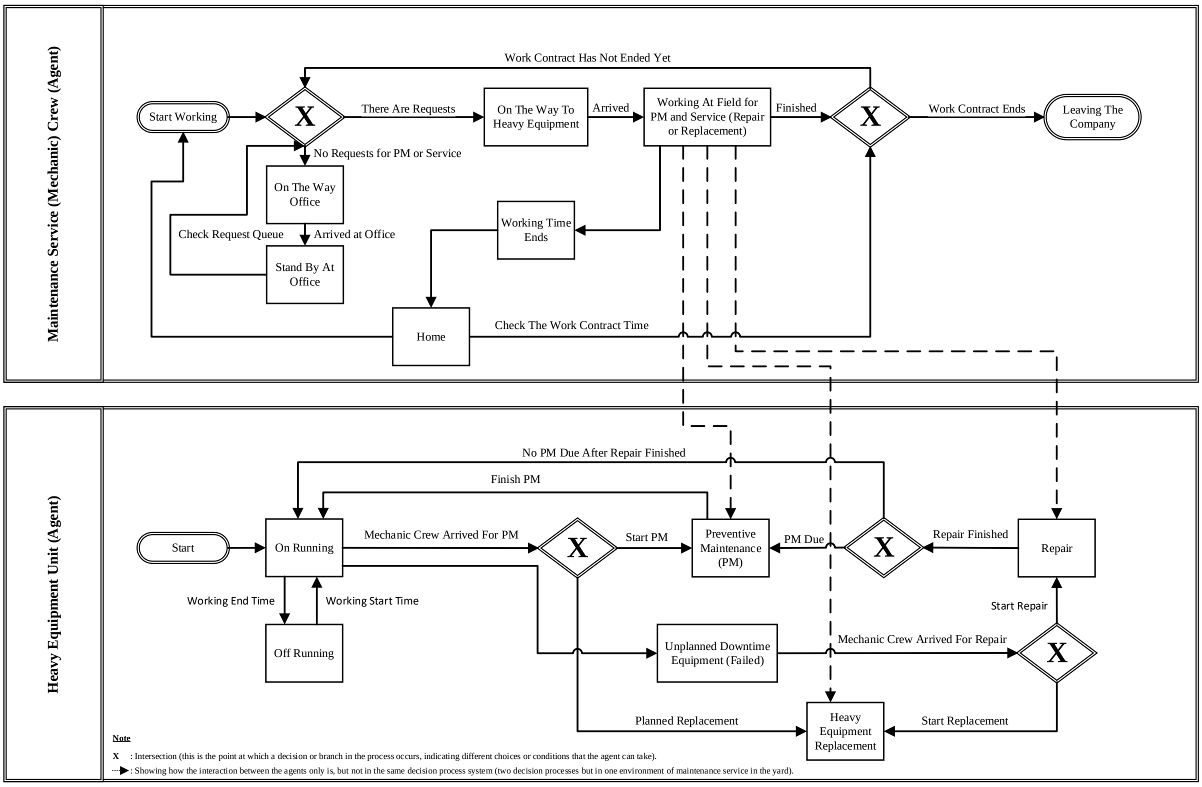
Based on (Utomo Sarjono Putro et al., 2015), Agent-based simulation (ABS) is a computational modeling technique that simulates the actions and interactions of autonomous agents (individual entities) to assess their effects on the system as a whole, providing researchers with insights into complex systems and phenomena through micro-level interactions that lead to macro-level behavior. Also, according to (Deguchi et al., 2013), Agent-based modeling (ABM) is used is a modeling approach for modeling complex systems by using the simulation of interactions of autonomous agents in simulated environment. ABM enables a simulation of how systems evolve under different conditions and supports decision-makers by helping them assess potential outcomes of actions in a world where global interdependence remains unclear. Furthermore, according to (Araya, 2020; Macy & Willer, 2002), ABM's ultimate objective is to comprehend the processes that could arise in a complex system, not to optimize it. A depiction of how agents' actions influence the system's emergent behavior.

METHODS

Conceptual Agent Decision Process Model Framework

It will be implemented into modeling simulation using AnyLogic software to study complex systems by modeling the interaction between Maintenance Service (Mechanic) Crew and Heavy Equipment Unit as individuals (agents) in the construction project activity environment in the field.

Figure 1. Conceptual Agent Decision Process Model Framework



This agent decision process model based on ABM is divided into Maintenance Service (Mechanic) Crew agent and Heavy Equipment Unit agent. For Maintenance Service (Mechanic) Crew agent, the mechanic's work starts when the refit service presentation begins, and they wait for requests for preventive maintenance (PM) or repairs. If no requests come in, they stand by at the office until they are assigned a task. Upon receiving a request, the mechanic checks the work contract time and verifies the schedule. If the contract is still valid, the mechanic heads to the yard to work on the heavy equipment. After completing a task in the field, they return to the office and prepare for the next task. If the work contract ends, the mechanic leaves, confirming the task is finished. For Heavy Equipment Unit agent, it is ready when the operator starts it and performs its tasks in the yard. If preventive maintenance (PM) is due, the mechanic conducts it and marks it as complete. In case of unplanned downtime, the mechanic checks the equipment's status and determines if it needs repair or replacement. After repairing or replacing the equipment, the mechanic verifies if any PM is required. If no PM is due, the process ends, and the equipment is ready for use. If the equipment requires replacement due to age, the mechanic proceeds with the planned replacement and performs the necessary actions based on the contract conditions.

Quantitative research methodologies are used in this research. Firstl, the researcher will use AnyLogic software version 8.9.4 to run a simulation. In order to model characteristics and variables like the availability of heavy equipment, maintenance service (mechanic) crew utilization, and other variation cost such as PM cost, equipment replacement cost, mechanic salary, etc. that the researcher will analyze the data that was gathered. Secondly, following the determination of the input data for each element, a simulation is carried out to make sure that the measurements obtained from the simulation and the collected data. Thirdly, conducting the validation to compare the output result between the real condition data and simulation data in order to know the output data from simulation is valid. Finally, to forecast system performance or compare the performance of two or more alternative designs, the simulation output analysis must be looked at. Lastly, the researcher wants to know which simulation option offers the best optimal solution.

Defining n_1, n_2, and α:

Amount of Monthly Average Revenue Per Unit

$$\frac{\textit{Total Amount of Monthly Revenue Per Unit}}{\textit{Total Number of Heavy Equipment}} \tag{1}$$

Amount of average PM Cost Per Unit

$$\frac{\textit{Total Amount of Average PM Cost Per Unit}}{\textit{Total Number of Heavy Equipment}} \tag{2}$$

Amount of Average Repair Cost Per Unit

$$\frac{\textit{Total Amount of Repair Cost Per Unit}}{\textit{Total Number of Heavy Equipment}} \tag{3}$$

Amount of Average Replacement Cost Per Unit

$$\frac{\textit{Total Amount of Replacement Cost Per Unit}}{\textit{Total Number of Heavy Equipment}} \tag{4}$$

Amount of Monthly Average Mechanics (MSC) Salary Cost Per Person

$$\frac{\textit{Total Amount of Mechanic Salary Cost Per Person}}{\textit{Total Number of Mechanic Crew}} \tag{5}$$

Normal Failure Rate (NFR)

$$\frac{\textit{Number of Normal Failures in a Given Period (Within A Certain Time)}}{\textit{Total Number of Operating Time (Within A Certain Time)}} \tag{6}$$

Probability Replacement Needed

$$\frac{\textit{Number of Replacements in a Given Period (Within A Certain Time)}}{\textit{Total Number of Service (Repair + Replacement) in a Given Period}} \tag{7}$$

Yearly Average Heavy Equipment On Running

$$\frac{\sum_{i=1}^{n}(Days\ of\ Heavy\ Equipment\ Running_i \times Number\ of\ Heavy\ Equipment\ Units\ Running_i)}{Total\ Days\ in\ A\ Year} \quad (8)$$

Yearly Average Mechanic Crew Size

$$\frac{\sum_{i=1}^{n}(Days\ of\ Mechanic\ Working_i \times Number\ of\ Mechanic\ Working_i)}{Total\ Days\ in\ A\ Year} \quad (9)$$

Yearly Heavy Equipment Cost

$$Yearly\ Total\ PM\ Cost + Yearly\ Total\ Repair\ Cost + Yearly\ Total\ Replacement\ Cost \quad (10)$$

Yearly Revenue from The Heavy Equipment Units

$$Yearly\ Average\ Heavy\ Equipment\ Running \times (Monthly\ Revenue\ Per\ Unit \times 12\ Months) \quad (11)$$

Yearly Expenses from The Heavy Equipment Units' Cost

$$(Yearly\ Average\ Mechanic\ Crew\ Size \times (Monthly\ Mechanic\ Crew\ Salary \times 12\ Months)) + Heavy\ Equipment\ Cost \quad (12)$$

Yearly Heavy Equipment's Profit

$$Yearly\ Revenue\ -\ Yearly\ Expenses \quad (13)$$

Average $(\bar{X})$

$$\frac{\sum X}{n} \quad (14)$$

Standard Deviation (*SD*):

$$\sqrt{\frac{(X_i - \bar{X})^2}{n-1}} \quad (15)$$

Variation (*SD*^{2}):

$$\frac{(X_i - \bar{X}_1)^2}{n_1 - 1} \quad (16)$$

Two Independent Sample t-count (t_{count}):

$$\frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{SD_1^{\ 2}}{n_1} + \frac{SD_2^{\ 2}}{n_2}}} \quad (17)$$

Degrees of freedom (*df*) By using Welch–Satterthwaite's formula:

$$\frac{\left(\frac{SD_1^{\ 2}}{n_1} + \frac{SD_2^{\ 2}}{n_2}\right)^2}{\frac{\left(\frac{SD_1^{\ 2}}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{SD_2^{\ 2}}{n_2}\right)^2}{n_2 - 1}} \quad (18)$$

t-critical ($t_{critical}$):

$$t_{\left(\frac{\alpha}{2}, df\right)} \quad (19)$$

Find P_{value} by using Linier Interpolation:

$$P_1 + \frac{(t - t_1)}{(t_2 - t_1)} \times (P_2 - P_1) \quad (20)$$

For two-tailed test, P_{value}:

$$2x\, P(T > |t|) \quad (21)$$

Where:

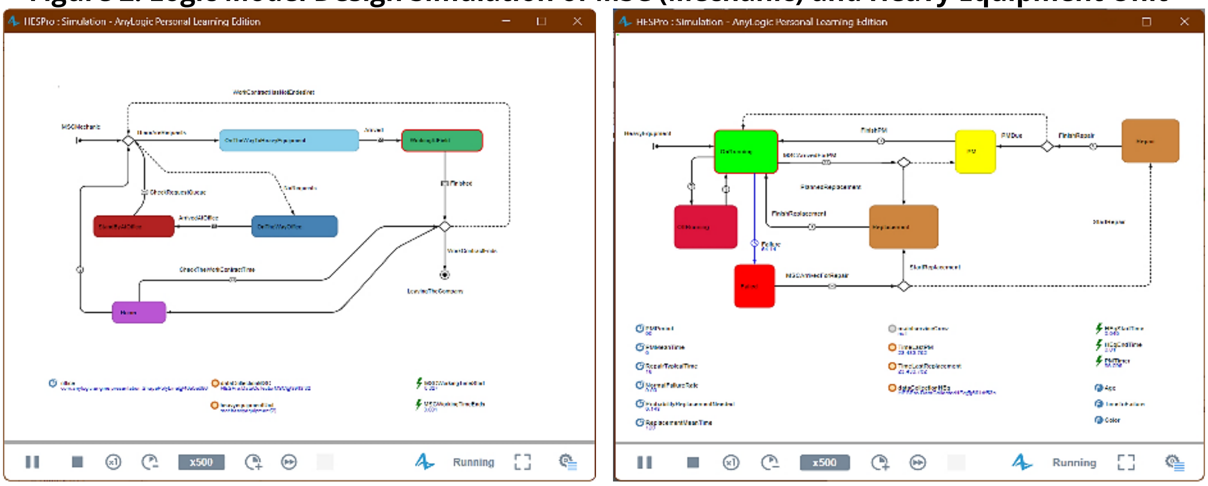
n_1 : Count of real condition data
n_2 : Count of simulation data
α : Critical limits in statistical tests
$(\bar{X})$: Average
$\sum X$: Number of data
n : Count of data
SD : Standard Deviation
SD^2 : Variation
t_{count} : Two Independent Sample Value
$t_{critical}$: Area in Upper Tail which obtained from the t-distribution table
P_{value} : Probability of obtaining a test statistic at least as extreme as the one observed
$|t|$: Statistic value based on the t-count
$P(T>|t|)$: Statistic value based on P_{value}

RESULTS

Computational Model (Logic Model Simulation Design)

The researcher developed an Agent-Based Modelling (ABM) simulation design using AnyLogic software version 8.9.4 from the components and model conceptualization grounded in real condition of heavy equipment availability and mechanic utilization. This computational model is divided into each agent.

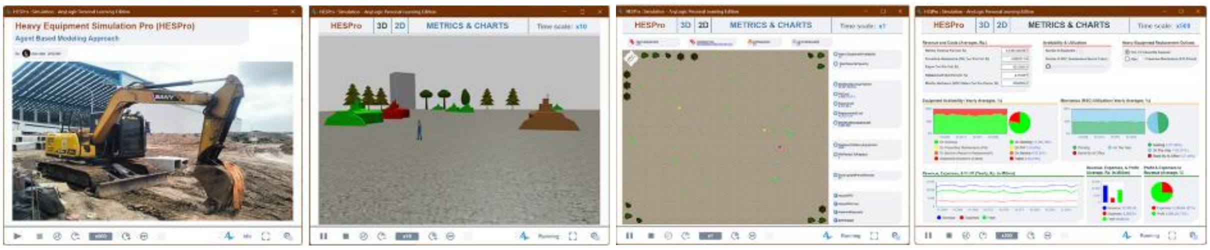
Figure 2. Logic Model Design Simulation of MSC (Mechanic) and Heavy Equipment Unit



Verification

The outcomes of executing the model in AnyLogic version 8.9.4 developed in 3D view, 2D view, and one for metrics & charts are shown in the figure below, demonstrating that the model is devoid of errors. Thus, the model has completed the subsequent verification phases.

Figure 3. View of Start-Up Screen, 3D & 2D, and Metrics & Charts Running Without Errors



Validation

The researcher ran the simulation model by the model time unit based on yearly as the real one from this business case, with the real time scale 1 to 500 as the execution mode by the stop at specified time during 2 calendar years (2023-2024). Based on (Banks, 2014), the researcher conducted the validation method by using historical data (historical data validation) – compare the output of the simulation model with real data.

In a two-sample independent t-test statistic method, researcher wanted to test the hypotheses:

- H_0 (Null hypothesis): There is no significant difference between real data and the simulated data.
- H_1 (Alternative hypothesis): There is a significant difference between real data and simulated data.

To gain the validation result will be H_0 or either H_1, researcher will use the t-critical and P-value in order to be analyzed as the summary validation. Below is the table for the real data and the simulation data obtained from the output of revenue, expenses, and profit by inputting the same data as per the collection data for the parameters.

Tabel 1. Real Data and Simulation Data for Validation

Heavy Equipment's Output	Year	Real Condition Data	Simulation Data
Revenue	2023	Rp. 9,808,277,321.22	Rp. 13,353,545,402.23
	2024	Rp. 10,400,135,937.50	Rp. 13,101,117,961.98
Expenses	2023	Rp. 2,029,628,128.64	Rp. 3,227,738,260.92
	2024	Rp. 4,213,189,753.76	Rp. 3,125,492,695.70
Profit	2023	Rp. 7,778,649,192.58	Rp. 10,125,807,141.31
	2024	Rp. 6,186,946,183.74	Rp. 9,975,625,266.28

Source: Internal Company Document and AnyLogic Software Data Processed, 2025

The following calculation steps by using the equation formula from the method in the previous section that carrying out the following result of the validation (table 3) are:

- **Step 1 and 2:** Defining α, n_1, and n_2, where n_1 = 6; n_1 = 6; α = 0.05 (due to the confidence level is 95%).
- **Step 3:** Calculating Average ($\bar{X}$) by using equation (14) for real data ($\bar{X}_1$) and Simulation data ($\bar{X}_2$) Then, ($\bar{X}_1$) = Rp. 6,736,137,752.91; ($\bar{X}_2$) = Rp. 8,818,221,121.40.
- **Step 4:** Standard Deviation (*SD*) by using equation (15) for real data SD_1 and Simulation data SD_2. Then, SD_1 = Rp. 3,248,626,329.85; SD_2 = Rp. 4,596,137,351.64.
- **Step 5:** Calculating Variation (SD^2) by using equation (16) for real data (SD_1^2) and Simulation data (SD_2^2). Then, SD_1^2 = Rp. 1.05536E+19; SD_2^2 = Rp. 2.11245E+19.
- **Step 6:** Calculating Two Independent Sample t-count (t_{count}) by using equation (17). Then, t_{count} = -0.906

- **Step 7:** Calculating degrees of freedom (*df*) by using Welch–Satterthwaite's equation (18) due to difference SD and varian (unequal varians) between real data and simulation data. Then, *df* = 9
- **Step 8:** Defining t-critical ($t_{critical}$) in the student's t-distribution table according to *df* and α from (Syihab, n.d.) and due to a two-tailed test by using equation (19). Then, $t_{critical}$ = ± 2.262
- **Step 9, 10, 11, and 12:** Defining t_{A1}, t_{A2}, P_{A1} or ($P_{A1}(T_{A1} > t_{A1})$, and P_{A2} or ($P_{A2}(T_{A2} > t_{A2})$. Since the t-distribution is a symmetric distribution centered at 0, and also, the probability to the left of a negative t value (e.g. $P(T < -0.906)$) is equal to the probability to the right of a positive *t* value (e.g. $P(T > 0.906)$) due to the symmetric property, then, $P(T < -0.906) \rightarrow P(T > 0.906)$
  To find the closest t-value to -0.906 in the table t-distribution according to its *df* = 9, then from the table t-distribution:
  $t_1 = 0.883 \rightarrow P_1 = 0.20 \rightarrow P_1(T_1 > t_1) = 0.20$
  $t = 0.906$
  $t_2 = 1.100 \rightarrow P_2 = ? \rightarrow P_2(T_2 > t_2) = ?$ (due to it not being shown on the table, but it will be interpolated in the next step).
  To interpolate t_2 = 1.100 that is not explicitly in the table, researcher can use Linear Interpolation (LI) between the two closest known t-values from the table. So, let's estimate between for t-count = 1.100
  $t_{A1} = 0.883 \rightarrow P_{A1} = 0.20$
  $t_{count} = 1.100 \rightarrow P_A = ?$
  $t_{A2} = 1.383 \rightarrow P_{A2} = 0.10$
- **Step 13:** Calculating P_A or $P_{value\ A}$. Find $P_A(T_A > 1.100)$ using linear interpolation between these two points by using equation (20). Then, $P_{value\ A} = 0.1566$
- **Step 14, 15, 16, and 17:** Defining t_1, t_2, P_1 or ($P_1(T_1 > t_1)$, and P_2 or ($P_2(T_2 > t_2)$. After getting $P_A(T_A > 1.100) = 0.1566$, then find $P(T > 0.906)$:
  $t_1 = 0.883 \rightarrow P_1 = 0.20$
  $t = 0.906 \rightarrow P = ?$ (due to it not being shown on the table, but it will be interpolated below)
  $t_2 = 1.100 \rightarrow P_2 = 0.1566 \rightarrow P(T > t_2) = 0.1566$
- **Step 18:** Calculating *P* or P_{value}. Since -0.906 is not available directly in the table t-distribution, then researcher will use linear interpolation to find the *P*-value by using equation (20). Then, $P_{value} = 0.1954$
- **Step 19:** Calculating two-tailed test, P_{value} by using equation (21). Then, Two-tailed test, $P_{value} = 0.3908$.

After conducting the calculation and obtaining the result, then, they had to be interpreted based on two-tailed *t*-test, thus, researcher compared:

- $|t_{count}|$ to $t_{critical}$:
  The rule:
  (i.) If $|t_{count}| \geq t_{critical}$, then reject H_0 (null hypothesis) → the model is invalid → H_1 (alternative hypothesis)
  (ii.) If $|t_{count}| < t_{critical}$, then accept H_0 (null hypothesis) → the model is valid.
  $|t_{count}| = |-0.906| = 0.906$; $t_{critical} = 2.262$. Due to $|t_{count}| = 0.906 < 2.262$, then, accept H_0 (null hypothesis) → the model is valid because there is no significant difference between the real data and the simulated data.
- P_{value} to α :
  The rule:
  (i.) If $P_{value} \leq \alpha$, then reject H_0 (null hypothesis) → the model is invalid → H_1 (alternative hypothesis).

(ii.) If $P_{value} > \alpha$, then accept H_0 (null hypothesis) → the model is valid.

Due to $P_{value} \approx 0.3908 > 0.05$, then accept H_0 (null hypothesis), then, the model is valid because there is no significant difference between the real data and the simulated data.

Thus, due to $t_{count} < t_{critical}$ and $P_{value} > \alpha$, then accept H_0 (null hypothesis). Thus, the simulation model can be considered valid because there is no significant evidence that the simulation results differ from the real data at the 0.05 (5%) significance level.

Experiment Scenario Designs

In real condition, the average monthly income per unit reaches Rp. 60,391,304.35, while the periodic maintenance (PM) cost per unit is Rp. 4,588,521.74, and the average repair cost per unit is Rp. 8,212,000.00. If the equipment cannot be repaired, it will be replaced at an average cost of Rp. 42,332,000.00. The monthly salary of a mechanic is set at Rp. 8,500,000.00 with two mechanics involved. The heavy equipment is 23 units, PM schedule period is 90 days, PM mean time is 6 hours, repair typical time is 18 hours, NFR is 0.03 failures per day, probability replacement needed is 0.1429, replacement mean time is 120 hours. The heavy equipment replacement strategy is only carried out if the equipment cannot be repaired.

In simulation, the following experiment scenario will be divided into two parts according to the choice of the heavy equipment replacement rule options:

A. **Only if it cannot be repaired:** In this rule option, all the data input is the same as in real condition (remain unchanged). However, in the number of mechanics, there are differences in scenarios, namely in experiment #1 for 3 mechanics, experiment #2 for 4 mechanics, experiment #3 for 5 mechanics, experiment #4 for 6 mechanics, and experiment #5 for 7 mechanics.
B. **After 5 PM periods**: In this rule option, all the data input is the same as in real condition. However, in the number of mechanics, there are differences in scenarios, namely in experiment #6 for 2 mechanics, experiment #7 for 3 mechanics, experiment #8 for 4 mechanics, experiment #9 for 5 mechanics, experiment #10 for 6 mechanics, and experiment #11 for 7 mechanics.

Comparison of The Experiment Scenario Output

Researcher has compared and analyzed the previous output result from the simulation model (table 2-7) according to each experiment scenario design. Real Condition takes place at the end of the year: 2023 and 2024. Because the construction project plan will finish at the end of 2026, the simulation takes the average forecast for the next two ends of the year: 2025 and 2026. It must be noted that the color of "Green" means the value gap is increasing, while the "Red" one means the value gap is decreasing.

1. **Heavy Equipment's Availability Section**

Tabel 2. Comparison of Experiments for Heavy Equipment's Availability on Options for Heavy Equipment Replacement Rule: Only If It Cannot Be Repaired

Description	On Running (Yearly Averages, %)	On Preventive Maintenance (PM) (Yearly Averages, %)	On Service (Repair or Replacement) (Yearly Averages, %)	Unplanned Downtime (Failed) (Yearly Averages, %)
Real Condition	60.62%	0.13%	2.91%	12.73%
Experiment #1	86.93%	0.21%	4.19%	8.67%
Gap to Real	26.31%	0.08%	1.28%	4.06%
Experiment #2	88.26%	0.21%	4.52%	7.02%

Gap to Real	27.63%	0.08%	1.60%	5.71%
Experiment #3	88.66%	0.22%	4.37%	6.74%
Gap to Real	28.04%	0.10%	1.46%	5.99%
Experiment #4	88.83%	0.23%	4.49%	6.45%
Gap to Real	28.21%	0.10%	1.57%	6.28%
Experiment #5	89.10%	0.21%	4.35%	6.33%
Gap to Real	28.48%	0.09%	1.44%	6.40%

Source: Data Processed by Author in AnyLogic Software

Tabel 3. Comparison of Experiments for Heavy Equipment's Availability on Options for Heavy Equipment Replacement Rule: After 5 PM Periods

Description	On Running (Yearly Averages, %)	On Preventive Maintenance (PM) (Yearly Averages, %)	On Service (Repair or Replacement) (Yearly Averages, %)	Unplanned Downtime (Failed) (Yearly Averages, %)
Experiment #6	78.93%	0.17%	3.90%	17.00%
Gap to Real	18.30%	0.04%	0.99%	4.27%
Experiment #7	87.05%	0.20%	4.17%	8.59%
Gap to Real	26.43%	0.07%	1.25%	4.14%
Experiment #8	88.17%	0.21%	4.62%	7.00%
Gap to Real	27.55%	0.09%	1.71%	5.73%
Experiment #9	89.32%	0.21%	4.33%	6.13%
Gap to Real	28.70%	0.08%	1.42%	6.60%
Experiment #10	88.96%	0.22%	4.40%	6.43%
Gap to Real	28.34%	0.09%	1.48%	6.30%
Experiment #11	89.18%	0.20%	4.62%	6.00%
Gap to Real	28.56%	0.07%	1.70%	6.73%

Source: Data Processed by Author in AnyLogic Software

2. Mechanics' Utilization Section

Tabel 4. Comparison of Experiments for Mechanics' Utilization On Options for Heavy Equipment Replacement Rule: Only If It Cannot Be Repaired

Description	Working (Yearly Averages, %)	On The Way (Yearly Averages, %)	Stand By At Office (Yearly Averages, %)
Real Condition	34.95%	41.02%	0.42%
Experiment #1	33.73%	57.43%	8.87%
Gap to Real	1.21%	16.41%	8.45%
Experiment #2	27.18%	55.85%	16.98%
Gap to Real	7.77%	14.83%	16.55%
Experiment #3	21.14%	56.42%	22.42%
Gap to Real	13.81%	15.40%	22.00%
Experiment #4	18.05%	54.27%	27.67%
Gap to Real	16.90%	13.25%	27.25%
Experiment #5	15.00%	50.49%	34.51%
Gap to Real	19.95%	9.46%	34.09%

Source: Data Processed by Author in AnyLogic Software

Tabel 5. Comparison of Experiments for Mechanics' Utilization on Options for Heavy Equipment Replacement Rule: After 5 PM Periods

Description	Working (Yearly Averages, %)	On The Way (Yearly Averages, %)	Stand By At Office (Yearly Averages, %)
Experiment #6	46.85%	52.65%	0.50%
Gap to Real	11.90%	11.63%	0.08%
Experiment #7	33.47%	56.63%	9.90%
Gap to Real	1.48%	15.61%	9.48%
Experiment #8	27.80%	55.85%	16.35%
Gap to Real	7.15%	14.83%	15.93%
Experiment #9	20.92%	53.28%	25.80%
Gap to Real	14.03%	12.26%	25.38%
Experiment #10	17.68%	53.78%	28.53%
Gap to Real	17.26%	12.76%	28.11%
Experiment #11	15.83%	48.43%	35.73%
Gap to Real	19.12%	7.41%	35.31%

Source: Data Processed by Author in AnyLogic Software

3. Revenue, Expenses, and Profit Section

Tabel 6. Comparison of Experiments for Revenue, Expenses, and Profit on Options for Heavy Equipment Replacement Rule: Only If It Cannot Be Repaired

Description	Revenue	Expenses	Profit
	Heavy Equipment (Yearly Averages, Rp. in Million)	Heavy Equipment & Mechanics (Yearly Averages, Rp. in Million)	Heavy Equipment (Yearly Averages, Rp. in Million)
Real Condition	Rp. 10,104.21	Rp. 3,121.41	Rp. 6,982.80
Experiment #1	Rp. 14,489.63	Rp. 3,585.46	Rp. 10,904.17
Gap to Real	Rp. 4,385.42	Rp. 464.05	Rp. 3,921.37
Experiment #2	Rp. 14,710.93	Rp. 3,922.19	Rp. 10,788.75
Gap to Real	Rp. 4,606.73	Rp. 800.78	Rp. 3,805.95
Experiment #3	Rp. 14,778.03	Rp. 3,877.21	Rp. 10,900.82
Gap to Real	Rp. 4,673.82	Rp. 755.80	Rp. 3,918.02
Experiment #4	Rp. 14,807.31	Rp. 4,072.33	Rp. 10,734.97
Gap to Real	Rp. 4,703.10	Rp. 950.92	Rp. 3,752.18
Experiment #5	Rp. 14,850.95	Rp. 4,116.81	Rp . 10,734.14
Gap to Real	Rp. 4,746.74	Rp. 995.40	Rp. 3,751.34

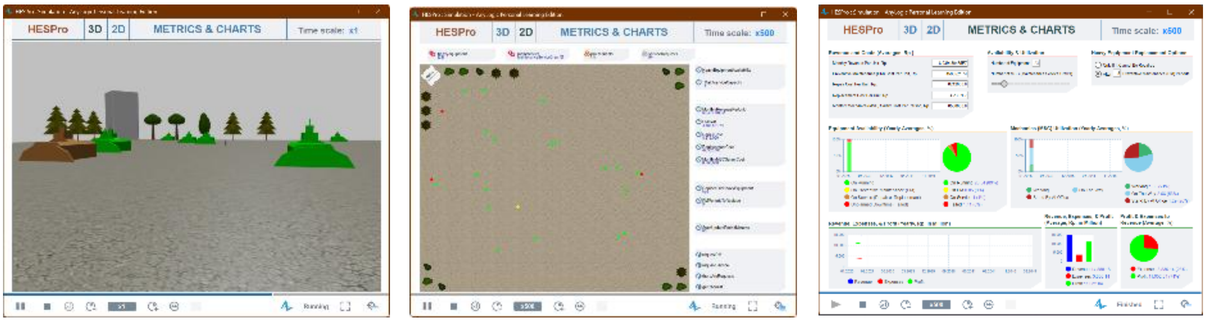
Source: Data Processed by Author in AnyLogic Software

Tabel 7. Comparison of Experiments for Revenue, Costs, and Profits on Options for Heavy Equipment Replacement Rule: After 5 Preventive Maintenance (PM) Periods.

Description	Revenue	Expenses	Profit
	Heavy Equipment (Yearly Averages, Rp. in Million)	Heavy Equipment & Mechanics (Yearly Averages, Rp. in Million)	Heavy Equipment (Yearly Averages, Rp. in Million)
Experiment #6	Rp. 13,155.64	Rp. 3,280.73	Rp. 9,874.91
Gap to Real	Rp. 3,051.44	Rp. 159.32	Rp. 2,892.12
Experiment #7	Rp. 14,508.90	Rp. 3,540.35	Rp. 10,968.55
Gap to Real	Rp. 4,404.69	Rp. 418.94	Rp. 3,985.76
Experiment #8	Rp. 14,695.79	Rp. 4,011.11	Rp. 10,684.68
Gap to Real	Rp. 4,591.59	Rp. 889.70	Rp. 3,701.88
Experiment #9	Rp. 14,888.18	Rp. 3,836.14	Rp. 11,052.04
Gap to Real	Rp. 4,783.97	Rp. 714.73	Rp. 4,069.24
Experiment #10	Rp. 14,827.87	Rp. 4,038.42	Rp. 10,789.44
Gap to Real	Rp. 4,723.66	Rp. 917.02	Rp. 3,806.64
Experiment #11	Rp. 14,864.23	Rp. 4,244.67	Rp. 10,619.56
Gap to Real	Rp. 4,760.02	Rp. 1,123.26	Rp. 3,636.76

Source: Data Processed by Author in AnyLogic Software

Figure 4. One of Example of 3D, 2D, and Metrics & Charts Outputs (Experiment #9)



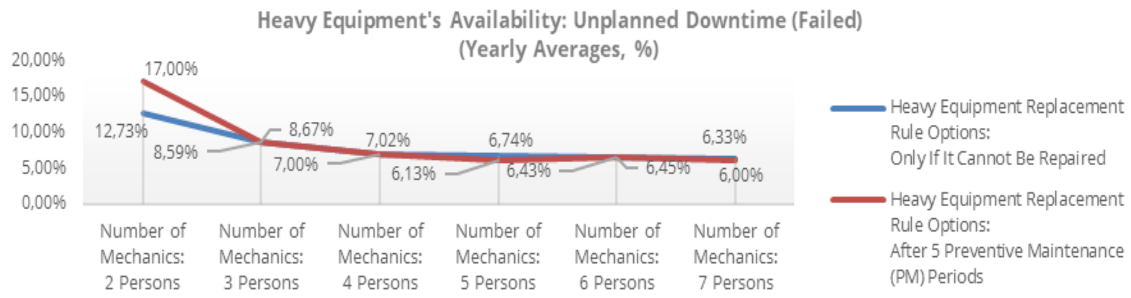
DISCUSSION

By establishing these conditions into a design simulation, then, according to the objective of this research and the comparison of the experiment scenario output (table 2-7), researcher obtained the best optimal results by experiment #9 compared to other experiment scenario designs. The following are the 3 main reasons:

Reducing heavy equipment unplanned downtime (failed)

The best experiment is experiment #9. In this experiment, unplanned downtime was successfully controlled with the lowest percentage of 6.13%. Compared to other experiments, especially experiment #6 (3 mechanics) which had the highest unplanned downtime of 17.00%, experiment #9 showed better performance in reducing unplanned downtime. This significant decrease in downtime indicates that by using five mechanics and placing equipment after the preventive maintenance period, heavy equipment availability can be maintained better. Although experiment #11 (7 mechanics) had slightly lower unplanned downtime (6.00%), experiment #9 (6.13%) was still more optimal because it used fewer mechanics, leading to lower operating costs without sacrificing significant performance. The use of 5 mechanics in experiment #9 provided better cost efficiency compared to 7 mechanics in experiment #11, even though the difference in downtime was very small (0.13% difference only). In addition, experiment #9 showed higher profitability, thus providing a better balance between reduced downtime, operating costs, and overall financial performance.

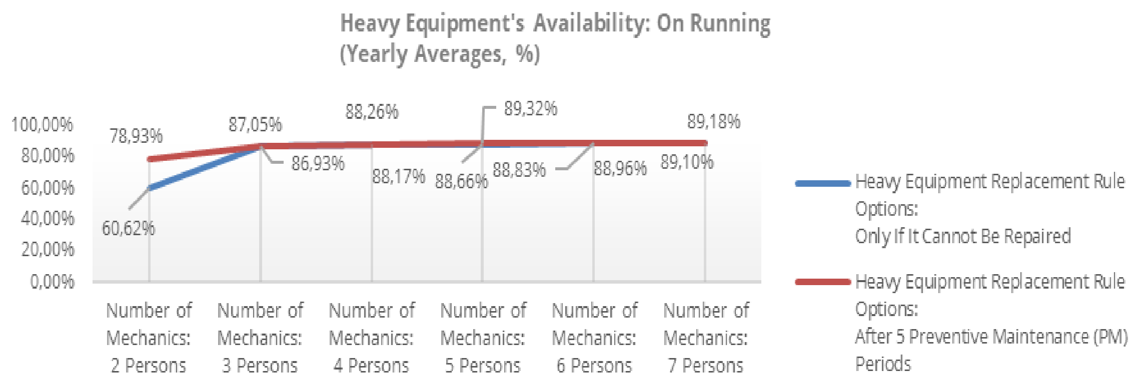
Figure 5. Output of Experiments for Heavy Equipment's Availability: Unplanned Downtime



Enhancing heavy equipment on running

To enhance heavy equipment's availability: on running, experiment #9 is a more maximal choice. In this experiment, heavy equipment availability reached 89.32%, which is the highest number compared to other experiments. Although experiment #11 (7 mechanics) showed a very close number, which was 89.18%, experiment #9 had the advantage of using fewer mechanics, which could reduce operational costs without sacrificing equipment availability. With 5 mechanics, this experiment showed better efficiency in terms of resource utilization and more scheduled preventive maintenance, thus increasing heavy equipment availability more efficiently. This shows that fewer mechanics can work more effectively with replacement regulation after 5 PM periods, making experiment #9 a better choice for optimizing machine availability in the long term.

Figure 6. Output of Experiments for Heavy Equipment's Availability: On Running



Maximizing Heavy Equipment Profits

According to the previous table 8-9 and the following figure 10, experiment #9 (5 mechanics with heavy equipment replacement rule options: after 5 Preventive Maintenance (PM) periods) is the best to maximize heavy equipment profits. In this experiment, the profit generated reached Rp. 11,052.04 million, which is the highest value compared to other experiments. In addition, this experiment uses 5 mechanics, which creates an efficient balance between operational costs and preventive maintenance, providing optimal results in terms of profitability. With more efficient resource management and higher profits, experiment #9 has proven to be the most effective in maximizing heavy equipment profits compared to other experiments.

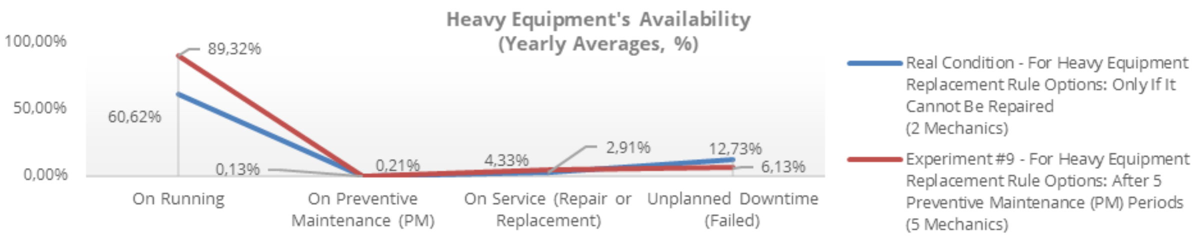
Figure 7. Output of Experiments for Heavy Equipment's Profit

In addition, the following are the outcomes of alternative experiment # 9 that have been simulated from each section compared to its real condition data:

Heavy Equipment's Availability Section

In the following charts (figure 11), it can be seen that experiment #9 successfully increased the percentage of heavy equipment that was on running from 60.62% to 89.32%, while significantly reducing heavy equipment unplanned downtime (failed) from 12.73% to only 6.13%. This improvement reflects the success of optimizing the combination of the number of mechanics (5 persons) and a more proactive heavy equipment replacement rule (replacing it after 5 PM periods). This performance shows that the heavy equipment is more operationally ready, which is the key to construction project efficiency. High availability reduces potential bottlenecks and increases project reliability.

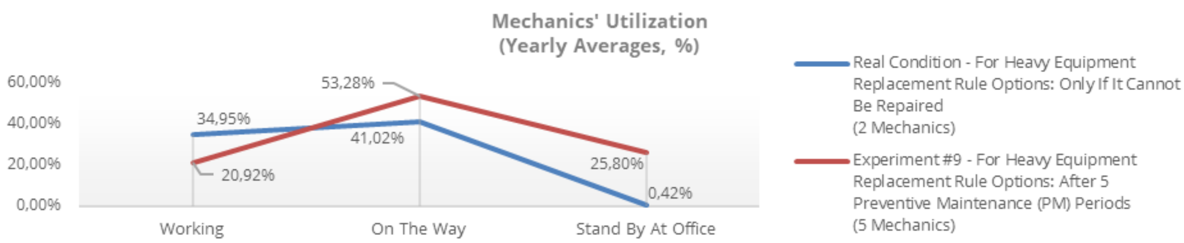
Figure 8. Comparison of Real vs. Experiments #9 for Heavy Equipment's Availability Section



Mechanics' Utilization Section

In the following charts (figure 12) indicate that experiment #9 is able to optimize the utilization of mechanic crew, where the proportion of standby at office time increases drastically from 0.42% in real conditions to 25.80% (experiment #9). This means that mechanics in real conditions are too heavily loaded with work, so that waiting time or rest time are almost non-existent. On the other hand, in experiment #9 with 5 mechanics, the distribution of working time is more even: Working 20.92% on the way 53.28%, and stand by 25.80%, indicating a balance between productivity and readiness (by standing by at office). This indicates a healthier work system and is more responsive to heavy equipment damage.

Figure 9. Comparison of Real vs. Experiments #9 for Mechanics' Utilization Section



Revenue, Expenses, and Profit Section

In the last following charts (figure 13) reinforces experiment #9's financial superiority. Profit increased from Rp. 6,982.80 million (real condition) to Rp. 11,052.04 million (experiment #9). This is a profit jump of more than 58%, driven by an increase in revenue from Rp. 10,104.21 million to Rp. 14,888.18 million. Although there was an increase in costs (from Rp. 3,121.41 million to Rp. 3,836.14 million), these additional costs were much smaller than the increase in revenue. This means that experiment #9's strategy significantly improved cost efficiency per operating heavy equipment and contributed to the achievement of a much larger profit margin.

Figure 10. Comparison of Real vs. Experiments #9 for Revenue, Expenses, and Profit Section

CONCLUSION

This research has successfully modeled Agent-Based Modeling (ABM) to optimize the number of mechanic crews and heavy equipment replacement development rules at PT. XYZ. There is also greater certainty about the outcome that hiring more mechanics does not always achieve the desired outcome. Therefore, the number of mechanical crews required is optimal, not maximum.

The simulation results showed that the use of 5 mechanic crews with a tool replacement policy after 5 PM periods resulted in the highest efficiency: unplanned downtime decreased to 6.13%, on-running time increased to 89.32%, and profit reached Rp. 11,052.04 million. This combination is superior to other scenarios because it balances operational costs and equipment availability.

Statistical validation confirmed the accuracy of the model (*P*-value 0.3908), making it a reliable tool for strategic decision making. These findings highlight the importance of a proactive approach in heavy equipment maintenance as well as proper resource allocation to minimize operational disruptions and maximize profits.

LIMITATION AND SUGESSTIONS

The research has been limited to how to reduce heavy equipment unplanned downtime, enhance heavy equipment running, and maximize heavy equipment profits at PT. XYZ in the construction of CFSPP Project by optimizing the number of mechanic crews and heavy equipment replacement rule options. Neither the EPC company's net profit nor tax has been calculated and shown in this research.

Thus, other construction projects might have different conditions that lead to different results from the modelling simulation. Future research suggestions should extend the model to consider external variables such as the influence of fuel price dynamics, supplier engagement, and the effect of weather on equipment performance. Moreover, incorporating machine learning to predict heavy equipment failures and adjustments in real-time can enhance the simulation predictive accuracy. Future researches should also investigate the use of ABM in various construction types (road infrastructure, buildings, etc.) or in another industrial branches.

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