



RESEARCH ARTICLE

Performance-Based Cycle Time Analysis for Improving the Operational Productivity of the Hauling Fleet at PT Rogomos Tapind Group

Ella Yula Ella Wati Simamora ^{1*} | Prihatin Lumban Raja ² | Fahmi Natigor Nasution ³

^{1*,2,3} Master of Management Program, Graduate School, Universitas Sumatera Utara, Kota Medan, Sumatera Utara. Indonesia.

Correspondence

¹ Master of Management Program, Graduate School, Universitas Sumatera Utara, Kota Medan, Sumatera Utara. Indonesia.
Email: ellasimamora75@gmail.com

Funding information

Universitas Sumatera Utara.

Abstract

PT Rogomos Tapind Group (PT RTG) provides wood-harvesting and hauling services in support of industrial plantation forestry; however, its hauling operations have not been profitable. Cycle time, defined as the time required for a single truck to complete one haul cycle, directly affects trip frequency, fleet utilization, and revenue. Yet PT RTG has neither a cycle-time standard nor dispatch discipline governing the start of successive cycles. This study analyzes the sources of unstable cycle time and low fleet productivity at PT RTG and proposes a conceptual control framework. The study applies a Business Process Improvement (BPI) approach using descriptive-quantitative analysis of unloading-ticket and GPS data from seven active hauling units. Cycle time is measured as the interval between two consecutive unloading tickets for the same unit, based on 763 unloading tickets recorded from January to October 2025, yielding 756 calculable cycles. GPS movement and parking records from May to October 2025 are decomposed by duration and location to identify non-productive time. Cycle time has a median of approximately 47 hours, close to an implicit 48-hour ideal, but a mean of about 63 hours. Approximately 53% of cycles were completed within 48 hours, while a small number of extreme cycles increased the average. GPS decomposition shows the fleet moving for only about 27% of monitored time and parked for about 73%, with prolonged parking and inter-cycle turnaround at mill and base areas as the main sources of waste. Current productivity averages about 10.9 trips per unit per month, below the fleet's demonstrated capacity.

Keywords

Cycle Time; Hauling, Productivity; Turnaround Control; Driver KPI.

1 | INTRODUCTION

Hauling is a critical activity in the wood supply chain of industrial plantation forestry (Hutan Tanaman Industri, HTI). PT Rogomos Tapind Group (PT RTG) provides harvesting and hauling services as a partner of PT Riau Andalan Pulp and Paper (PT RAPP). In this operational model, revenue is generated only after wood is transported, weighed, and accepted at the mill. Therefore, hauling performance has a direct effect on productivity, cost efficiency, and business continuity. Cycle time, defined as the total time required for a truck to complete one haul cycle, is a key operational indicator in transportation management. It influences trip frequency, fleet utilization, monthly output, and revenue generation. From an operations management perspective, long and unstable cycle times indicate inefficiency and reduce system performance. Previous studies have shown that lead time reliability and variability are important determinants of logistics performance, while bottleneck conditions can significantly disrupt transportation flow and reduce productivity (Dullaert & Zamparini, 2013; Ndubi *et al.*, 2016; Moeller *et al.*, 2008).

PT RTG's hauling operation has not been profitable. Fixed monthly obligations, particularly vehicle loan installments, must be covered by trip-based revenue, but the number of trips completed has remained insufficient. In addition, one unit in the eight-vehicle fleet has become unproductive because a liquidity shortfall has delayed a necessary repair. This condition reflects not only a financial issue but also an operational performance problem related to cycle time control, fleet availability, and workload balancing. Cost accounting perspectives emphasize that such conditions directly affect operating cost absorption and profitability (Horngren *et al.*, 2015). This study examines cycle time, fleet utilization, and operating cost to identify the main causes of underperformance and to develop a control framework. The analysis is consistent with lean thinking, which focuses on reducing non-value-added time and improving process flow (Argiyantari *et al.*, 2022; Macedo *et al.*, 2025). In transportation systems, performance improvement often requires the identification of waiting time, idle time, and other wasteful activities that do not contribute to output.

Measurement of cycle time, based on the interval between two consecutive unloading tickets for the same unit across seven active units from January to October 2025, shows that the median cycle time is approximately 47 hours, close to an implicit 48-hour target, while the mean is considerably higher at about 63 hours. GPS data for May to October 2025 further indicate that the fleet is moving for only about 27% of monitored time and parked for the remaining 73%. This pattern suggests that non-productive time is substantial and that operational flow is unstable. The difference between the median and the mean is meaningful. If hauling were uniformly slow, both values would be similar. However, the data show that more than half of all cycles are completed within 48 hours, while a smaller number of extreme cycles, some lasting several hundred hours, increase the average substantially. This indicates that the main issue is not uniformly long travel time, but variability in cycle completion and loss of operational rhythm. Research on lead time variability supports the view that unstable timing can reduce logistics performance even when average process time appears acceptable (Dullaert & Zamparini, 2013; Ndubi *et al.*, 2016).

Prior studies on dispatching and time-window scheduling generally assume that delay is caused by queuing at specific process points and address it through arrival regulation and scheduling rules (Liu *et al.*, 2017). In transportation services, vehicle tracking systems and performance feedback have also been shown to improve control and service outcomes when they are used consistently (Kluger & DeNisi, 1996; Orno *et al.*, 2023). However, studies that use GPS-based decomposition to distinguish genuine queuing from prolonged inter-cycle parking in wood hauling for industrial plantation forestry remain limited. As a result, there is a risk that control measures designed for one type of delay are applied to a system with a different waste structure.

Based on this diagnosis, the study pursues three objectives: (1) to analyze the factors underlying low fleet utilization and unstable cycle time by examining process structure, operational activities, and the pattern and location of stoppage time from GPS data; (2) to analyze how utilization and cycle time affect trip productivity and financial performance; and (3) to design a cycle-time control system based on turnaround control, dispatch discipline, driver-hour management, and GPS-based monitoring to improve fleet productivity. This study contributes an integrated diagnosis by combining unloading-ticket records with GPS data to identify where hauling time is lost. The findings also show that the initial assumption that pontoon and unloading queues are the main bottlenecks is not fully supported by the evidence. On this basis, the study proposes a conceptual cycle-time control framework for PT RTG management, with projected productivity and financial effects treated as prospective estimates rather than field-tested results.

2 | BACKGROUND THEORY

2.1 Cycle Time, Lean Operations, and Value-Added Classification

Heizer and Render (2017) frame operational efficiency as an organization's ability to convert input into output with shorter processing time, higher throughput, and more controlled costs, positioning cycle time as an indicator of system efficiency rather than as a measure of time alone. Extend this through the concept of total cycle time,

arguing that compressing cycle time across a process is a foundation of supply-chain agility because shorter and more stable time improves responsiveness and reduces waste in material and information flow. Ng, Ferrin, and Pearson (1997) identify transportation as one of the components most decisive for total cycle time, so managing transport and waiting time is central to productivity improvement. Argyantari, Simatupang, and Basri (2022) provide empirical support from an Indonesian context, showing that applying lean thinking to transport operations can reduce lead time and increase vehicle productivity. To understand what fills a cycle, this study also draws on lean operations and value-stream analysis. Ohno (1988) identifies waste in several forms, including waiting time, unnecessary movement, repeated processing, and activities that do not add value. Accordingly, this study classifies activity within a haul cycle into Value Added (VA), Business Necessary but Non-Value Added (BNVA), and Non-Value Added (NVA) categories. Macedo *et al.* (2025) show that VA/NVA classification in logistics operations helps reveal inefficiency that is otherwise hidden within routine activity, a function this classification serves in the present study by separating genuinely productive time from time that only consumes fleet capacity and cost.

2.2 Bottleneck, Process Variability, and Dispatching

Small (2015) explains that bottlenecks in transportation systems arise not only from limited capacity but also from uncontrolled scheduling choices and arrival patterns, so a process point can become a source of queuing even without any change in physical capacity. Show that a bottleneck is systemic: a delay at one point propagates through the process via a domino effect. Dullaert and Zamparini (2013) and Ndubi, Iravo, and Ochiri (2016) show that lead-time variability increases logistics cost and lowers service reliability independent of average duration. This provides the theoretical basis for this study's emphasis on variability, not merely average cycle time, as the object of control. Where the dominant waste is arrival bunching at a process point, dispatching and time-window scheduling are established responses. Subtil, Silva, and Alves (2011) show that systematically designed truck dispatching can increase productivity and reduce operational delay without adding equipment. Liu *et al.* (2017) and Su *et al.* (2021) show that time-window scheduling can improve scheduling stability and fleet utilization under conditions of simultaneous or clustered arrival at service points. These studies establish dispatching as a valid control principle in general, while making explicit the condition, namely arrival bunching, under which time-window scheduling is the appropriate instrument.

2.3 Driver Performance and GPS-Based Logistics Visibility

Because cycle time is also shaped by how a vehicle is operated, this study draws on driver-performance literature. Ping *et al.* (2019) show that driver behavior is a significant predictor of fuel consumption, and Yuniar *et al.* (2020) show, using GPS tracking, that driver behavior materially affects travel-time effectiveness and the consistency of trip rhythm. To translate this into a control mechanism, Goal-Setting Theory, which holds that specific, measurable, and time-bound goals produce higher performance than vague instruction, Finding that feedback interventions are effective when directed at task and performance rather than personal evaluation. Together, these studies support the use of time-based, measurable driver KPIs with regular feedback rather than subjective supervisory judgment. Objective visibility into fleet activity is a precondition for this kind of control. Shamsuzzoha *et al.* (2013) show that tracking and tracing improve the visibility, monitoring accuracy, and controllability of logistics operations; Zhang *et al.* (2026) show that integrated vehicle-and-shipment tracking improves the quality of operational data available for behavior and time analysis; and Orno, Risra, and Gunawan (2023) show that vehicle tracking improves service reliability. In this study, GPS functions not merely as a positioning tool but as the instrument used to measure actual cycle time, verify idle time, and identify deviation from the departure thresholds proposed in Section 4.6.

2.4 Logistics Cost Control

Horngren, Datar, and Rajan (2015) define cost control as the systematic process of monitoring, comparing, and controlling cost against operational targets. In logistics specifically, Silva, Gonçalves, and Leite (2014) argue that Activity-Based Costing is better suited than aggregate costing to identify cost drivers, because cost can be traced to actual activity, such as waiting, idling, delay, and inefficient movement, rather than treated as an undifferentiated total. Škerlić and Muha (2016) show that systematic logistics cost control reduces process disruption. Wojuade and Oladosu (2020) show that managerial decisions on fuel use, drivers, and maintenance directly shape truck operating cost, and Nariendra, Santosa, and Sutandi (2026) show that heavy-truck fuel consumption can be modeled from operational variables such as speed, load, and road condition. Together, this literature supports treating PT RTG's operating loss as a consequence of time lost in the process, traceable through trip volume and the resulting cost per trip, rather than as an unexplained aggregate deficit.

2.5 Business Process Improvement as an Analytical Framework

The study adopts Business Process Improvement (BPI) approach, a systematic method for improving work

processes by understanding current conditions, measuring process performance, identifying sources of waste, and redesigning the process. BPI is an appropriate framework for PT RTG because the company's problem is process-based rather than technical or individual: the activities within a haul cycle already function, but no mechanism governs when the next cycle should begin.

2.6 Research Gap

Two gaps position this study. First, dispatching and time-window scheduling research is generally conducted in general logistics, distribution, or mining contexts where the dominant waste is arrival bunching at process points. This study's GPS evidence shows a different dominant pattern for PT RTG: prolonged parking during inter-cycle turnaround at the mill and base areas. Therefore, applying time-window scheduling without a GPS-based diagnosis risks targeting the wrong intervention. Second, most prior studies treat cycle time, driver behavior, GPS-based visibility, and logistics cost separately; this study integrates them into a single operational diagnosis and control framework for a wood-hauling fleet in an industrial plantation forestry context, where such integration has rarely been reported.

3 | METHOD

3.1 Research Approach

This study uses an applied research approach with a single-company case study design at PT RTG. The analysis is descriptive-quantitative: findings are derived from operational and financial records, including unloading-ticket timestamps, GPS movement logs, trip revenue recapitulations, and spare-parts purchase records. Field observation and unstructured interviews with management and drivers were used only to provide interpretive context for patterns found in the numerical data. Because they did not follow a structured instrument or repeated sampling, they are not treated as a basis for generalization, and the study does not claim a mixed-methods design.

3.2 Business Process Improvement Framework

The study applies Business Process Improvement in five sequential stages: (1) AS-IS process mapping and activity classification (SIPOC, flowchart, VA–BNVA–NVA); (2) quantitative measurement of actual cycle time, trip productivity, and cost structure; (3) identification of time-loss sources through GPS decomposition and low-performing unit-month tracing; (4) design of the TO-BE process; and (5) conceptual estimation of impact and evaluation of the design's internal consistency. The study stops at the design stage. No component of the proposed system has been field-implemented, so every TO-BE figure discussed in Sections 4.6–4.7 is a conceptual projection, not a measured outcome.

3.3 Research Object and Data Sources

The primary dataset consists of trip-ticket records for seven active hauling units, covering 763 unloading tickets from January to October 2025. GPS movement data (Group Activity Report) for six of the seven units are available for May to October 2025; the GPS device on unit BM-9094-QU had not yet been installed during this period. Financial recapitulations covering revenue, direct operating cost, and loan installments are available for the same seven units from January to October 2025. Table 1 summarizes the data sources and their functions in the analysis.

Table 1. Data Sources and Their Function in the Analysis

No.	Data type	Source and coverage	Function in analysis
1	Unloading tickets (trip tickets)	PT RTG trip recapitulation; 763 tickets, 7 units, Jan–Oct 2025	Measures actual cycle time via ticket-to-ticket intervals; computes trips per unit-month
2	GPS fleet records	Group Activity Report, 6 of 7 units, 1 May–31 Oct 2025	Separates moving from parked time; groups parking duration; locates non-productive time
3	Trip revenue and cost recapitulation	PT RTG financial records, 7 units, Jan–Oct 2025	Computes revenue, direct cost, and margin per trip, and positions them against loan installments
4	Spare-parts and service records	PT RTG internal records	Traces low-performing unit-months to documented repairs
5	Field observation and informal interviews	Direct observation; unstructured interviews with management and drivers	Provides interpretive context for AS-IS mapping and VA–BNVA–NVA classification (not a basis for generalization)

3.4 Cycle-Time and Productivity Measurement

Cycle time is measured as the interval between the empty-weight time of two consecutive unloading tickets for the same unit, calculated per license plate and ordered chronologically across the full study period rather than within monthly files, so that cycles spanning a month boundary remain intact. The first ticket for each unit has no predecessor and is excluded, so 763 tickets yield 756 calculable cycles. Both median and mean are reported: the median indicates the typical cycle and is insensitive to extreme values, while the mean reflects the burden created by long cycles. The gap between the two is itself part of the finding. Productivity is measured in trips per unit-month and related to cycle time through the identity. Trips per unit-month = $(30 \text{ days} \times 24 \text{ hours}) / \text{cycle time in hours}$. This translates a productivity gap into an operating-time target that can be acted on directly.

3.5 GPS-Based Movement and Parking Decomposition

GPS records are decomposed in three steps: (1) recapitulating moving hours, engine hours, and parked hours per unit, from which the share of moving to parked time and engine-idle hours (engine hours minus moving hours) are derived; (2) aggregating the duration of all discrete parking events; and (3) grouping parking events by duration band to separate short stops at route process points from long parking associated with inter-cycle turnaround. Location is classified into only two categories: mill/base area and all other locations, because a finer classification of harvest-area points would require field verification that is not available from the current dataset. Queuing theory is invoked only descriptively, to explain how a queue can form at a route point at a given moment; no formal queuing model is estimated, and no conclusion rests on such a model.

3.6 Cost and Low-Performing Unit-Month Analysis

Direct operating cost, including fuel, spare parts, tires, and per diem, and fixed cost, including vehicle loan installments, are analyzed separately because the two behave differently as trip volume changes. Direct cost tracks trip volume, whereas the loan installment is fixed per month, so installment cost per trip falls as trip volume rises. Unit-months with markedly low trip counts are traced individually against spare-parts and service records to distinguish a documented major repair from an undocumented cause. Where no supporting record exists, the unit-month is reported as unexplained rather than attributed to an assumed cause.

3.7 Distinguishing Actual Results from Conceptual Targets

All figures reported in Sections 4.1–4.5, including baseline productivity, cycle-time distribution, GPS decomposition, and cost structure, are measured outcomes drawn directly from the January–October 2025 dataset. All figures associated with the proposed control framework and its productivity or financial projection in Sections 4.6–4.7 are conceptual targets or arithmetic projections that hold the actual cost structure constant and vary only the number of trips; none has been observed under field implementation.

3.8 Limitations

Four limitations bound the study's claims. First, no statistical hypothesis test is performed; the conceptual relationships reviewed in Section 2 organize the analysis but are not tested inferentially. Second, the GPS dataset covers six months and six of seven units, sufficient to describe the current operating pattern but not year-on-year or seasonal trends. Third, the trip-ticket calculation relies on tickets as recorded; an unrecorded destination could make two apparently consecutive tickets not truly consecutive in practice. Fourth, driver behavior and fleet maintenance condition are treated as contributing rather than primary factors, because the available data cannot separate their individual contributions from the effect of turnaround control itself.

4 | RESULTS AND DISCUSSION

4.1 Results

4.1.1 Baseline Hauling Productivity

Across January–October 2025, the seven active units completed 763 trips, with an average of 10.9 trips per unit per month. This average, however, combines three months affected by conditions outside management's control—January, when most drivers were on holiday leave, and July–August, when local authorities closed the haul road—with seven months of normal operation. Restricting the baseline to the seven normal months yields 633 trips across 49 unit-months, or 12.92 trips per unit per month, which this study uses for target-setting and gap analysis. Individual-unit performance varies widely: two units, BM-8063-KU and BM-8093-KU, already average above 15 trips per month; five of the seven units have reached at least 15 trips in at least one month; the fleet-wide monthly record is 21 trips; and the average of each unit's own monthly record is 17.43 trips. Because all seven units operate on the same route, tariff, and assignment pattern, this spread cannot be attributed to differing external conditions. This points toward operational time control, rather than

route or contractual factors, as the source of the gap. On this basis, the study sets a productivity target of 15 trips per unit per month, a level below the fleet's own demonstrated record rather than an external or industry benchmark.

4.1.2 Cycle-Time Distribution and Variability

Cycle time, measured as the interval between two consecutive unloading tickets for the same unit, yields 756 calculable cycles from 763 tickets (Table 2, Figure 1). The median is 47.1 hours, close to the implicit 48-hour ideal, while the mean is 63.1 hours. Just over half of all cycles, 52.9%, are completed within 48 hours; about 19.5% exceed 72 hours; and the distribution has a long tail reaching 1,028 hours. This 16-hour gap between the median and the mean is the central finding of the analysis. If the fleet were uniformly slow, the two measures would be close together, and the response would be to accelerate the physical activities within a cycle. Instead, the typical cycle already approaches the target, but a minority of extreme cycles cannot be sustained consistently. The management problem is therefore one of controlling variability and restoring operational rhythm, not of shortening travel time.

Table 2. Distribution of Cycle Time Between Consecutive Unloading Tickets, Seven Active Units, January–October 2025
(n = 756)

Cycle-time band	Number of cycles	Share	Cumulative share
≤ 48 hours	400	52.9%	52.9%
> 48–72 hours	209	27.6%	80.6%
> 72–96 hours	71	9.4%	90.0%
> 96 hours	76	10.1%	100.0%
Total	756	100.0%	
Median	47.1 hours		
Mean	63.1 hours		
Fastest / longest cycle	19.9 h / 1,028.1 h		

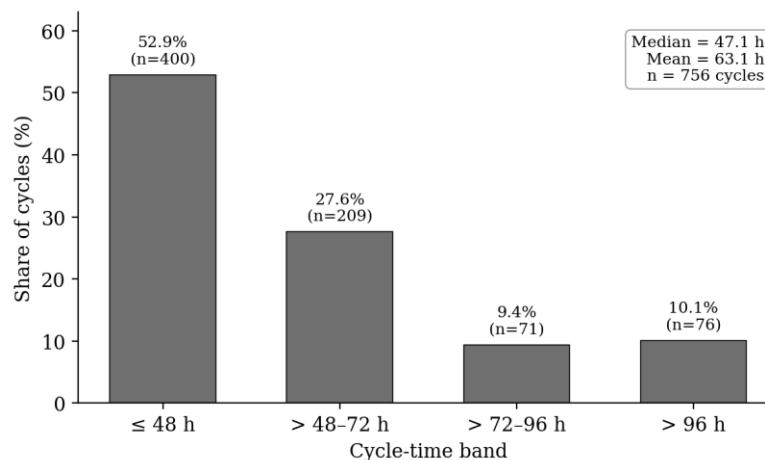


Figure 1. Distribution of Cycle Time by Duration Band, with Median and Mean (n = 756)

4.1.3 GPS-Based Movement and Parking Analysis

Decomposition of GPS records for six units, May–October 2025 (Table 3, Figure 2), shows the fleet moving only about 27% of monitored time and parked for about 73%, with an additional approximately 1,011 hours of engine-on, non-moving idling. Average travel speed of 22–33 km/h on the roughly 160–170 km one-way haul route is within a normal range, indicating that core travel time is not the primary source of the long, unstable cycle.

Table 3. Fleet Time Utilization Based on GPS Data, Six Units, May–October 2025

Measure	Value (6 units, aggregate)	Notes
Distance traveled	137,165 km	May–Oct 2025
Moving hours	6,395 h	—
Engine hours	7,407 h	—
Parked hours	16,882 h	—
Share of time parked	73%	Share moving ≈ 27%
Engine idle (engine on, not moving)	1,011 h	Engine hours minus moving hours

Fleet time utilization (GPS, 6 units, May–Oct 2025)

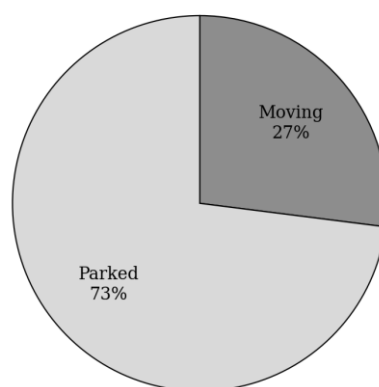


Figure 2. Share of Fleet Time Moving versus Parked, GPS Data, Six Units, May–October 2025

Parking events, grouped by duration and location (Table 4), show that short stops under four hours—which include pontoon crossing, loading, and checkpoint queues—account for only about 34% of total parking hours and occur mostly away from the mill/base area. Parking of eight hours or more accounts for about 51% of parking hours, of which roughly 62% occurs at the mill/base area. Parking exceeding three days, a subset of this long-parking category, accounts for about 14% of parking hours, 83% of it at the base. This directly corrects the study’s initial hypothesis: queues at route process points are real and are felt by drivers, but in aggregate they are a minor contributor to non-productive time. The dominant source of waste is prolonged parking during inter-cycle turnaround at the mill and base areas—the interval between finishing one cycle and departing on the next—rather than congestion at pontoon or unloading points.

Table 4. Parking Duration and Location Composition, GPS Data, May–October 2025

Parking duration	Share of total parking hours	Concentration at mill/base area
< 4 hours (route-point queues: pontoon, loading, checkpoint)	≈ 34%	≈ 23% at mill/base (mostly elsewhere)
≥ 8 hours (prolonged / inter-cycle turnaround)	≈ 51%	≈ 62% at mill/base
— of which > 3 days	≈ 14%	≈ 83% at base

Note: Short- and long-duration bands are reported as in the source data; a residual mid-range band of about 15% of parking hours is not decomposed by location in the source data.

4.1.4 Identification of Operational Time Losses

Reconciling the cycle-time and GPS findings clarifies where the productivity gap originates. Against the 15-trip target, 49 normal-operation unit-months required 735 trips but delivered 633, a net gap of 102 trips. Decomposing this gap shows that 96 trips, about 71% of the gross shortfall, come from unit-months that operated normally but still fell short of target, while 39 trips, about 29%, come from three unit-months that did not operate near capacity at all. One unit recorded zero trips in a month, one recorded a single trip, and one recorded five. The majority of the gap therefore comes from units that were working but not completing enough cycles, not from idle or broken equipment, consistent with the GPS finding that the dominant loss is uncontrolled turnaround rather than unavailability. For the three low-trip unit-months, spare-parts and service records could not confirm a specific cause in any case, which is itself a finding: PT RTG currently has no daily fleet-status record that would let management distinguish a unit under repair from one without a driver or one awaiting a load assignment.

4.1.5 Cost and Productivity Implications

Trip-level cost structure (Table 5) shows that operations are not inherently loss-making: average revenue per trip is about IDR 5.84 million against direct operating cost of about IDR 4.59 million, leaving a positive operating margin of about IDR 1.25 million per trip. The loss appears only once the fixed vehicle loan installment is allocated across trips. At the observed productivity of 10.9 trips per unit per month—the ten-month average across all seven units, including the three disrupted months—the installment cost is about IDR 2.73 million per trip, more than double the operating margin, producing a net deficit of about IDR 1.48 million per trip and, across 763 trips over ten months, a structural operating loss of about IDR 112.8 million per month for the seven active units. Because direct cost tracks trip volume while the loan installment does not, raising trip count lowers installment cost per trip without any change in tariff, fleet size, or renegotiation with the client. This is the financial logic connecting the operational diagnosis in Sections 4.1–4.4 to the cost

outcome here.

Table 5. Cost and Margin Structure per Trip, Seven Active Units, January–October 2025

Item	Value per trip (IDR)	Share of revenue
Revenue	5,842,834	100.0%
Per-diem	796,383	13.6%
Fuel	2,340,272	40.1%
Spare parts and tires	1,456,447	24.9%
Direct operating cost	4,593,101	78.6%
Operating margin (before installment)	+1,249,732	21.4%
Vehicle loan installment	2,728,600	46.7%
Total cost per trip	7,321,702	125.3%
Net position per trip (after installment)	-1,478,868	-25.3%

4.1.6 Proposed Cycle-Time Control Framework

The proposed intervention is a conceptual cycle-time control system built from five layers: a target layer, a 48-hour cycle-time standard and a staged trip target of up to 15 per unit per month; a core-control layer addressing inter-cycle turnaround and dispatch discipline; an availability layer covering daily fleet-status recording, driver-availability management, and history-based maintenance; a driver and monitoring layer combining driver KPIs with GPS-based feedback; and a governance layer assigning departure decisions and escalation responsibility to existing roles Hauling Assistant, Operations Manager, Administrator, Director without creating new positions. Table 6 summarizes the framework's core components against the operational finding each is intended to address.

Table 6. Proposed Cycle-Time Control Framework: Layers and Core Components

Layer	Core components	Operational finding addressed
Target	48-hour cycle-time standard; staged trip target per unit (up to 15/month)	Median cycle time already near 48 h; two units already exceed 15 trips/month
Core control	Inter-cycle turnaround departure thresholds and dispatch authority (Hauling Assistant); GPS-based idle-exception monitoring (≥ 8 h, with escalation beyond 3 days)	Parking ≥ 8 h accounts for $\approx 51\%$ of parking hours, concentrated at mill/base (Table 4)
Availability	Daily fleet-status log (5 status codes); backup-driver mapping; history-based maintenance scheduling	$\approx 71\%$ of the trip gap comes from operating units below target; 3 unexplained low-trip unit-months
Driver and monitoring	Driver KPI cycle-time consistency (35%), turnaround compliance (30%), trip-target attainment (25%), reporting completeness (10%) with gain-sharing; weekly GPS feedback	No existing objective measure of driver performance
Governance	Defined roles and escalation chain (Director, Operations Manager, Hauling Assistant, Administrator, Driver); no new positions created	No current owner of the departure-timing decision

An explicit methodological point follows from Sections 4.2–4.4. Time Window Scheduling (TWS) was considered during the design stage, because prior literature (Liu *et al.*, 2017; Su *et al.*, 2021) shows it can raise scheduling stability where arrival bunching at process points is the dominant waste. The GPS evidence for PT RTG shows a different pattern: short stops at route points (pontoon, loading, checkpoint) account for only about 34% of parking hours, while parking of eight hours or more, concentrated at the mill and base, accounts for about 51%. Scheduling arrivals at loading and crossing points would target a minority source of waste and leave the dominant one inter-cycle turnaround unaddressed. The design therefore retains dispatching as a governing principle, with a defined party responsible for departure timing, but directs it at controlling the gap between finishing one cycle and starting the next through departure thresholds and GPS-based idle-exception monitoring, rather than at spreading arrivals through time windows.

4.1.7 Managerial Implications

The proposed target of 15 trips per unit per month, if reached, would raise fleet trips from about 90 to about 105 per month. This projection is benchmarked against the normal-operation baseline (12.92 trips per unit per month, 90.4 trips fleet-wide, corresponding to a deficit of about IDR 95.2 million per month under the same cost structure) rather than the raw ten-month average, so that normal conditions are compared with normal conditions. The raw ten-month actual average of 10.9 trips per unit per month corresponds instead to the IDR 112.8 million per month deficit reported in Section 4.5, which additionally reflects the three disrupted months. On the normal-operation baseline, reaching 105 trips per

month would narrow the deficit to about IDR 77.0 million, an improvement of roughly IDR 18.2 million per month at the upper end of the projected range, falling to about IDR 3 million if spare-parts cost rises proportionally with trip volume. Both figures are conceptual projections that hold cost structure constant and vary only trip count; neither is a measured outcome. A further, more consequential implication concerns the limits of what operational improvement alone can achieve. The fleet's operational break-even point is about 23.8 trips per unit per month for the seven active units, above the highest monthly record any single unit has ever achieved (21 trips) and above the fleet's own average monthly record (17.43 trips). Operational improvement can narrow PT RTG's deficit but cannot, by itself, eliminate it. The residual gap points to a financing-structure question the size of the loan obligation relative to per-trip margin and fleet capacity that lies outside the scope of a process-improvement intervention and is a separate decision for management.

4.2 Discussion

The findings of this study are consistent with the view that logistics performance depends not only on physical movement, but also on the effectiveness of time control, cost control, and operational coordination. Silva, Gonçalves, and Leite (2014) emphasize that logistics cost management requires tracing cost drivers to operational activities rather than treating cost as an aggregate burden. In the case of PT Rogomos Tapind Group, the data show that low productivity is closely related to prolonged non-productive time within the haul cycle. The fleet does not merely incur high cost because of distance traveled; it incurs high cost because the number of productive trips is too low relative to the fixed financing burden. This supports the idea that logistics cost control must be connected to process control, not only accounting measurement. The cycle-time results also align with Small's (2015) bottleneck model. Small argues that bottlenecks are not always caused by physical capacity limitations; they may also arise from process coordination problems that create delays and instability. PT RTG's median cycle time of 47.1 hours is close to the implicit target, but the mean is significantly higher because a smaller number of extremely long cycles distort the overall pattern. This indicates that the system is not uniformly slow. Rather, the bottleneck appears in the form of irregular turnaround and uneven release of units for the next trip. In bottleneck terms, the problem is not only how fast the truck travels, but how smoothly the cycle is restarted after completion. This explains why operational rhythm is more important than average travel time.

The GPS-based decomposition strengthens this interpretation. Yuniar *et al.* (2020) show that GPS can reveal how driver behavior and travel-time effectiveness are related, especially when operational data are examined in sequence. In the present study, GPS records show that the fleet spends most monitored time parked rather than moving. More importantly, the longest parking durations are concentrated at the mill and base areas. This suggests that the dominant waste is not at route checkpoints, pontoon crossings, or unloading points, but in the idle interval between completed cycles. The GPS evidence therefore supports a diagnostic approach that distinguishes genuine queueing from prolonged inter-cycle parking. That distinction is essential, because different waste structures require different control responses. The findings also support the literature on dispatching. Subtil, Silva, and Alves (2011) show that systematic truck dispatch can improve productivity in haulage systems by controlling the timing of vehicle release. Their work is relevant here because PT RTG's main issue is not simply lack of trucks, but weak control over when a truck departs for the next cycle. Dispatch discipline is therefore central. However, the present study also shows that dispatching alone is not enough if the organization does not have visibility over fleet status. Without daily status recording, management cannot clearly distinguish between a vehicle that is under repair, unavailable because of driver absence, or merely waiting for assignment. Thus, dispatch control must be supported by status information and accountability.

The importance of scheduling is also reflected in Su *et al.* (2021), who demonstrate that time-window scheduling can improve fleet stability when arrivals are clustered at service points. However, the PT RTG case shows that this logic does not fully apply. The GPS evidence indicates that only a minority of parking time is related to short route-point queues, while the majority occurs during prolonged turnaround at the mill and base. This means that a time-window approach would address only part of the waste. The main problem is not arrival bunching, but delayed departure after a cycle is completed. Therefore, the study correctly prioritizes cycle-time control and dispatch authority over a pure time-window strategy. In this sense, the findings refine the conditions under which scheduling interventions are effective. The results also resonate with Wojuade and Oladosu (2020), who show that truck operating costs are strongly shaped by managerial decisions on utilization, fuel use, and maintenance. At PT RTG, the cost structure demonstrates that each trip contributes a positive operating margin before loan installments are allocated, but the fixed installment becomes burdensome when trip volume is low. This supports the argument that productivity and cost are inseparable. Higher trip frequency reduces installment cost per trip and improves cost absorption. Accordingly, operational improvement is not merely about doing more trips; it is about spreading fixed cost over a larger productive base. This is why cycle-time control has direct financial relevance.

The study also contributes to the literature on driver behavior and performance control. Yuniar *et al.* (2020) show that driver behavior affects travel-time effectiveness, while Zhang *et al.* (2026) demonstrate the growing value of integrated vehicle-and-shipment tracking data for operational analysis. In the PT RTG case, the lack of objective driver KPIs is a managerial weakness. The proposed framework responds to this gap by linking driver performance to measurable indicators such as cycle-time consistency, turnaround compliance, and reporting completeness. This is

consistent with the broader logistics literature, which increasingly treats visibility and measurement as prerequisites for effective operational control. Škerlić and Muha (2016) argue that logistics cost control systems improve supply-chain performance when they are embedded in routine operational decision-making. This point is highly relevant to PT RTG. The proposed framework is not merely a conceptual model; it is designed to be embedded in daily operations through departure thresholds, GPS monitoring, and status logs. Such design is important because cost control fails when it remains at the level of accounting reports and does not influence real-time decisions. In the present study, the proposed system attempts to move cost control from retrospective recording to proactive operational management.

5 | CONCLUSIONS AND FUTURE WORK

This study examined the causes of low fleet utilization and unstable cycle time at PT Rogomos Tapind Group, assessed their effects on trip productivity and financial performance, and proposed a cycle-time control framework. Three conclusions are drawn. First, fleet productivity is limited primarily by unstable cycle time and low utilization rather than by uniformly slow operations. Based on 756 cycle intervals from seven active units during January–October 2025, the median cycle time was about 47 hours, close to the implicit target, whereas the mean was about 63 hours because a small number of extreme cycles increased the average. GPS data from six units during May–October 2025 show that the fleet moved for only about 27% of monitored time and was parked for about 73%. The main source of lost time is prolonged parking during inter-cycle turnaround at the mill and base areas, not pontoon or unloading queues. Current productivity averaged 10.9 trips per unit per month across the full period, or 12.92 trips on the baseline of seven undisturbed months. Second, this loss of time control has direct financial consequences. Each trip generates a positive operating margin of about IDR 1.25 million, but the fixed vehicle loan installment, when spread over too few trips, turns the operation into a net deficit of about IDR 1.48 million per trip, or roughly IDR 112.8 million per month for the seven active units. Third, the proposed cycle-time control framework combines a cycle-time standard, turnaround and dispatch control, GPS-based idle-exception management, driver KPIs, and daily fleet-status recording. The framework targets a conceptual productivity level of 15 trips per unit per month. Time Window Scheduling was considered, but the GPS evidence indicates that the dominant waste is inter-cycle delay rather than arrival bunching at process points. Therefore, dispatch control is directed at reducing the gap between cycles. Because the framework has not been field-implemented, the projected reduction in monthly deficit remains conceptual. The fleet's operational break-even point, about 23.8 trips per unit per month, is above the highest recorded unit performance. Thus, operational improvement can reduce the deficit, but not eliminate it without changes in financing structure.

REFERENCES

- Argiyantari, B., Simatupang, T. M., & Basri, M. H. (2022). Transportation performance improvement through lean thinking implementation. *International Journal of Lean Six Sigma*, 13(3), 622–647. <https://doi.org/10.1108/IJLSS-06-2020-0075>
- Dullaert, W., & Zamparini, L. (2013). The impact of lead time reliability in freight transport: A logistics assessment of transport economics findings. *Transportation Research Part E: Logistics and Transportation Review*, 49(1), 190–200.
- Heizer, J., & Render, B. (2017). *Operations management: Sustainability and supply chain management*. Pearson.
- Horngren, C. T., Datar, S. M., & Rajan, M. V. (2015). *Cost accounting: A managerial emphasis*. Pearson.
- Kluger, A. N., & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin*, 119(2), 254–284.
- Liu, W., Yang, Y., Wang, S., & Bai, E. (2017). A scheduling model of logistics service supply chain based on the time windows of the FLSP's operation and customer requirement. *Annals of Operations Research*, 257(1–2), 183–206.
- Macedo, H., Tomaz, L., Guimarães, L., Cerqueira-Pinto, L., Sá, J. C., & Dinis-Carvalho, J. (2025). Development of a classification model for value-added and non-value-added operations in retail logistics: Insights from a supermarket case study. *Sustainability*, 17(7), 3177.

- Moeller, D. P. F., Topp, A., Wittmann, J., Schroer, B., & Harris, G. (2008). Bottleneck-analysis of multimodal transportation. In *Conference proceedings, Huntsville Simulation Conference*.
- Nariendra, P. W., Santosa, W., & Sutandi, A. C. (2026). Modeling fuel consumption of heavy-duty trucks using telematics data. *Periodica Polytechnica Transportation Engineering*, 54(1), 41–48. <https://doi.org/10.3311/PPtr.38337>
- Ndubi, S. O., Iravo, M., & Ochiri, G. (2016). Effect of lead time variability on inbound logistics performance in Safaricom Limited. *International Academic Journal of Procurement and Supply Chain Management*, 2(2), 179–205.
- Orno, A. J., Risra, R., & Gunawan, A. (2023). The effect of vehicle tracking system implementation and service quality on customer satisfaction of goods delivery services at PT Kamanjaya Trans Logistik in 2023. *International Journal of Current Science Research and Review*, 6(7), 3994–4004.
- Ping, P., Qin, W., Xu, Y., Miyajima, C., & Takeda, K. (2019). Impact of driver behavior on fuel consumption: Classification, evaluation and prediction using machine learning. *IEEE Access*, 7, 78515–78532.
- Shamsuzzoha, A. H. M., Ehlers, M., Addo-Tenkorang, R., Nguyen, D., & Helo, P. T. (2013). Performance evaluation of tracking and tracing for logistics operations. *International Journal of Production Research*, 51(22), 6649–6667.
- Silva, T. F. G., Gonçalves, A. T. P., & Leite, M. S. A. (2014). Logistics cost management: Insights on tools and operations. *The International Journal of Logistics Management*, 25(2), 343–365.
- Škerlič, S., & Muha, R. (2016). The importance of systems for controlling logistics costs in the supply chain: A case study from the Slovenian automotive industry. *Promet – Traffic & Transportation*, 28(3), 299–310.
- Small, K. A. (2015). The bottleneck model: An assessment and interpretation. *Economics of Transportation*, 4(1–2), 110–117.
- Su, Z., Li, W., Li, J., & Cheng, B. (2021). Heterogeneous fleet vehicle scheduling problems for dynamic pickup and delivery problem with time windows in shared logistics platform: Formulation, instances and algorithms. *International Journal of Systems Science: Operations & Logistics*, 8(3), 199–223.
- Subtil, R. F., Silva, D. M., & Alves, J. C. (2011). A practical approach to truck dispatch for open pit mines. In *35th APCOM Symposium Proceedings* (pp. 765–777). The Australasian Institute of Mining and Metallurgy.
- Wojuade, C. A., & Oladosu, J. (2020). Decision making and truck operating costs on haulage business in Lagos, Nigeria. *Asian Research Journal of Arts & Social Sciences*, 11(4), 28–37.
- Yuniar, D., Djakfar, L., Wicaksono, A., & Efendi, A. (2020). Truck driver behavior and travel time effectiveness using smart GPS. *Civil Engineering Journal*, 6(4), 724–732.
- Zhang, Y., Guan, J., Jing, P., You, L., Zhao, F., & Ben-Akiva, M. (2026). Future freight and logistics survey: An integrated vehicle-and-shipment-tracking data collection method and a case study in the United States. *Transportation Research Part E: Logistics and Transportation Review*, 205, 104517.

How to cite this article: Simamora, E. Y. E. W., Raja, P. L., & Nasution, F. N. (2026). Performance-Based Cycle Time Analysis for Improving the Operational Productivity of the Hauling Fleet at PT Rogomos Tapind Group. *Indonesian Journal Economic Review (IJER)*, 6(3), 1405–1615. <https://doi.org/10.59431/ijer.v6i3.1015>.