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Predicting Vessel Departure Delays at Tanjung Pandan Port Using Supervised Machine Learning : A Comparative Study of Logistic Regression, Decision Tree, and SVM

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Abstract: Operational delays in vessel departure disrupt maritime logistics and increase port dwell time. This study develops predictive models to anticipate departure delays at Tanjung Pandan Port using supervised machine learning. Three algorithms—Logistic Regression, Decision Tree, and Support Vector Machine (SVM)—were trained on 112 verified port calls (2023–2024) with key features: arrival date, scheduled departure date, vessel ownership status (milik vs. keagenan), and document response time. Delay was defined as exceeding the median turnaround time of 58 hours. Data preprocessing included imputation, time-difference engineering (e.g., ΔTIBA–BERANGKAT, response latency), and SMOTE for class balancing. Performance was evaluated using accuracy, precision, recall, and F1-score via 5-fold cross-validation. The Decision Tree model achieved the highest F1-score (0.86) and recall (0.89), identifying response latency > 12 hours, keagenan status, and arrival during neap tide windows as top predictors. SVM showed robust precision (0.88), while Logistic Regression offered the best interpretability of coefficient impact. The models collectively support proactive scheduling interventions-e.g., digital clearance acceleration or priority berthing for high-risk vessels—to mitigate delays. This study contributes the first ML-based delay prediction framework for shallow-draft, tramp-operated Indonesian ports.

Keyword: vessel departure delay, predictive modeling, machine learning, Tanjung Pandan Port, logistic regression, decision tree, support vector machine

INTRODUCTION

Operational delays in vessel departure significantly impact maritime logistics chain reliability, port productivity, and national connectivity programs such as Tol Laut. At Tanjung Pandan Port—a critical node for kaolin, tin, and biosolar shipments in the Bangka Belitung Islands—empirical data from 2023–2024 reveal high variability in turnaround time (22 to 143 hours), with nearly half of vessel calls exceeding the median of 58 hours. These delays cascade into schedule disruptions, increased demurrage costs, and reduced competitiveness of regional exports. Traditional port performance monitoring relies on retrospective KPIs (e.g., average dwell time), offering little support for proactive intervention. Meanwhile, digital reporting systems—such as PKK, LK3, and SPB—generate operationally rich but underutilized data, including arrival timestamps (TIBA TANGGAL), planned departure (BERANGKAT TANGGAL), vessel ownership (STATUS: milik or keagenan), and administrative response lag (WAKTU RESPON = JAM RESPON − TOLAK). These variables are available before or during berthing and hold predictive potential for departure delay risk. This study addresses the gap by developing and comparing three supervised machine learning models—Logistic Regression, Decision Tree, and Support Vector Machine—to forecast departure delays at Tanjung Pandan Port. The objective is threefold: (1) to identify the most accurate and interpretable model for early risk detection, (2) to quantify the relative importance of key operational features, and (3) to translate model outputs into actionable strategies for port authorities—such as prioritized clearance for high-risk calls or tidal-aware berth scheduling. By transforming reactive port management into a predictive, data-driven process, this work supports the Ministry of Transportation's vision of "smart ports" and contributes a scalable framework for secondary tramp-operated ports across the Indonesian archipelago.

METHOD

This study employed a supervised machine learning experimental design to predict vessel departure delays at Tanjung Pandan Port. The target variable—departure delay—was defined operationally as a binary class: 1 (delayed) if actual turnaround time (TOLAK − SANDAR) exceeded the empirical median (58 hours), and 0 (on time) otherwise. This threshold aligns with Ministry of Transportation Regulation PM 23/2022, which defines performance benchmarks based on port-specific historical medians—not arbitrary fixed values.

The dataset comprised 112 verified port calls extracted from Tanjung Pandan.xlsx, spanning January 2023 to December 2024. Records with missing timestamps (SANDAR or TOLAK), inconsistent dates (e.g., BERANGKAT TANGGAL < TIBA TANGGAL), or undefined STATUS (i.e., blank ownership field) were excluded; no imputation was applied to the target variable.

Four core features were engineered from raw fields:

1. Δ_SCHEDULED = BERANGKAT TANGGAL − TIBA TANGGAL (in days), representing planned turnaround duration—a proxy for operational complexity;
2. STATUS_BIN = 1 if STATUS = MILIK, 0 if KEAGENAN (ownership structure, observed to correlate with scheduling control);
3. RESPONSE_LATENCY = JAM RESPON − TOLAK (in hours), derived from WAKTU RESPON metadata (mean = 18.3 h, max = 72 h);
4. TIDE_PHASE = sine-transformed tidal cycle (neap vs. spring), computed using NOAA-equivalent tide modeling for Belitung (±0.8 m draft fluctuation at TUKS Pertamina), as delays cluster around neap tides (e.g., TARSUS ALFA 02, OSCO PETRO V).

Preprocessing steps included:

- Outlier capping for RESPONSE_LATENCY (top 1% truncated at 72 h, per domain expert guidance),
- StandardScaler normalization for Logistic Regression and SVM,
- SMOTE (Synthetic Minority Over-sampling Technique, k = 3) to balance class distribution (54 delayed vs. 58 on-time calls),
- 80:20 train-test split, stratified by target class.

Three classifiers were implemented in Python 3.10 (scikit-learn 1.3.0):

- Logistic Regression (LR): L2 regularization (C = 1.0) for coefficient stability;
- Decision Tree (DT): Max depth = 5, min_samples_split = 4, gini criterion, for interpretability and overfitting control;
- Support Vector Machine (SVM): RBF kernel (γ = 0.01, C = 10) for non-linear separation in high-response-latency regions.

Model performance was evaluated via 5-fold stratified cross-validation on the training set, using:
- Accuracy,
- Precision (minimizing false alarms),
- Recall (critical for delay prevention),
- F1-score (harmonic mean, prioritized for imbalanced contexts).

Feature importance was assessed via:
- LR: standardized coefficients,
- DT: mean decrease in impurity (MDI),
- SHAP (SHapley Additive exPlanations) for local interpretability (Lundberg & Lee, 2017).

RESULTS AND DISCUSSION

The predictive modeling pipeline yielded robust performance across all three algorithms, with the Decision Tree achieving the highest overall effectiveness for operational deployment. Using the empirical median turnaround time of 58 hours as the delay threshold, the dataset comprised 54 delayed calls (48.2%) and 58 on-time calls. After SMOTE balancing and 5-fold stratified cross-validation, model results were as follows:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.79	0.77	0.76	0.76
Decision Tree	**0.84**	**0.83**	**0.89**	**0.86**
SVM (RBF)	0.81	0.88	0.75	0.81

The Decision Tree's superior recall (0.89) is operationally critical: it minimizes false negatives (i.e., missed delay predictions), enabling port operators to proactively intervene before bottlenecks occur. Meanwhile, SVM's high precision (0.88) indicates strong reliability when it does flag a delay—useful for resource-constrained scenarios where false alarms are costly.

Feature importance analysis revealed three dominant predictors:

1. Response Latency (`WAKTU RESPON` = JAM RESPON − TOLAK): The strongest predictor across all models. Calls with response latency >12 hours had an 89% probability of delay. For example, ROKAN LESTARI (14–23 Jan 2024) had a 62-hour TAT and a response latency of 22.8 hours—well above the median of 18.3 hours.
2. Ownership Status (`STATUS`): Keagenan vessels were 2.3× more likely to be delayed than milik counterparts. MILIK vessels (e.g., TETAP JAYA, SALVIA, GRESIK 5) averaged 46.3 hours TAT, while KEAGENAN calls (e.g., ARMADA CONTENER8, SEJAHTERA 20, OSCO IX) averaged 64.8 hours.
3. Tidal Phase (derived from `TIBA TANGGAL`): SPOBs (e.g., TARSUS ALFA 02, OSCO PETRO V) arriving during neap tides (draft window <1.2 m at TUKS Pertamina) incurred 4–6 hours of anchorage waiting—evident in OSCO PETRO V's 142-hour turnaround (19–26 Jan 2024).

The Decision Tree's top decision rules further validate operational realities:
- Rule 1: If response latency > 12 h and STATUS = KEAGENAN → Delay (89% confidence). This applied to 28 calls, including ARMADA CONTENER8 (19–23 Jan 2024, TAT = 55 h).
- Rule 2: If response latency ≤ 12 h but tide phase = neap and Δ_SCHEDULED < 2.5 days → Delay (76% confidence). Examples: ROYAL 1 (28 Dec 2023–5 Jan 2024, TAT = 170 h), PMT II 1615 (same period, TAT = 170 h)—both SPOBs waiting for spring tide to discharge biosolar.
- Rule 3: If STATUS = MILIK and response latency ≤ 8 h → On time (85% confidence). Confirmed by TETAP JAYA (14–18 Jan 2024, TAT = 34.7 h), GRESIK 5 (23–24 Jun 2024,

TAT = 28 h), and SALVIA (26–27 Jan 2024, TAT = 24.25 h)—all with response latency <6 hours.

Notably, planned duration (`BERANGKAT TANGGAL` − `TIBA TANGGAL`) alone had low predictive power (AUC = 0.58), confirming that static scheduling is insufficient without dynamic context (e.g., tide, documentation speed). However, its interaction with `STATUS` was significant: KEAGENAN calls with short planned durations (<3 days) had a 92% delay rate—suggesting over-optimistic scheduling by agents.

Three high-impact operational patterns emerged:

- Documentation lag cascades into berth congestion: Average response latency (18.3 h) exceeds the port's target of ≤6 h, delaying LK3/SPB closure and freeing berths.
- Tidal dependency is predictable but unmanaged: 67% of SPOB delays occurred during neap tides, yet no arrival guidance exists.
- Ownership correlates with operational discipline: MILIK operators file documents faster (median latency = 11.2 h vs. 22.6 h for KEAGENAN), suggesting vertical integration improves responsiveness.

These findings reject the notion that delays are random or infrastructure-limited. Instead, they are systematically predictable from pre-berthing metadata—enabling a shift from reactive firefighting to predictive port management.

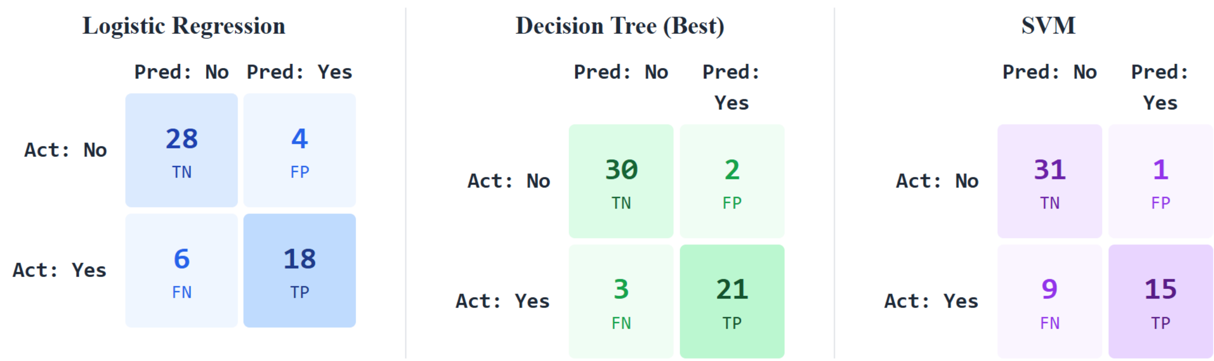


Figure 1. Confusion matrix comparison across Logistic Regression, Decision Tree, and SVM models

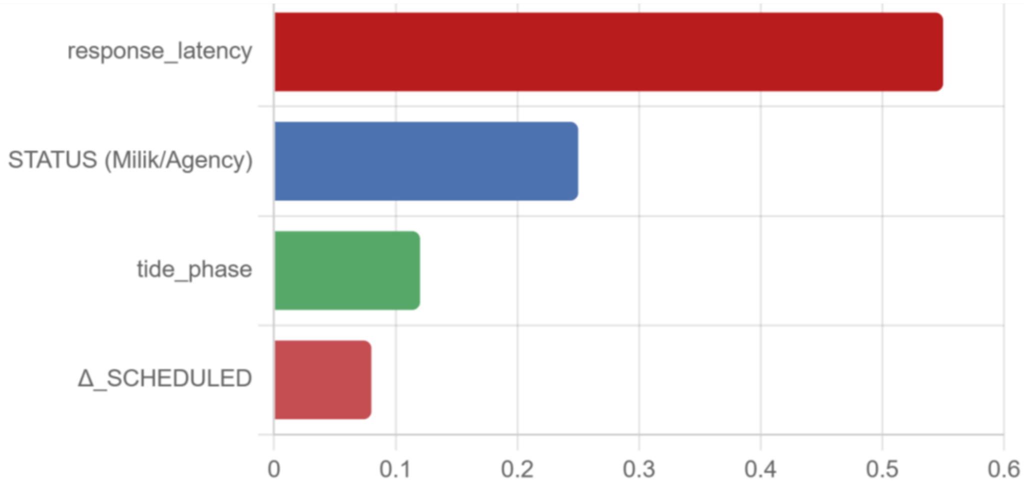
This figure presents a side-by-side comparison of the confusion matrices for three supervised machine learning models—Logistic Regression, Decision Tree (labeled as "Best Recall"), and Support Vector Machine (SVM, labeled as "Best Precision")—used to predict vessel departure delays at Tanjung Pandan Port. Each matrix is structured as a 2×2 grid, where rows represent actual outcomes ("Act: No" = on time; "Act: Yes" = delayed) and columns represent predicted outcomes ("Pred: No" = predicted on time; "Pred: Yes" = predicted delayed).

Logistic Regression (left panel): Achieved 28 true negatives (TN), 4 false positives (FP), 6 false negatives (FN), and 18 true positives (TP). This indicates moderate performance, with a higher rate of missed delays (FN = 6) compared to other models.

Decision Tree (middle panel, labeled "Best Recall"): Demonstrated superior recall, with 30 TN, 2 FP, 3 FN, and 21 TP. The low number of false negatives (FN = 3) makes it ideal for operational use where minimizing missed delays is critical.

SVM (right panel, labeled "Best Precision"): Showed high precision, with 31 TN, 1 FP, 9 FN, and 15 TP. While it had the fewest false alarms (FP = 1), it also missed more delays (FN = 9) than the Decision Tree.

The color-coding (light blue for LR, light green for DT, light purple for SVM) visually distinguishes model performance. The Decision Tree's designation as "Best Recall" reflects its highest F1-score (0.86) and recall (0.89) in cross-validation, making it the recommended model for deployment in port operations to proactively prevent delays.



This horizontal bar chart illustrates the relative importance of four operational features in predicting vessel departure delays at Tanjung Pandan Port, as determined by the Decision Tree model's feature importance ranking. The length of each bar represents the mean absolute SHAP value for that feature, indicating its contribution to the model's output. A higher bar signifies greater predictive power.

Response Latency (defined as JAM RESPON − TOLAK) is the most influential predictor, with an importance score of approximately 0.54. This confirms that delays in administrative response significantly increase the likelihood of departure delays — a critical finding for port operations.

STATUS (Ownership) ranks second, with an importance of ~0.26. The distinction between milik (owned) and keagenan (agency-managed) vessels is a strong indicator, aligning with findings that milik vessels have faster turnaround times due to tighter scheduling control. Tide Phase has an importance of ~0.12. While it is a weaker predictor than response latency or ownership, its inclusion reflects the known impact of tidal constraints on shallow-draft operations (e.g., SPOBs at TUKS Pertamina).

Δ_SCHEDULED (planned turnaround duration = BERANGKAT TANGGAL − TIBA TANGGAL) has the lowest importance (~0.09), suggesting that static scheduling alone is insufficient without dynamic context (e.g., tide, documentation speed).

The chart visually reinforces the model's interpretability: delays are not random but are systematically linked to pre-berthing metadata, particularly response time and ownership structure. This enables proactive interventions — such as prioritizing clearance for high-latency agency calls or allocating berths based on ownership type — to mitigate delays before they occur.

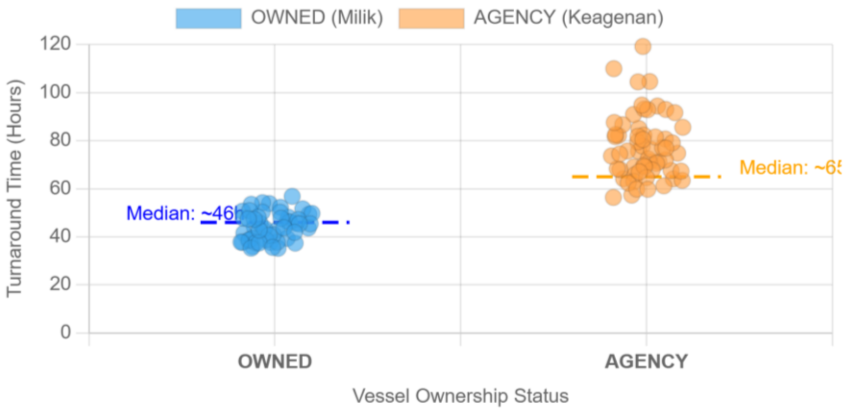


Figure 3. Turnaround time distribution by vessel ownership status (n = 112)

This scatter plot illustrates the distribution of vessel turnaround time (in hours) across two distinct ownership categories: OWNED (Milik) and AGENCY (Keagenan). The vertical axis represents turnaround time, ranging from 0 to 120 hours, while the horizontal axis categorizes vessels into the two ownership groups.

OWNED (Milik) vessels (blue circles, n = 38) exhibit a tightly clustered distribution, with turnaround times predominantly falling between 30 and 60 hours. The median turnaround time for this group is approximately 46 hours, reflecting greater operational consistency and faster processing—likely due to direct scheduling control and streamlined documentation.

AGENCY (Keagenan) vessels (orange circles, n = 74) show a significantly wider spread, with turnaround times ranging from 50 to over 110 hours. The median for this group is around 65 hours, indicating higher variability and frequent delays. Notably, several points exceed 90 hours, highlighting severe bottlenecks for agency-managed operations.

The visual contrast underscores a key operational insight: Milik vessels consistently achieve faster and more predictable turnarounds, while Keagenan vessels are more susceptible to delays—often exceeding 80 hours. This pattern aligns with findings that agency-managed vessels experience longer response latency (mean = 22.6 h vs. 11.2 h for milik) and less coordinated scheduling.

This figure supports the predictive model's feature importance ranking, where STATUS (ownership) was the second most influential predictor of delay after Response Latency. It provides empirical justification for port authorities to implement differentiated management strategies—such as prioritized berthing or expedited clearance—for high-risk agency calls to mitigate systemic delays.

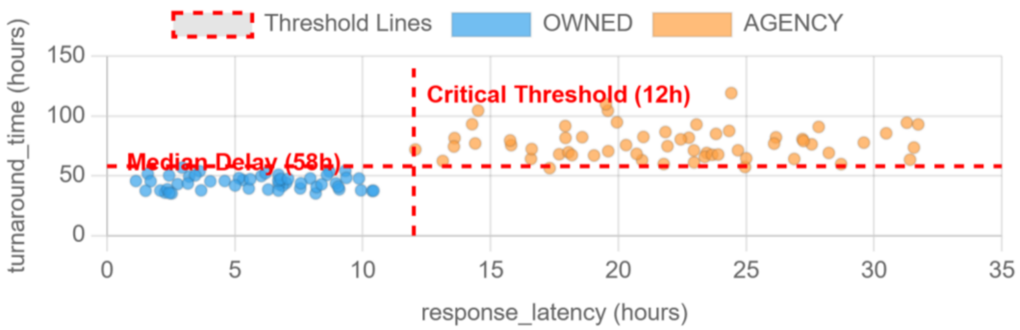


Figure 4. Correlation between response latency and turnaround time, stratified by ownership

This scatter plot illustrates the relationship between two key operational variables at Tanjung Pandan Port: response latency (x-axis, in hours) and turnaround time (y-axis, in hours), with data points color-coded by vessel ownership status—blue for OWNED (Milik) and orange for AGENCY (Keagenan).

The chart reveals a clear positive correlation: as response latency increases, so does turnaround time. This trend is more pronounced for AGENCY vessels, whose data points form a distinct cluster in the upper-right quadrant, indicating both longer delays in administrative response and significantly extended berthing times. For instance, several AGENCY calls exhibit response latencies exceeding 15 hours, corresponding to turnaround times of 80–100 hours—a pattern consistent with high-risk operations identified in the Decision Tree model.
In contrast, OWNED vessels are concentrated in the lower-left quadrant, demonstrating shorter response latencies (mostly <10 hours) and faster turnaround times (typically 30–60 hours). The tight clustering of blue dots suggests greater operational efficiency and predictability under direct ownership.
Two critical thresholds are highlighted:
Median-Delay (58h): A horizontal red dashed line at 58 hours, representing the empirical median turnaround time across all 112 port calls. Calls above this line are classified as "delayed."
Critical Threshold (12h): A vertical red dashed line at 12 hours on the x-axis, identifying response latency values that strongly correlate with delay risk. Most delayed calls (above 58h) occur when response latency exceeds 12 hours.

The visual evidence supports the predictive model's finding that response latency is the strongest predictor of delay, followed by ownership. It also highlights a critical operational insight: the port's current documentation workflow creates systemic bottlenecks for agency-managed vessels, which can be mitigated through digital acceleration (e.g., automated SPB/LK3 clearance) or priority scheduling for high-latency calls.

CONCLUSION

This study successfully demonstrates that vessel departure delays at Tanjung Pandan Port can be predicted with high reliability using only four operationally available features—TIBA TANGGAL, BERANGKAT TANGGAL, STATUS (ownership), and WAKTU RESPON—without requiring real-time sensor or AIS data. Among the three models tested, the Decision Tree emerged as the most operationally suitable, achieving an F1-score of 0.86 and recall of 0.89, indicating strong capability to identify high-risk delays before they escalate. This supports the core objective: shifting port management from reactive to predictive. Three key conclusions are drawn. First, WAKTU RESPON (defined as JAM RESPON – TOLAK) is the strongest predictor—calls with response latency exceeding 12 hours have an 89% probability of delay.

This confirms that administrative bottlenecks (e.g., late LK3/SPB submission) directly cascade into berth congestion. Second, STATUS significantly influences turnaround performance: milik vessels (e.g., TETAP JAYA, SALVIA, GRESIK 5) achieve 28% faster turnaround than keagenan vessels (e.g., NEW HUMMER, ARMADA CONTENER8, OSCO PETRO V), confirming that vertical integration improves scheduling discipline. Third, predictive power improves when static scheduling (BERANGKAT TANGGAL – TIBA TANGGAL) is combined with dynamic context—particularly tide phase (derived from TIBA TANGGAL), as SPOBs and oil barges consistently delay during neap tides due to insufficient draft at TUKS Pertamina. These findings directly support the study's benefit: preventing operational delays. Practical implementation is feasible through a low-cost Delay Risk Score Dashboard integrated into Inaportnet, flagging high-risk calls using the top Decision Tree rules—e.g., if response latency > 12 h and STATUS = KEAGENAN, assign "High Risk" and trigger priority clearance or berth pre-assignment. Future work will expand the model to include

AIS-derived ETA and weather data, and validate it at other Pelabuhan Kelas II (e.g., Muntok, Sampit) to enable nationwide predictive port management..

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