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# Scenario-Based Waste Generation Estimation and Bin Capacity Evaluation from Visitor Patterns: Mann–Whitney and Kruskal–Wallis Tests at Alun-Alun Timur, Depok

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## ABSTRACT

This study estimates visitor-related waste generation and evaluates stream-specific bin capacity at Alun-Alun Timur, Depok. Daily visitor records for 2025 and January–March 2026 were validated and connected to a peak-event waste scenario and bin inventory. Mann–Whitney tests compared weekdays with weekends and matched first-quarter periods. Kruskal–Wallis tests compared operating days and months, followed by Dunn–Bonferroni tests and effect sizes. Waste volume, utilization, deficits, and ±20% sensitivity scenarios were then calculated by waste stream. The dataset contained 382 valid operating days. Weekend attendance exceeded weekday attendance in 2025 ($U = 18{,}479$; $p < 0.001$; $r = 0.785$) and 2026 Q1 ($U = 1{,}004$; $p < 0.001$; $r = 0.575$). Operating-day distributions differed in both periods, whereas 2025 Q1 and 2026 Q1 were similar ($p = 0.913$). Under the base peak scenario, organic and inorganic utilization reached 119% and 400%, requiring 120 L and 750 L of additional capacity; mixed-bin utilization was 14%. The inorganic stream remained above capacity under every sensitivity scenario. Waste coefficients were calibrated from one documented event rather than repeated daily weighing, so results represent planning estimates. The results support weekend inspections, temporary separated-bin deployment, and stream-specific collection schedules. The study combines nonparametric visitor-pattern inference, uncertainty-aware waste estimation, and capacity-deficit rules for a public recreational facility.

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## 1. INTRODUCTION

Municipal solid waste management requires infrastructure to be matched with fluctuating demand rather than average demand alone. Global waste generation and service costs continue to increase, while insufficient collection and poorly allocated containers create environmental, operational, and public-health burdens (United Nations Environment Programme [UNEP] & International Solid Waste Association [ISWA], 2024). In public recreational spaces, demand can change sharply with visitor volume, weekends, events, food consumption, and seasonal activity. Waste-management quality is therefore part of the environmental performance and usability of public space (Arteaga et al., 2023; Perkumienė et al., 2023).

Advanced waste systems increasingly combine prediction, fill-level monitoring, routing, and digital decision support. Internet of Things and deep-learning applications can detect waste, monitor bins, and improve vehicle or facility decisions (Mohammadi et al., 2023; Rekabi et al., 2024; Wang et al., 2021). GIS dashboards and urban digital twins extend these systems by linking temporal indicators to locations and service actions (Cárdenas-León et al., 2024; Xu et al., 2023). Nevertheless, many municipal facilities do not yet possess repeated waste weighing or bin-level sensor histories. They commonly have visitor records, a bin inventory, and occasional event observations.

Waste-generation studies have used artificial neural networks, support-vector machines, time-series deep learning, and multi-city models to forecast municipal quantities (Ahmed et al., 2022; Ayeleru et al., 2021; Elshaboury et al., 2021; Lu et al., 2022). Such models require reliable response variables and sufficiently long histories. Reviews of smart waste management emphasize that data quality, interpretability, and local validation should precede complex modelling (Anuardo et al., 2022; Hoy et al., 2024; Manik et al., 2024). When daily waste measurements are unavailable, a transparent scenario model is more defensible than training a predictive algorithm on an inferred target.

This study examines Alun-Alun Timur, Depok, through three engineering questions: (1) how strongly do visitor distributions differ between weekdays and weekends and among operating days; (2) are matched first-quarter distributions different between 2025 and 2026; and (3) under a documented peak-event waste scenario, which waste streams require additional capacity? Mann–Whitney and Kruskal–Wallis procedures are used to identify statistically distinct visitor patterns, while scenario coefficients translate attendance into stream-specific planning loads. The novelty lies in maintaining a visible boundary between measured records, documented assumptions, and estimated engineering outputs.

## 2. METHODS

### Study design and data preprocessing

A retrospective quantitative design was combined with scenario-based capacity assessment. Three administrative documents formed the quantitative dataset: daily visitor charts for January–December 2025, daily visitor charts for January–March 2026, and a site report containing the bin inventory and a peak-event waste scenario. Two supplementary local sources were used only to contextualize spatial service and material types: a monitoring-and-evaluation map of bin distribution and collection routes and a peer-reviewed field report on landscape-biomass categories (Wiseno et al., 2026). Mondays were excluded because the facility was normally closed. Dates were parsed, stated weekdays were checked against calendar weekdays, counts were standardized, and duplicate dates were assessed. The malformed value ‘1/520’ on 5 July 2025 was retained as missing instead of being silently converted to 1,520. The final dataset contained 306 valid 2025 days and 76 valid 2026 Q1 days. Data sources, evidence status, and analytical use are shown in Table 1

**Table 1.** Data sources, evidence status, and analytical use

| Source | Coverage | Evidence status | Analytical use |
|---|---|---|---|
| Visitor chart 2025 | Jan–Dec; daily counts | Measured administrative record | Annual pattern and hypothesis tests |
| Visitor chart 2026 | Jan–Mar; daily counts | Measured administrative record | Q1 profile and matched-period test |
| Site report | 62 bins; peak-event scenario | Documented inventory/scenario | Waste coefficients and stream capacities |
| Monev spatial map | 62 bins; two collection zones | Documented operational map | Spatial service context; no fill levels |
| Wiseno et al. (2026) | Logs, branches, and leaves | Peer-reviewed field observation | Landscape-biomass typology |
| Derived dataset | 382 operating days | Estimated variables flagged | Utilization, deficit, and sensitivity analysis |

*Note. Daily visitor counts are measured; waste quantities and capacity-pressure indicators are scenario-derived estimates. The supplementary sources provide spatial and typological context, not daily waste measurements.*

**Scenario-based waste estimation and capacity evaluation**

The site documentation associated 12,573 peak visitors with 150 kg (750 L) organic waste, 200 kg (1,000 L) inorganic waste, and 350 kg (1,750 L) mixed waste. Available capacity was 630 L organic, 250 L inorganic, and 12,480 L mixed, giving 13,360 L in total. For stream s on day t, the volume coefficient αs was the scenario volume divided by 12,573 visitors. Daily volume, utilization, and capacity deficit were calculated as:

$$\begin{aligned} W\_hat(s,t) &= V(t) \times alpha(s) \\ U(s,t) &= [W\_hat(s,t) / C(s)] \times 100\% \\ D(s,t) &= max[0, W\_hat(s,t) - C(s)] \end{aligned}$$

Where:
V(t) is the measured visitor count,
W_hat(s,t) is estimated volume,
C(s) is available capacity,
U(s,t) is utilization,
D(s,t) is additional volume required.

A stream was flagged when U(s,t) ≥ 100%. The combined base coefficient was 0.2784 L/visitor (0.0557 kg/visitor). Because estimated waste is a deterministic monotonic transformation of visitor counts, hypothesis tests were performed on visitor data rather than repeated on the estimates.

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**Nonparametric statistical analysis**

Descriptive statistics included n, median, interquartile range (IQR), mean, standard deviation, minimum, and maximum. Shapiro–Wilk tests indicated strong non-normality in 2025 ($W = 0.672$, $p < 0.001$) and 2026 Q1 ($W = 0.671$, $p < 0.001$). Two-sided Mann–Whitney U tests compared weekday and weekend observations within each period and compared 2025 Q1 with 2026 Q1. Rank-biserial correlation quantified two-group effects. Kruskal–Wallis tests compared the six operating days in each period and the 12 months of 2025; epsilon-squared quantified omnibus effects. Significant day-of-week results were followed by Dunn pairwise tests with Bonferroni adjustment. The significance level was 0.05. These procedures follow current guidance for skewed independent-group data and effect-size reporting (Chicco et al., 2025).

**Sensitivity and decision-support rules**

Uncertainty in the one-event waste coefficient was examined using low (80% of base), base (100%), and high (120%) scenarios. For each stream, peak utilization, deficit, and an engineering target were calculated. The design target was defined as the capacity needed under the high scenario, not as proof of daily generation. A lightweight browser-based scenario panel was also constructed to allow visitor count and coefficient factor to be changed while preserving an interpretation warning. The analytical sequence and evidence status are summarized in Figure 1.

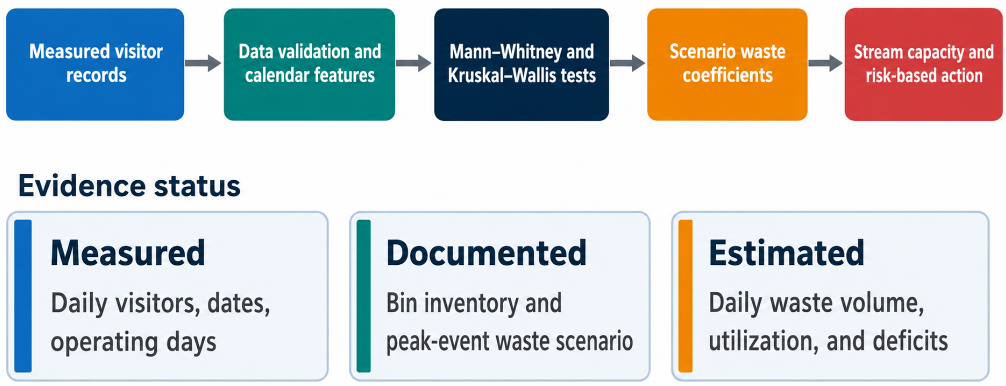


**Figure 1.** Scenario-based waste and capacity assessment framework.
Source: authors' design.

## 3. RESULTS

**Site distribution and documented waste typology**

Table 2 shows supplementary spatial and material evidence. The monitoring-and-evaluation map documented 62 receptacles across Alun-Alun Timur: 52 general 240-L bins, six 50-L bins, two plastic-bottle cages, and two leaf-waste cages. Zone 1 served commercial, recreational, and cultural functions, while Zone 2 served sports and public facilities. Both routes converged at temporary storage beside the BPJS office before transfer to Cipayung (DLHK Depok, 2026). Without bin-level fill or zone-specific mass, the source establishes service topology rather than generation intensity.

Wiseno et al. (2026) separately documented three landscape-biomass categories: logs or stems, branches, and leaves. Their density, flexibility, and moisture require different mechanical handling. This maintenance-waste typology is not equivalent to the visitor-related

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organic, inorganic, and mixed scenario streams; it was retained as contextual field evidence rather than converted into an unmeasured daily coefficient.

**Table 2.** Supplementary spatial and material evidence

| Evidence | Recorded categories | Spatial/operational meaning | Use in this study |
|---|---|---|---|
| Mapped bin inventory | 52 × 240 L; 6 × 50 L; 2 plastic-bottle cages; 2 leaf cages | Distributed across public activity areas | Location/type context; no zone load |
| Zone 1 route | Commercial, recreation, and culture | Route to common temporary storage | Operational service context |
| Zone 2 route | Sports and public facilities | Route to common temporary storage | Operational service context |
| Landscape biomass | Logs/stems, branches, and leaves | Maintenance waste with distinct handling | Material typology kept separate from visitor scenario |

Sources: Wiseno et al. (2026)

### 3.2. Visitor distributions

The 2025 dataset contained 387,196 visits across 306 valid operating days. The median was 384 visitors/day (IQR 245–1,572), while the mean was 1,265 and the maximum was 12,573. The separation between the median and mean confirmed a strong right tail. The 2026 Q1 dataset contained 52,091 visits across 76 operating days, with a median of 315.5 (IQR 159.8–745.8), mean of 685, and maximum of 3,856. Sunday recorded the highest median in both periods, followed by Saturday. See Table 3 and Figure 2.

**Table 3.** Visitor distributions by operating day

| Day | 2025 n | 2025 median (IQR) | 2026 Q1 n | 2026 Q1 median (IQR) |
|---|---|---|---|---|
| Tuesday | 50 | 254 (181–361) | 13 | 227 (126–482) |
| Wednesday | 53 | 317 (245–568) | 12 | 244 (120–397) |
| Thursday | 51 | 266 (179–489) | 13 | 227 (130–310) |
| Friday | 51 | 347 (237–600) | 13 | 316 (149–518) |
| Saturday | 50 | 1,391 (899–2,315) | 12 | 984 (236–1,499) |
| Sunday | 51 | 3,453 (2,278–4,808) | 13 | 1,130 (342–2,363) |

Note: IQR = first to third quartile; visitor values are rounded to the nearest whole person.

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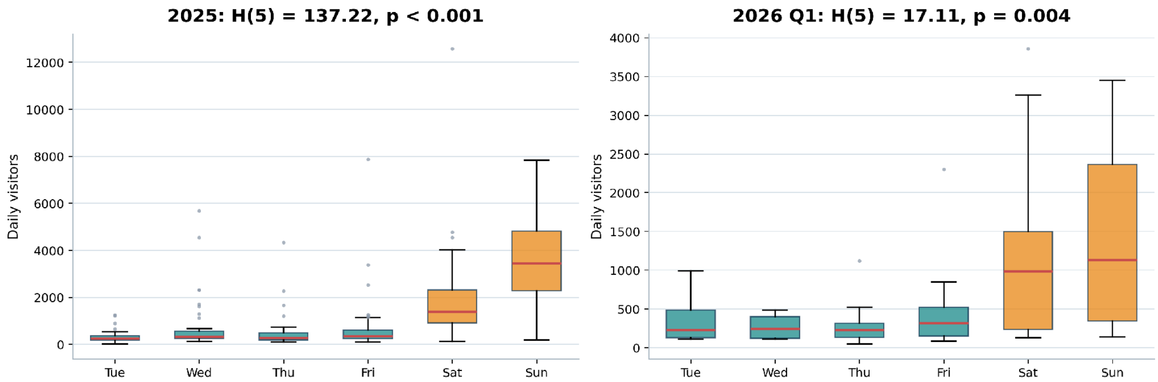


**Figure 2.** Visitor distributions by operating day. Boxes show interquartile ranges and red lines show medians.

Source: authors' analysis

### 3.3. Mann–Whitney and Kruskal–Wallis results

Weekend visitor counts were higher than weekday counts in 2025 (weekend median 2,307; weekday median 287; U = 18,479; $p < 0.001$; rank-biserial r = 0.785) and in 2026 Q1 (1,026 versus 282; U = 1,004; $p < 0.001$; r = 0.575). In 2025, visitor distributions differed across operating days, $H(5) = 137.22$, $p < 0.001$, $\varepsilon^2 = 0.441$. Dunn–Bonferroni tests showed that Saturday and Sunday each differed from all Tuesday–Friday categories (all adjusted $p < 0.001$). In 2026 Q1, the operating-day result remained significant, $H(5) = 17.11$, $p = 0.004$, $\varepsilon^2 = 0.173$; only Thursday–Sunday remained significant after correction (adjusted $p = 0.047$).

Monthly distributions differed in 2025, $H(11) = 57.99$, $p < 0.001$, $\varepsilon^2 = 0.160$. However, the matched 2025 Q1 and 2026 Q1 distributions were similar (medians 281.5 and 315.5; U = 2,765; $p = 0.913$; r = 0.011). Therefore, the lower full-period mean observed in 2026 Q1 cannot be interpreted as an annual decline. See Table 4 for details.

**Table 4.** Inferential results and effect sizes

| Comparison | Statistic | p | Effect | Result |
|---|---|---|---|---|
| 2025 weekend vs weekday | U = 18,479 | <0.001 | r = 0.785 | Large weekend concentration |
| 2026 Q1 weekend vs weekday | U = 1,004 | <0.001 | r = 0.575 | Substantial weekend concentration |
| 2025 Q1 vs 2026 Q1 | U = 2,765 | 0.913 | r = 0.011 | No detectable shift |
| Operating day, 2025 | H(5) = 137.22 | <0.001 | $\varepsilon^2 = 0.441$ | Large differentiation |
| Operating day, 2026 Q1 | H(5) = 17.11 | 0.004 | $\varepsilon^2 = 0.173$ | Moderate differentiation |
| Month, 2025 | H(11) = 57.99 | <0.001 | $\varepsilon^2 = 0.160$ | Meaningful temporal variation |

Note. r = rank-biserial correlation; $\varepsilon^2$ = epsilon-squared. Tests were two-sided.

### 3.4. Waste estimates and capacity pressure

As shows in Table 5. The base scenario produced coefficients of 0.0597 L/visitor for organic, 0.0795 L/visitor for inorganic, and 0.1392 L/visitor for mixed waste. At the documented peak, estimated volumes were 750 L, 1,000 L, and 1,750 L. Total utilization was

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only 26.2% of the site's combined capacity, but this aggregate concealed severe imbalance: organic utilization was 119%, inorganic utilization was 400%, and mixed utilization was 14%. The corresponding base deficits were 120 L organic and 750 L inorganic.

**Table 5.** Scenario coefficients, capacity thresholds, and observed risk

| Stream | Coefficient (L/visitor) | Capacity (L) | Visitor threshold | Peak use | 2025 days ≥100% |
|---|---|---|---|---|---|
| Organic | 0.0597 | 630 | 10,561 | 119% | 1 (0.3%) |
| Inorganic | 0.0795 | 250 | 3,143 | 400% | 40 (13.1%) |
| Mixed | 0.1392 | 12,480 | 89,663 | 14% | 0 (0.0%) |
| Total* | 0.2784 | 13,360 | 47,993 | 26% | 0 (0.0%) |

Note. *The total is shown for scale; operational alerts use stream-specific capacity. Thresholds assume a constant scenario composition.

### 3.5. Sensitivity and capacity deficits

Table 6 and Figure 3. shows the sensitivity analysis did not change the primary engineering diagnosis. Under the low scenario, organic utilization fell to 95%, but inorganic utilization remained 320%. Under the high scenario, utilization reached 143% organic and 480% inorganic. Mixed utilization remained between 11% and 17%. A conservative peak design target would therefore provide at least 900 L organic capacity and 1,200 L inorganic capacity, representing additions of 270 L and 950 L above the documented capacities.

**Table 6.** Peak sensitivity scenarios and additional capacity requirements

| Stream | Low use / deficit | Base use / deficit | High use / deficit | High-scenario target |
|---|---|---|---|---|
| Organic | 95% / 0 L | 119% / 120 L | 143% / 270 L | 900 L |
| Inorganic | 320% / 550 L | 400% / 750 L | 480% / 950 L | 1,200 L |
| Mixed | 11% / 0 L | 14% / 0 L | 17% / 0 L | 12,480 L retained |

Note. Low and high scenarios equal 80% and 120% of the documented event coefficients. Targets are planning values, not measured requirements

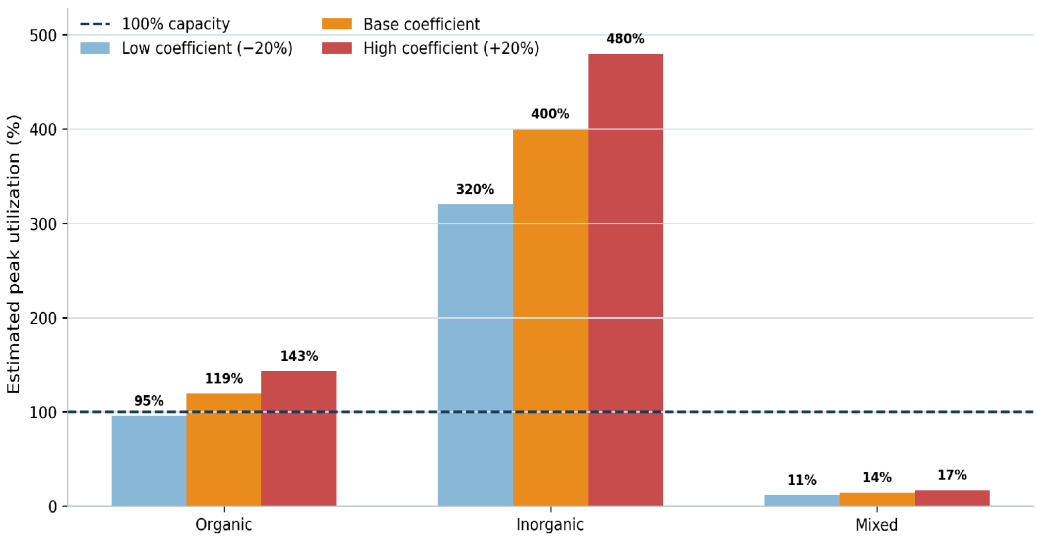


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**Figure 3.** Sensitivity of estimated peak utilization to the waste coefficient.
Source: authors' analysis.

Applying base thresholds to the recorded days produced an estimated inorganic exceedance on 40 days in 2025 (13.1%) and four days in 2026 Q1 (5.3%) (Figure 4). Organic capacity was exceeded on one 2025 day, and mixed capacity was never exceeded. The 95th-percentile 2025 utilization was 45.7% organic, 153.6% inorganic, and 5.4% mixed, confirming that inorganic pressure was not limited to a single extreme observation.

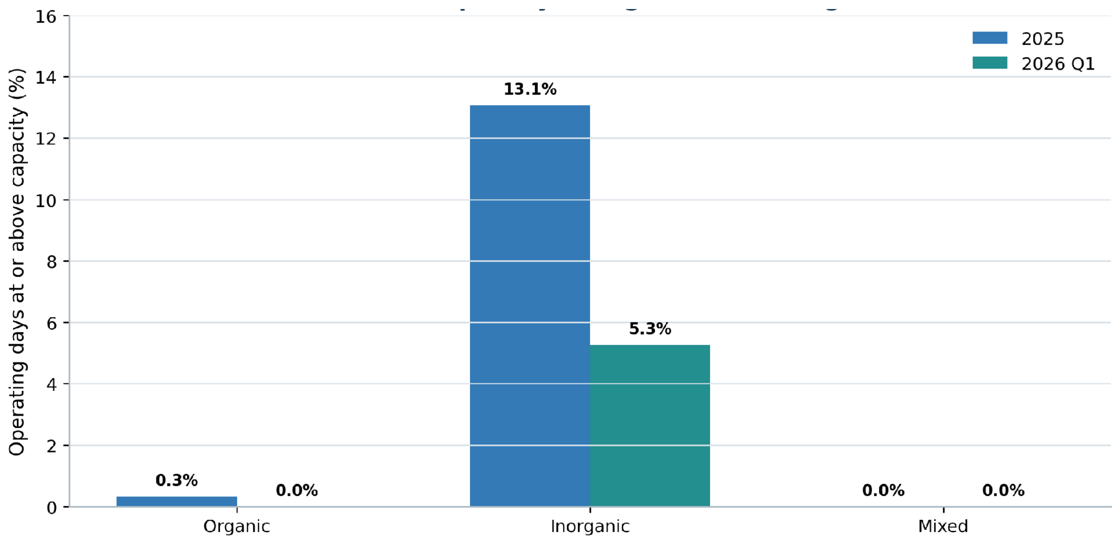


**Figure 4.** Share of operating days at or above scenario-derived stream capacity.
Source: authors' analysis.

## 4. DISCUSSION

### 4.1. Engineering interpretation

The nonparametric results establish that attendance demand is structured rather than random across operating days. Large weekend effects in both periods support differentiated service planning. The matched-quarter result is equally important: no detectable Q1 shift means that capacity decisions should not be justified by an unsupported claim of annual decline. Instead, weekend status, special events, and real-time attendance should be used as operational triggers. Short-horizon multi-site research similarly shows the value of temporal segmentation for collection planning (Fokker et al., 2023).

From an engineering perspective, the decisive finding is the mismatch between stream-level and total capacity. A combined 13,360 L appears ample, yet the inorganic stream reaches 400% at the base peak. Total-capacity reporting would therefore produce a false sense of adequacy. The first intervention should be to raise effective inorganic capacity toward 1,200 L for a high peak scenario, either through temporary containers, faster emptying, or compatible reassignment of underused mixed bins. Organic capacity should be raised toward 900 L during high-attendance events. Any reassignment requires appropriate container compatibility, cleaning, labels, and user guidance.

The spatial evidence adds an operational layer to this diagnosis. General 240-L bins provide broad coverage, whereas only two dedicated plastic-bottle cages and two leaf-waste cages form source-separated nodes. Counts and locations alone do not demonstrate adequacy, but the two-zone network supports inspections and servicing by activity cluster

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before transfer to the common temporary-storage point. Landscape biomass should remain on a separate handling pathway—such as shredding for mulch or compost feedstock—rather than being pooled analytically with visitor-generated waste (Wiseno et al., 2026).

4.2 **Decision-support and technology pathway**

The scenario panel translates these rules into an interactive engineering view (Figure 5). A manager can change visitor count and coefficient factor, inspect stream utilization, and read a capacity action while the interface continuously labels the outputs as estimates. This modest tool is appropriate for the current evidence base. It can later be connected to weighing scales, fill-level sensors, weather, event calendars, and spatial data. Such staged development is consistent with current smart-waste and urban-digital-twin research, in which operational visualization precedes optimization and automated routing (Cárdenas-León et al., 2024; Lee & Shin, 2025; Mohammadi et al., 2023; Xu et al., 2023).

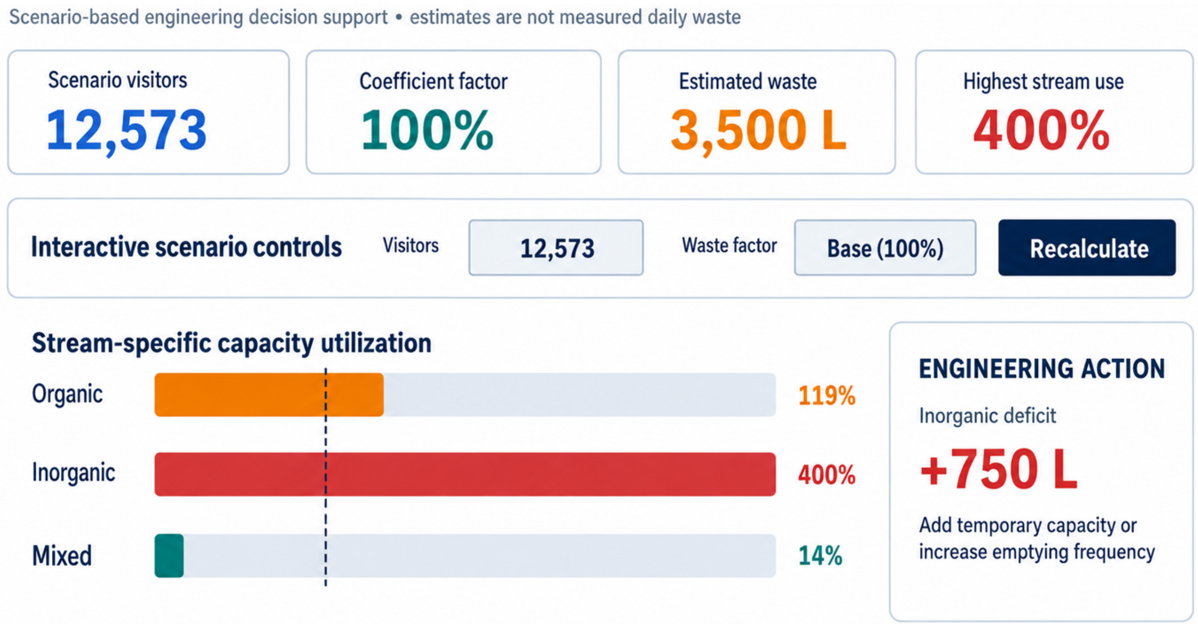


**Figure 5.** Interactive scenario-assessment prototype with stream-level capacity rules and an interpretation safeguard.

Source: authors' implementation

**4.3 Limitations and future research**

The main limitation is that waste coefficients were derived from one documented peak-event scenario rather than repeated daily weighing. The ±20% sensitivity range demonstrates robustness of the inorganic diagnosis but is not a statistical confidence interval. Sorting behavior, cross-disposal, collection timing, compaction, and actual fill levels were not recorded. The supplementary spatial source maps containers and routes but provides no bin-level fill, collection frequency, or zone-specific mass. Daily visitor observations are also time-indexed, so serial dependence and holidays may weaken the independence assumption of rank tests. Finally, 2026 covers only one quarter. Future work should record stream-specific mass and volume before and after collection by zone, identify events and weather conditions, and validate visitor-based coefficients. With a measured response series, forecasting methods can be compared objectively rather than applied to estimated targets (Lee & Shin, 2025; Paulauskaite-Taraseviciene et al., 2022).

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## 5. CONCLUSION

The study shows that limited municipal records can support a defensible capacity assessment when measured data, documented assumptions, and estimates are separated. Supplementary local evidence documented 62 receptacles arranged across two collection zones and differentiated logs, branches, and leaves as maintenance-biomass types; neither source was treated as a daily waste measurement. Visitor counts at Alun-Alun Timur were substantially higher on weekends and differed among operating days, while matched Q1 distributions for 2025 and 2026 were similar. Under the documented base scenario, peak organic and inorganic utilization reached 119% and 400%, creating estimated deficits of 120L and 750 L. The inorganic stream remained over capacity under every sensitivity scenario. A conservative high-scenario target is therefore 900 L organic and 1,200 L inorganic capacity, combined with weekend inspections and event-based servicing. These outputs are screening values for engineering planning; repeated weighing and fill-level observations are required before confirming physical overflow or calibrating a predictive model.

## 6. ACKNOWLEDGMENT

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## 7. AUTHORS' NOTE

The authors confirm that no conflicts of interest are associated with the publication of this article. They also affirm that the manuscript is an original work prepared in compliance with established academic integrity principles. To the best of their knowledge, the manuscript contains no plagiarized content or unauthorized use or reproduction of materials belonging to other parties.

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