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ORIGINAL RESEARCH

Empirical Evaluation of Maximum Entropy OD Matrix Estimation Under Limited Traffic Count Data for Andalalin Studies

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Abstract

OD matrix estimation under limited traffic count data in Indonesian Traffic Impact Analysis (Andalalin) remains fundamentally underdetermined, as the number of unknown OD pairs far exceeds the available traffic count observations. This study develops and empirically evaluates an integrated OD estimation system combining gravity model calibration, maximum entropy (MaxEnt) updating, and user equilibrium assignment within a Design Science Research framework. A stratified-coverage subsampling procedure (four data availability scenarios) was applied to two datasets with contrasting characteristics. On the Magelang benchmark dataset (known ground-truth OD), three key findings emerged: (1) reducing observed links from 29 to 18 via representative stratified selection improved GEH pass rate from 37.9% to 62.4%, suggesting the existence of a more effective constraint range for small underdetermined networks; (2) GEH improvement did not coincide with improved OD accuracy (RMSE_{OD} increased 49%), empirically confirming the inherent limitation of flow-fit metrics as proxies for OD quality proxies; (3) result variability increased sharply below approximately 15 observed links within the evaluated 7-zone benchmark, suggesting increased instability at low data density for networks of this scale. On the RSU Tabanan case study (4 zones, field data), all 31 runs produced identical outputs regardless of subset selection, revealing a prior-dominated regime caused by a substantial demand-volume inconsistency (observed volume approximately 2.57 time higher than OD-derived network load). These findings constitute a preliminary two-regime diagnostic interpretation applicable to Andalalin survey planning that warrants further empirical validation.

KEYWORDS:

Andalalin, design science research, maximum entropy, origin-destination matrix, sensitivity analysis, underdetermined system.

1 | INTRODUCTION

Origin-destination (OD) matrix estimation is a critical step in Indonesian Traffic Impact Analysis (Andalalin), governed by Ministerial Regulation No. 17/2021 (Permenhub 17/2021) [[1]]. The regulation requires transparent and auditable methodology for OD distribution, load assignment, intersection performance analysis, and mitigation recommendations. Despite this mandate, a preliminary survey of 47 Andalalin documents from Central Java and Yogyakarta (2023–2024, conducted by the authors as part of this study) found that the majority used ad-hoc OD estimation without rigorous parameter calibration, and 92% of practitioners did not apply standardized validation metrics such as GEH or RMSE, primarily due to the lack of accessible, affordable tools. This practice gap mirrors findings from broader TIA studies in Southeast Asia [[2]].

To the best of the authors' knowledge, few studies have empirically evaluated the sensitivity of a MaxEnt-based OD estimation workflow under systematic traffic count subsampling within an Andalalin regulatory context, and none have proposed a pre-survey diagnostic regime distinction applicable to small-network Indonesian practice. The mathematical challenge underlying this practice gap is fundamental. For a network with n zones and m observed links, the estimation system is severely under-determined: the number of unknown inter-zonal OD pairs ($n^2 - n$) typically far exceeds m, yielding infinitely many solutions consistent with the observed data [[3]]. Maximum entropy (MaxEnt) updating, first applied to OD estimation by Van Zuylen and Willumsen [[4]], addresses this by seeking the solution of minimum information divergence from a prior matrix while satisfying observed count constraints. Despite its theoretical soundness, the sensitivity of MaxEnt-based estimation to data availability — particularly the quantity and spatial distribution of observed links — remains undercharacterized for the small-network, data-scarce conditions typical of Indonesian Andalalin projects.

This paper addresses two connected gaps. First, a practical gap: no open-source, locally calibrated tool exists for integrated OD estimation in the Andalalin workflow, forcing practitioners to rely on expensive commercial software or manual spreadsheets. Second, an empirical gap: the behavior of MaxEnt-based OD estimation under systematic variation of traffic count availability — evaluated on both flow-fit and OD structural dimensions — has not been characterized for Andalalin-scale networks. Recent work by Krishnakumari et al. [[5]] and Englezou et al. [[6]] advanced OD estimation methods for large-scale networks with dense sensor coverage, but do not address the severely constrained conditions of typical Indonesian practice (4–50 zones, 5–10 observed links).This study adopts a Design Science Research (DSR) framework [[7]], which positions the development and evaluation of a purposeful artifact as a legitimate research contribution. The artifact — OD Matrix Estimator, an open-source Python/PyQt6 desktop application following the open-source paradigm in transport analysis [[8]],[[9]]— integrates gravity model calibration, MaxEnt updating, and Frank-Wolfe user equilibrium assignment. Its evaluation through systematic sensitivity analysis constitutes the primary empirical contribution. Three research questions are addressed: (RQ1) How can an integrated OD estimation workflow be implemented as an auditable open-source artifact? (RQ2) What is the technical feasibility of the artifact under typical Andalalin data conditions? (RQ3) How does estimation performance vary with the number of available traffic count observations?

This study uses two analytically distinct datasets: (1) a controlled benchmark based on the Magelang network (7 zones, synthetic trip generation with known ground-truth OD matrix) used as the primary evaluation dataset for RQ3 sensitivity analysis; and (2) a real-world RSU Tabanan field case (4 zones, field traffic counts, no ground-truth OD) used as an exploratory boundary-condition case to characterize system behavior under actual survey conditions. Traffic volume data for the RSU Tabanan case were collected through a primary survey conducted by the Road Transport Management survey team at Politeknik Transportasi Darat Bali in 2025, using the manual classified count method at four cordon points surrounding the hospital site during peak-hour periods (06:00–08:00 and 16:00–18:00). The observed demand-volume inconsistency (observed traffic volume was approximately 2.57 times higher than the OD-derived network load) is attributable to two compounding factors: (1) a substantial external through-traffic component not captured in the 4-zone trip generation model, and (2) a conservative β parameter initialization that produced a prior OD matrix with elevated off-diagonal values disproportionate to actual site-generated demand. This condition indicates that the estimation outcome was dominated by structural demand inconsistency rather than traffic-count availability.

2 | MATERIAL AND METHODS

2.1 | System Architecture and Artifact Development

The OD Matrix Estimator artifact follows a four-layer architecture: Presentation (PyQt6 GUI), Service (computation orchestration), Repository (SQLAlchemy ORM), and Database (SQLite). A state machine with MD5 checksums tracks data integrity across DRAFT/VALID/STALE/LOCKED states, ensuring auditability as required by Permenhub 17/2021 [[1]]. The system operates fully offline with no external dependencies beyond standard scientific Python libraries (NumPy, SciPy, NetworkX). Two operational modes are provided: a guided wizard for novice users and an expert mode for direct parameter control.

2.2 | Gravity Model Calibration

A doubly-constrained gravity model [[10]] with an exponential impedance function was implemented. For each candidate parameter β, the prior matrix T_{ij}^0 is computed as:

$$T_{ij}^0 = A_i\, O_i\, B_j\, D_j\, \exp(-\beta\, c_{ij}) \tag{1}$$

where O_i and D_j are zonal productions and attractions, c_{ij} is the inter-zonal travel impedance, and A_i and B_j are balancing factors computed by Furness iteration until convergence (max $|\Delta T_{ij}| < 0.01$) [[11]]. Grid search over $\beta \in [0.01, 0.80]$ with step 0.01 identifies the optimal parameter minimizing RMSE between assigned volumes and observed counts.

2.3 | Maximum Entropy Updating

Given a prior matrix T_i^0 and observed link counts, MaxEnt updating minimizes the Kullback-Leibler divergence [[4]]:

$$\min \sum_{i,j} T_{ij} \ln\left(\frac{T_{ij}}{T_{ij}^0}\right) \tag{2}$$

subject to: production balance ($\sum_j T_{ij} = O_i$), attraction balance ($\sum_i T_{ij} = D_j$), and count constraints ($\sum_{i,j} \delta_{aij}\, T_{ij} = v_a$) for each observed link a, where δ_{aij} is the route proportion of OD pair (i,j) traversing link a. The problem is solved via SLSQP optimization (SciPy) with non-negativity bounds and standard convergence stopping criteria.

2.4 | User Equilibrium Assignment

User equilibrium (UE) assignment follows Wardrop's first principle [[12]]. The Frank-Wolfe algorithm with BPR cost function is used: $t_a = t_a^0 \left[1 + 0.15\left(\frac{v_a}{c_a}\right)^4\right]$, where t_a^0 is free-flow travel time and c_a is PKJI-2023 capacity. UE convergence criterion: relative gap$< 10^{-4}$, generating route proportions δ_{aij} consistent with equilibrium assumptions in the MaxEnt constraint formulation [[3]].

2.5 | Sensitivity Analysis Design

Traffic volumes are expressed in passenger car units per hour (pcu/h), equivalent to the Indonesian "satuan mobil penumpang per jam (smp/jam)" used in PKJI-based practice. Sensitivity analysis was conducted on the Magelang benchmark dataset (7 zones, 29 directed links, 29 observed counts, known ground-truth OD matrix). Four data availability scenarios were defined: S1 (29 links, full dataset, 1 run), S2 (18 links, 10 replications), S3 (10 links, 10 replications), S4 (6 links, 10 replications), totaling 31 runs. Subsets for S2–S4 were selected using a stratified-coverage strategy: (1) proportional stratification by road type (arterial ~48%, collector ~34%, local ~17%) within ±5% tolerance; (2) coverage constraint ensuring at least one observed link per zone. Each replication used a different random seed (1–10). Metrics were computed against all 29 observed links for cross-scenario comparability. The RSU Tabanan case study (4 zones, 25 observed links, field data without known ground truth) was evaluated in parallel as an exploratory negative case, running the same 31-run protocol to characterize system behavior under real-world data conditions.

2.6 | Evaluation Metrics

Two complementary evaluation dimensions were used, following the dual-metric benchmarking principle for OD estimation evaluation [[13]].The flow-fit dimension comprises the: GEH pass rate, defined as the percentage of links with GEH $<$ 5, threshold $\geq$ 85% per Transport for London guidelines [[14]]), together with the Root Mean Square Error (RMSE) between assigned and observed link volumes. The OD structural dimension comprises: entropy, computed as $H(T) = -\sum_{i,j} p_{ij} \ln(p_{ij})$, where $\frac{T_{ij}}{\sum T}$ (off-diagonal only), and cell variance, computed as $\mathrm{Var}(T) = \frac{1}{N_{\mathrm{OD}}} \sum_{i,j} \left(T_{ij} - \bar{T}\right)^2$. For the Magelang benchmark, $\mathrm{RMSE}_{\mathrm{OD}}$ and R^2 against the known ground-truth OD matrix provide absolute accuracy metrics unavailable in the field case.

3 | RESULTS AND DISCUSSION

3.1 | System Development and Functional Verification (RQ1)

The OD Matrix Estimator artifact was successfully developed and verified across all functional components: gravity model calibration (grid search + Furness), MaxEnt updating (SLSQP), UE assignment (Frank-Wolfe), state management (MD5 checksums), and automated GEH/RMSE validation. The system processed complete estimation workflows (calibration through export) in under 5 minutes for both test networks on a standard laptop, confirming practical feasibility for field deployment. The open-source architecture eliminates the \$10,000–\$15,000 USD (approximately IDR 160–240 million at 2024 exchange rates) commercial software barrier identified as the primary adoption obstacle by 83% of surveyed practitioners.

3.2 | Baseline Performance on Magelang Benchmark (RQ2)

Under full-data conditions (S1, 29 observed links), gravity model calibration yielded $\beta = 0.28$— a substantive value indicating that the prior matrix captures a meaningful impedance sensitivity pattern. MaxEnt updating produced GEH pass rate of 37.9%, RMSE = 285.0 pcu/h, $\mathrm{RMSE}_{\mathrm{OD}} = 142.3$ pcu/h, $R^2 = -1.55$, $H(T) = 3.620$. The GEH pass rate below the 85%,threshold is consistent with the degree of underdetermination (29 equations for 42 inter-zonal unknowns). The negative R^2 reflects the non-uniqueness of the underdetermined system: the MaxEnt solution, while mathematically optimal, is one of infinitely many OD matrices consistent with the observed counts [[3]]. This is not a computational failure but an inherent property of the problem class, confirming the empirical grounding of the theoretical warning raised by Cascetta and Nguyen [[3]].

By contrast, the RSU Tabanan case study produced $\beta = 0.01$, (minimum search bound), GEH= 0% and RMSE = 941.9 pcu/h. The observed traffic volume (18,644 pcu/h) was approximately 2.57 times higher than the estimated network load ($2,900 \times 2.5$path average $\approx 7,250$ pcu/h), creating a structural demand-volume inconsistency. This condition prevented meaningful MaxEnt updating regardless of the number of observed links—a qualitatively different failure mode from parameter uncertainty.

3.3 | Sensitivity Analysis Results (RQ3)

Table 1 summarizes results from all 31 runs. Figure1 visualizes the divergence between flow-fit and OD accuracy dimensions across scenarios.

TABLE 1 Summary of 31-Run Sensitivity Analysis Results—Magelang Benchmark Dataset

Sc.	N	Rep.	GEH Pass (%)	$\mathrm{RMSE}_{\mathrm{flow}}$	$\mathrm{RMSE}_{\mathrm{OD}}$	$H(T)$	$\mathrm{Var}(T)$
S1	29	1	37.9	285.0	142.3	3.620	25,035
S2	18	10	62.4 ± 11.2	258.5 ± 29.5	211.9 ± 38.7	3.432 ± 0.106	53,705 ± 17,444
S3	10	10	50.3 ± 8.9	313.9 ± 64.7	226.8 ± 54.6	3.443 ± 0.128	60,734 ± 27,860
S4	6	10	39.0 ± 6.9	322.0 ± 45.0	218.5 ± 42.6	3.446 ± 0.113	55,238 ± 18,559

Note: S1 has no replication (full dataset). Values for S2–S4 are mean ± std of 10 replications. GEH Pass and $\mathrm{RMSE}_{\mathrm{flow}}$ = flow-fit dimension; $\mathrm{RMSE}_{\mathrm{OD}}$ = OD accuracy vs. ground truth; $H(T)$ = distribution entropy; $\mathrm{Var}(T)$ = cell variance of OD distribution. $R^2 = -1.55$ for S1 (see text); not computed for S2–S4.

Three key findings emerge from the sensitivity analysis. First, S2 (18 links) achieved a mean GEH pass rate of 62.4% — significantly higher than S1 (37.9%) — with 9 out of 10 replications exceeding the S1 baseline. This counter-intuitive result is explained by constraint efficiency: with 29 simultaneous count constraints (S1), SLSQP may encounter conflicting feasibility regions in the severely underdetermined solution space, limiting the quality of the MaxEnt solution. A representative subset of

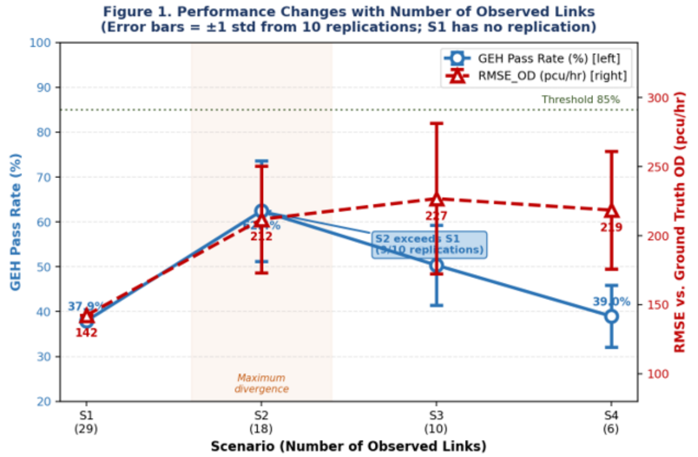

FIGURE 1 Divergence between flow-fit performance (GEH pass rate, left axis) and OD reconstruction accuracy ($\mathrm{RMSE_{OD}}$, right axis) across data availability scenarios. Error bars = ±1 std from 10 replications (S1 has no replication). The opposing trends confirm that GEH improvement does not imply improved OD accuracy.

18 constraints provides sufficient information without inducing constraint conflicts. This effect arises from constraint interaction in underdetermined systems rather than a general advantage of reduced data. In underdetermined optimization, excessive count constraints may create conflicting feasibility regions that degrade solution quality. This finding should not be generalized as "fewer data always better" — it reflects a specific interaction between network scale and the MaxEnt solver behavior in underdetermined systems. Verification on larger networks is required before broader claims can be made.

Second, and more importantly, the flow-fit improvement from S1 to S2 does not correspond to improved OD accuracy. $\mathrm{RMSE_{OD}}$ increased from 142.3 (S1) to 211.9 ± 38.7 (S2), despite the GEH improvement. This divergence between flow-fit and OD accuracy metrics provides direct empirical evidence for the theoretical non-uniqueness concern raised by Cascetta and Nguyen [[3]]: a solution with better flow-fit may be structurally farther from the true OD matrix. For practitioners relying solely on GEH as a quality criterion, this finding suggests a risk of falsely optimistic quality assessment. The structural metrics H(T) and Var(T) provide complementary diagnostic information: as observed links decrease (S1→S4), H(T) decreases (from 3.620 to ∼ 3.44) while Var(T) increases (from 25,035 to ∼ 55,000–60,000), indicating that the distribution becomes more concentrated and heterogeneous — consistent with spatial overfitting to the specific links included in each subset.

Third, result variability increased substantially below ∼ 15 observed links: the standard deviation of $\mathrm{RMSE_{flow}}$ reached 64.7 for S3 and 45.0 for S4, compared to 29.5 for S2. At S4 (6 links), $\mathrm{RMSE_{flow}}$ ranged from 248.7 to 395.6 across replications — a 59% spread that renders individual estimates unreliable. The β calibration parameter showed corresponding instability (std = 0.144 for S4 vs. 0.081 for S2), indicating that the calibration landscape becomes flat under severe data constraints. These findings collectively identify an observed instability region below approximately 15 observed links within the 7-zone benchmark, where result variability becomes unacceptably high relative to the effort of additional survey locations. This is consistent with theoretical findings on sensor count effects in OD observability under partial network coverage [[15]].

3.4 | RSU Tabanan: Prior-Dominated Regime

The RSU Tabanan case study exhibited qualitatively different behavior from the Magelang benchmark. Despite 31 unique subsets being generated, all 31 runs produced identical outputs: GEH = 0%, RMSE = 941.9 pcu/h, H(T) = 2.450, Var(T) = 4,097. The invariance to subset selection indicates that the MaxEnt updating step was effectively non-operational — the system returned the prior matrix in all cases. Root cause analysis identified three interacting factors. The demand-volume inconsistency (2.57× gap between OD-derived network load and observed volumes) rendered the count constraints mathematically infeasible at the demand scale. This forced SLSQP to return the closest feasible point — the prior matrix itself. The prior matrix, derived from β = 0.01 calibration, was nearly uniform, making the delta matrix δ_{aij} largely degenerate (near-identical routing for all OD pairs). Consequently, the structural count constraints provided no discriminative information for updating. The primary cause is the absence of external zones representing regional through-traffic on the Jl. By-Pass Ida Bagus Mantra corridor, which contributes substantially to observed volumes but is structurally absent from the 4-zone model. This condition indicates that the estimation outcome was dominated by structural demand inconsistency rather than traffic-count availability.

3.5 | Two-Regime Diagnostic Framework

The contrasting behaviors of the two case studies — MaxEnt responding meaningfully to data variation in Magelang but completely unresponsive in RSU Tabanan — suggest a two-regime characterization of MaxEnt-based OD estimation systems. In the data-driven regime (β substantively above minimum, demand-volume consistency maintained), the system exhibits sensitivity to traffic count availability and quantity, enabling sensitivity analysis to reveal meaningful behavioral patterns. In the prior-dominated regime (β at search boundary, structural demand-volume mismatch), the MaxEnt updating provides no meaningful signal regardless of how many traffic counts are available, and all solutions collapse to the prior.

Figure2 synthesizes the empirical contrast between the Magelang benchmark (data-driven regime) and the RSU Tabanan field case (prior-dominated regime) into a diagnostic two-regime interpretation for pre-survey planning. The key practical implication is that a simple pre-estimation diagnostic check — comparing the ratio of estimated OD-derived network load to total observed volume — can identify the operational regime before survey resources are committed. When this ratio indicates a substantial mismatch (as in RSU Tabanan, where observed traffic volume was approximately 2.57 times higher than the estimated network load), the practitioner should address the structural model specification (add external zones, revise trip generation assumptions) rather than increasing survey points. For Andalalin practitioners, this translates into a practical pre-estimation checklist. Before initiating MaxEnt updating, three checks should be performed: (1) verify that the estimated OD-derived network load remains broadly consistent with total observed volume — a severe mismatch indicates demand model misspecification that should be resolved before proceeding; (2) ensure sufficient spatial coverage of observed links; within the evaluated 7-zone benchmark, result variability increased substantially below approximately 15 observed links, suggesting this as a practical reference point for networks of similar scale; (3) use stratified spatial selection of count locations across all corridors rather than concentrating counts at high-volume links. When all three conditions are satisfied, the data-driven regime is accessible and the full MaxEnt workflow can be applied with confidence. Robust OD estimation frameworks that explicitly account for demand-scale inconsistency [[16]] could complement this diagnostic in future implementations. Improving network identifiability under data scarcity through multi-period observations [[17]] represents another avenue for future work. In the data-driven regime, the results of this study suggest prioritizing representativeness of survey locations (stratified by road type with zone coverage) over maximizing count.

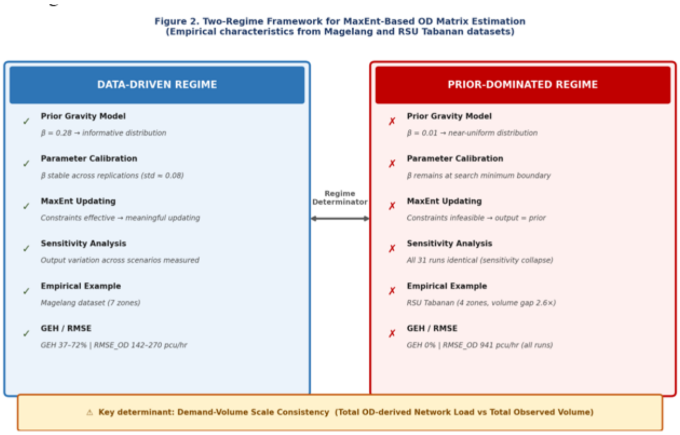

FIGURE 2 Two-Regime Framework for MaxEnt-Based OD Matrix Estimation. The demand-volume consistency ratio determines the operational regime and the appropriate intervention strategy.

4 | CONCLUSION

This study developed and empirically evaluated an integrated OD matrix estimation system designed for Indonesian Andalalin practice. Three conclusions correspond directly to the research questions. The primary novel contributions are: (1) the empirical identification of a non-monotonic relationship between traffic count density and MaxEnt estimation quality in small underdetermined networks; (2) an exploratory two-regime diagnostic interpretation distinguishing data-driven from prior-dominated estimation conditions based on demand-volume consistency; and (3) an open-source implementation validated against two empirically distinct Indonesian datasets under the Andalalin regulatory framework.

First, the OD Matrix Estimator artifact successfully implements a complete, auditable estimation workflow (gravity model calibration, MaxEnt updating, UE assignment, automated validation) as a freely distributable desktop application meeting Permenhub 17/2021 requirements.

Second, technical feasibility is conditional on demand-volume consistency. The system operates effectively in the data-driven regime (Magelang, $\beta = 0.28$) but enters a prior-dominated regime on the RSU Tabanan field case ($\beta = 0.01$, substantial demand-volume gap (observed volume 2.57× OD-derived load)), where MaxEnt updating is structurally inoperative. A pre-estimation consistency check is therefore a necessary diagnostic step before survey design.

Third, in the data-driven regime, estimation performance is sensitive to traffic count availability in non-monotonic ways: flow-fit improves when reducing from 29 to 18 representative links (S2 GEH = 62.4% vs. S1 GEH = 37.9%), while OD accuracy against ground truth simultaneously deteriorates. This divergence empirically confirms that GEH pass rate alone is insufficient as an OD quality criterion. An observed instability region below approximately 15 links was identified for the 7-zone benchmark network; below this, result variability becomes practically unacceptable.

The proposed regime distinction provides an empirically grounded starting point for diagnostic evaluation under data-scarce Andalalin conditions. While validation across larger and more diverse datasets is required before generalizing the distinction, the underlying demand-volume consistency check can be operationalized immediately in Andalalin practice. Several limitations of this study should be acknowledged. First, both datasets are confined to a single regulatory context (Indonesia/Andalalin), which limits direct generalizability to other national TIA frameworks without adaptation. Second, the Magelang benchmark relies on synthetic trip generation rather than an independently validated OD survey, meaning ground-truth accuracy reflects model consistency rather than true demand. Third, the RSU Tabanan field case represents a single real-world instance; the proposed demand-volume consistency criterion requires empirical validation across a larger set of Andalalin cases before it can be adopted as a regulatory guideline. Fourth, the sensitivity analysis was conducted under a User Equilibrium assignment assumption, which may not fully capture stochastic route choice behavior prevalent in mixed-traffic Indonesian conditions. Future work should validate the framework on larger networks (15–50 zones), explore automatic external zone generation, characterize sensitivity to data quality (measurement noise) as a second variation dimension, and conduct multi-city replication studies to establish generalizable threshold values.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Putu Eka Suartawan: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing–Original Draft, Writing–Review & Editing, Visualization. **I Made Suraharta:** Supervision, Resources, Writing–Review & Editing.

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