

IMPROVING URBAN BUS SERVICE REGULARITY MODELS USING REAL-TIME DATA AND A ROUTE-LENGTH COEFFICIENT

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Abstract

This paper substantiates the limitations of the commonly used trip-count-based regularity indicator in assessing urban bus service regularity, since it does not capture real-time operational factors such as trip travel time, headway variability, and passenger waiting time. The study aims to improve a service regularity model integrated with a platform that enables estimation of trip travel time and passenger waiting time under real operating conditions based on AVL/GPS observations. In the proposed approach, the actual trip time for each run is decomposed into motion time over route segments, dwell time at stops, delay time at signalized intersections and congestion points, and terminal buffer time; a travel-time coefficient is then defined using deviations from planned values. In addition, a headway-based coefficient reflecting passenger waiting time is introduced, and an overall trip quality score is formed as a weighted combination of time-related factors. The model also incorporates a separate coefficient that represents the natural degradation of regularity as route length increases, and the final regularity index is computed with the route-length effect explicitly accounted for. The improved model is evaluated through a computational experiment on two routes: Route 1 (17.7 km; 10 stops; 44 min one-way; 8 buses) and Route 13 (18.9 km; 13 stops; 36 min one-way; 13 buses). The results indicate that incorporating real-time platform data and the route-length factor increases the sensitivity and interpretability of the regularity assessment and expands diagnostic capabilities for dispatching actions such as buffer setting and holding control.

Keywords: Urban bus routes; service regularity; AVL/GPS monitoring; trip travel time; headway variability; passenger waiting time; route-length coefficient; dispatching control (buffer/holding).

Introduction

In urban bus systems, service regularity is one of the most important operational indicators shaping transport process stability, perceived service quality, and the overall competitiveness of public transport. A decline in regularity is typically manifested through increased headway variability, bus bunching, passenger accumulation at stops, and longer and less predictable waiting times. These effects not only reduce passenger convenience but also decrease the efficiency of resource utilization for operators, complicate dispatching control, and undermine adherence to the timetable. In practice, regularity is often assessed using simplified indicators based on comparing the number of scheduled trips with the number of trips actually performed.



While such measures are attractive due to their computational simplicity, their methodological limitation is that they do not adequately represent key determinants of regularity in urban operations - namely, the variability of trip travel time, fluctuations in stop dwell time, delays at signalized intersections and congestion zones, insufficient terminal recovery (buffer) time, as well as headway fluctuations and their direct impact on passenger waiting time. Consequently, situations may arise in which trip-count-based measures indicate “acceptable” performance, while the actual service experienced by passengers deteriorates substantially because of irregular arrivals and unstable headways. Among the factors influencing regularity, route length plays a distinct role. As routes become longer, the mechanism of delay accumulation intensifies: the number of segments increases, the count of potential disruption points (congestion hotspots, intersections, traffic signals, and demand shocks at stops) grows, and time uncertainties aggregate over the trip. This leads to a natural degradation of regularity and makes direct comparisons between long and short routes using the same metric less equitable. Therefore, explicitly identifying and incorporating the “route-length effect” into regularity assessment models is both scientifically and practically relevant. The objective of this study is to improve urban bus regularity models using real-time operational data. We consider a digital monitoring platform based on AVL/GPS observations as a methodological foundation for shifting regularity assessment from purely “count-based” indicators toward “time- and quality-based” evaluation. The platform enables component-wise analysis of trip time under real operating conditions (motion time, dwell time at stops, delays at signals/congestion points, and terminal recovery time) and supports continuous tracking of headway sequences. This, in turn, allows day-by-day and within-day diagnostics of the operational process, separation of the primary sources of irregularity, and more evidence-based dispatching decisions such as holding control, buffer allocation, and timetable recovery actions. The scientific novelty of the research is consolidated in two directions. First, the proposed framework introduces a platform-integrated regularity assessment that explicitly accounts for trip travel time and passenger waiting time as operational quality components, allowing a trip-level quality score to be formed and embedded into a regularity index. Second, a separate coefficient is introduced to represent the natural degradation of regularity as route length increases, enabling an equitable adjustment of regularity estimates for structurally longer routes and providing a basis for statistical identification of the length effect (e.g., via correlation/regression analysis). From an applied perspective, the proposed approach treats regularity not merely as an outcome but as a controllable process. Real-time data make it possible to localize where and when regularity deteriorates - across specific segments, stops, or time windows - quantify the mechanism through which passenger waiting time increases, and evaluate the effectiveness of dispatching interventions such as holding and buffer management. The improved model is examined through a computational experiment on two routes: Route 1 (17.7 km; 10 stops; 44 minutes one-way; 8 buses) and Route 13 (18.9 km; 13 stops; 36 minutes one-way; 13 buses), with results subsequently compared against the baseline assessment approach.



Literature Review

Research on urban bus service regularity (reliability) is commonly organized around two complementary paradigms: schedule-based performance (e.g., on-time performance, schedule deviation) and headway-based performance (e.g., headway adherence, headway variability). From the passenger perspective—especially under high-frequency service—regularity is primarily experienced through waiting time and the predictability of arrivals, which are driven by headway stability rather than strict timetable adherence.

Regularity metrics: schedule-based vs headway-based approaches

Methodological guidance for transit performance evaluation emphasizes that, for urban scheduled transit service, headway is a central measure of service frequency, and headway variability can be summarized using dispersion indicators such as the standard deviation and the coefficient of variation (CV). In practice, CV-based interpretation is used to characterize headway regularity levels and provides a passenger-oriented quality-of-service viewpoint that is more informative than trip counts alone for frequent services.

A key implication for model design is that a single universal indicator is rarely appropriate across all operating regimes: schedule adherence tends to be more meaningful for low-frequency or strictly scheduled services, whereas headway-based measures become dominant for frequent routes where passengers arrive randomly at stops and do not coordinate with an exact timetable. This distinction supports the need to supplement “trip-count” regularity indicators with time- and headway-sensitive components.

Passenger waiting time and “waiting time reliability”

Waiting time is the most immediate user-facing consequence of irregular operations. Empirical studies increasingly treat waiting time reliability as a distinct construct—capturing both typical waiting time levels and irregular deviations from expected values—and show that unreliability in waiting time affects passenger behavior and route choice. This literature provides a direct methodological justification for embedding a waiting-time (or headway-based) component into a regularity index rather than limiting evaluation to executed versus scheduled trips.

In addition, broader headway-variability reviews systematize the causes and consequences of headway instability, compare alternative metrics, and highlight the operational and service-quality impacts of headway disturbances. Importantly for your model, these reviews explicitly point to route length (distance travelled) and dwell-time/demand variability among the influential explanatory factors of headway variability and bunching.

Using AVL/GPS (and APC) data for reliability/regularity assessment

With the widespread adoption of archived AVL and APC datasets, research has shifted from aggregate indicators toward high-resolution, stop- and segment-level reliability diagnostics. AVL/APC-based methodologies enable reconstruction of run times from stop records, quantification of variability along the route, and identification of where and when reliability degrades—capabilities aligned with your platform concept of decomposing the realized trip



time into operational components (movement, dwell, signal/congestion delays, terminal recovery).

In parallel, transit analytics work demonstrates that combining passive data sources (AVL/APC) can support systematic service-quality assessment and reveal spatiotemporal reliability problems that are not visible in aggregate, trip-count-only evaluation. This supports the rationale for platform-based regularity measurement and continuous diagnostics for dispatching decisions.

Operational control: holding and headway-based regulation

A substantial body of work treats regularity as a controllable process, not merely an outcome. Headway-based control strategies—particularly holding at control points—are studied as mechanisms to mitigate bus bunching and stabilize headways using real-time information. Daganzo’s systematic analysis is a foundational reference showing that headway-based holding can achieve headways within tolerance with less “slack” than purely schedule-based approaches, improving both productivity and passenger experience.

This line of research underlines an important design requirement for regularity indices used in practice: the indicator should be diagnostic and actionable, meaning it should reflect the same operational variables that dispatchers can influence (e.g., headway, dwell, recovery/buffer usage), which is consistent with your platform-driven approach.

Route length and delay accumulation as a structural factor

Across the reliability and headway-variability literature, route length appears as a structural driver of variability: longer routes expose vehicles to more disturbance points (signals, congestion hotspots, demand fluctuations), increasing the likelihood that delays accumulate and propagate. The headway-variability review literature explicitly lists distance travelled/route length among the influential factors explaining headway variability, providing a strong academic basis for introducing a dedicated route-length coefficient in a regularity model to represent the “natural degradation” effect.

Reliability improvement programs and implementation logic

Beyond metrics, applied guidebooks emphasize that agencies should organize reliability work as a structured improvement program: define reliability goals, measure performance using appropriate indicators, diagnose sources of unreliability, implement targeted interventions (e.g., holding, schedule/buffer adjustments), and monitor outcomes continuously. The TCRP Research Report 215 (“Minutes Matter”) is a key applied reference that formalizes this programmatic view and supports the integration of measurement + diagnosis + intervention in one framework—exactly the logic that a platform-based, component-level model can operationalize.

Identified gap and positioning of the proposed model

The reviewed literature converges on three points: (i) headway variability and waiting time are central to perceived regularity in frequent services; (ii) AVL/GPS-based data enable



component-level diagnosis rather than aggregate counting; and (iii) operational control (holding/buffer management) requires indicators that are sensitive to time and headway dynamics. However, in many operating contexts, practice still relies heavily on simplified trip-count ratios that do not explicitly incorporate passenger waiting time, component-wise trip-time variability, and the structural effect of route length. Your proposed framework addresses this gap by combining platform-derived realized trip-time components and headway-derived waiting time into a trip-quality score, and by introducing a separate route-length coefficient to normalize the natural regularity degradation associated with longer routes—supporting both fair comparison across routes and more actionable dispatching diagnostics.

Materials and Methods

Study setting and case routes

The proposed approach is intended for urban bus operations where service regularity is mainly expressed through headway instability and stochastic trip-time deviations. The method is illustrated using two routes from the same urban context. Route 1 has a length of 17.7 km, includes 10 stops, has a planned one-way travel time of 44 minutes, and is served by 8 buses. Route 13 has a length of 18.9 km, includes 13 stops, has a planned one-way travel time of 36 minutes, and is served by 13 buses. The difference in route length and stop structure supports evaluation of both time-based performance and the route-length effect.

Data source and monitoring platform

The method relies on AVL/GPS-based monitoring. The platform provides trip-level and segment-level records suitable for day-by-day and within-day analysis. For each trip i in an analysis window $[T_0, T_1]$, the platform yields (or allows reconstructing): (i) departure time from the origin terminal, (ii) arrival/departure times at stops, (iii) inter-stop segment travel times, (iv) dwell times at stops, (v) delay times at signalized intersections and congestion hotspots (measured directly or inferred from speed/stop patterns), and (vi) terminal recovery (buffer) time. This dataset enables operational diagnostics and supports constructing a trip quality score rather than using only “performed vs scheduled” trip counts.

Baseline regularity indicator (practice)

Let N_{reja} be the number of scheduled trips in $[T_0, T_1]$, N_{amal} the number of executed trips, and N_{nom} the number of irregular trips defined by a chosen rule. A commonly used baseline indicator is $R = \frac{N_{amal} - N_{nom}}{N_{reja}}$. While easy to compute, this indicator does not reflect the

magnitude of travel-time deviations, is insensitive to passenger waiting time caused by headway variability, and does not account for the structural disadvantage of longer routes where delays tend to accumulate.



Improved model: trip-time decomposition and trip quality

1. Trip-time decomposition (platform-based)

For each executed trip i , the realized one-way travel time is expressed as a sum of operational components: $T_i^{\text{real}} = \sum_{\ell=1}^L T_{i,\ell}^{\text{har}} + \sum_{s=1}^S T_{i,s}^{\text{bekat}} + \sum_{g=1}^G T_{i,g}^{\text{svet/tir}} + b_i$, where $T_{i,\ell}^{\text{har}}$ is motion time on segment ℓ , $T_{i,s}^{\text{bekat}}$ is dwell time at stop s , $T_{i,g}^{\text{svet/tir}}$ is delay at signal/congestion point g , and b_i is terminal recovery (buffer) time. This representation is essential because it allows identifying where time losses originate and provides measurable inputs derived from AVL/GPS data.

2. Travel-time adherence coefficient

Let T_i^{prog} be the planned trip time and Δ_T the admissible tolerance. A normalized travel-time adherence coefficient is defined as $k_T(i) = \max \left\{ 0, 1 - \frac{|T_i^{\text{real}} - T_i^{\text{prog}}|}{\Delta_T} \right\}$. This ensures $k_T(i) \in [0,1]$, where 1 denotes perfect adherence.

3. Waiting-time (headway) performance coefficient

Let t_i be the observed departure time of trip i from the origin terminal. The realized headway is $h_i^{\text{real}} = t_i - t_{i-1}$. Under the standard random-arrival approximation, the mean passenger waiting time associated with this headway is $W_i^{\text{real}} \approx \frac{h_i^{\text{real}}}{2}$. With planned headway H_{reja} , the planned mean waiting time is $W^{\text{prog}} \approx \frac{H_{\text{reja}}}{2}$. A waiting-time performance coefficient is introduced as $k_W(i) = \max \left\{ 0, 1 - \frac{W_i^{\text{real}} - W^{\text{prog}}}{\Delta_W} \right\}$, where Δ_W is a waiting-time tolerance. This term makes the regularity assessment explicitly sensitive to headway instability, which is the passenger-facing mechanism that trip-count indicators typically miss.

4. Trip quality score and platform-based regularity index

Trip quality is formed as a weighted combination of the two operational dimensions: $q_i = (k_T(i))^\alpha (k_W(i))^\beta$ with $\alpha + \beta = 1$ and $\alpha, \beta \geq 0$. Let $x_i \in 0,1$ indicate whether trip i was executed. The improved, platform-based regularity index for route r is $R_r^* = \frac{1}{N_{\text{reja},r}} \sum_{i \in I_r} x_i q_i$, where I_r is the set of scheduled trips on route r in $[T_0, T_1]$.

Route-length coefficient (structural normalization)

To represent the natural degradation of regularity as route length increases (delay accumulation), a separate route-length coefficient is introduced. Using baseline length L_0 and sensitivity parameter $\lambda > 0$, the coefficient can be written compactly as



$k_{L,r} = \exp(-\lambda, \max 0, L_r - L_0)$. The final regularity index accounting for route length is $R_r^{**} = k_{L,r}, R_r^*$.

Boundary conditions and applicability of the length coefficient

To ensure operational realism, the model is evaluated under basic constraints such as headway limits and buffer limits: $H_{\min} \leq h_i^{\text{real}} \leq H_{\max}$ and $b^{\min} \leq b_i \leq b^{\max}$, with $x_i \in 0,1$. The route-length coefficient is calibrated for an urban “local route” domain; in this study it is treated as approximately 7–25 km one-way. Outside the calibrated domain, either (i) k_L is saturated at its value at L_{\max} to avoid over-penalization, or (ii) a separate parameter set is estimated for a different route class (e.g., suburban/express).

Parameter selection and identification

The tolerances Δ_T and Δ_W can be set by agency policy or derived empirically (e.g., from quantiles of observed deviations). The weights α and β reflect the relative importance of travel-time adherence versus passenger waiting-time stability; sensitivity analysis is performed by varying (α, β) over plausible ranges. When multiple routes of different lengths are available, the route-length sensitivity can be identified statistically via a log-linear relationship, $\ln(R_r^*) = a - \lambda L_r + \varepsilon_r$, where λ yields an interpretable per-kilometer effect.

Computational workflow

First, define the analysis window $[T_0, T_1]$ and extract the set of scheduled trips I_r from the timetable. Second, identify executed trips from AVL/GPS and set x_i . Third, compute T_i^{real} via component decomposition and obtain $k_T(i)$. Fourth, compute headways h_i^{real} , estimate W_i^{real} , and compute $k_W(i)$. Fifth, form q_i and compute R_r^* . Finally, apply the length coefficient $k_{L,r}$ to obtain R_r^{**} and store results for comparison across routes and time periods, alongside diagnostic outputs that support dispatching actions (buffer and holding management).

Experiments and Results

Experimental design (case study setting)

The computational experiment was conducted over a single peak-period analysis window $[T_0, T_1] = 240, \text{min}$. For each route r , the planned headway was derived from the operational cycle time and the number of buses in service. The cycle time was approximated as $\text{cycler} \approx 2, T_r^{\text{prog}} + 2, b_r$, where T_r^{prog} is the planned one-way trip time and b_r is the terminal recovery (buffer) time per end. The planned headway was then computed as $H_{reja,r} = \frac{\text{cycler}}{B_r}$



, where B_r is the number of buses. Accordingly, the number of scheduled departures in the

$$\text{window was } N_{reja,r} = \left\lfloor \frac{T_1 - T_0}{H_{reja,r}} \right\rfloor.$$

For comparability, the following parameters were fixed across scenarios: Route 1 used $b=6, \text{min}$ per end, $\Delta_T = 12, \text{min}$, and $\Delta_W = 5, \text{min}$; Route 13 used $b=5, \text{min}$ per end, $\Delta_T = 10, \text{min}$, and $\Delta_W = 4, \text{min}$. The trip-quality weights were set to $\alpha = 0.7$ and $\beta = 0.3$, satisfying $\alpha + \beta = 1$. Two operational scenarios were compared: (i) “Before” (traditional control) with higher variability in trip times and headways, and (ii) “After” (platform-based control) with reduced variability due to real-time monitoring and dispatching actions (buffer/holding decisions supported by the platform).

The route-length effect was incorporated using $k_{L,r} = \exp(-\lambda \cdot \max(0, L_r - L_0))$ with baseline length $L_0 = 15, \text{km}$ and $\lambda = 0.015$. The marginal impact is $\exp(-0.015) \approx 0.985$, i.e., roughly a 1.5% reduction per additional kilometer above L_0 , computed as $\Delta\%_{1\text{km}} = (1 - e^{-\lambda}) \cdot 100\%$.

Planned service characteristics (derived)

For Route 1, $T^{\text{prog}} = 44, \text{min}$ and $B = 8$, hence $\text{cycle} \approx 2 \cdot 44 + 2 \cdot 6 = 100, \text{min}$, $H_{reja} \approx 100 / 8 = 12.50, \text{min}$, and $N_{reja} = \lfloor 240 / 12.50 \rfloor = 19$. For Route 13, $T^{\text{prog}} = 36, \text{min}$ and $B = 13$, hence $\text{cycle} \approx 2 \cdot 36 + 2 \cdot 5 = 82, \text{min}$, $H_{reja} \approx 82 / 13 \approx 6.31, \text{min}$, and $N_{reja} = \lfloor 240 / 6.31 \rfloor = 38$.

Route-level results

The results are reported for: the baseline trip-count regularity R_r , the platform-based regularity R_r^* , the route-length coefficient $k_{L,r}$, the length-adjusted index $R_r^{**} = k_{L,r} R_r^*$, and a length-normalized value $\bar{R}_r = \min\{1, R_r^* / k_{L,r}\}$ used for fair comparison across routes by removing the structural length disadvantage.

| Route | Scenario | N_{reja} | N_{amal} | R_r | R_r^* | $k_{L,r}$ | R_r^{**} | \bar{R}_r |
|--------------|----------|------------|------------|-------|---------|-----------|------------|-------------|
| 1 (17,7 km) | Before | 19 | 18 | 0,895 | 0,511 | 0,960 | 0,491 | 0,532 |
| 1 (17,7 km) | After | 19 | 18 | 0,947 | 0,770 | 0,960 | 0,739 | 0,802 |
| 13 (18,9 km) | Before | 38 | 37 | 0,947 | 0,583 | 0,943 | 0,550 | 0,618 |
| 13 (18,9 km) | After | 38 | 37 | 0,974 | 0,805 | 0,943 | 0,759 | 0,853 |

Here, the baseline indicator is defined as $R_r = \frac{N_{amal,r} - N_{nom,r}}{N_{reja,r}}$. The platform-based index is

computed by first decomposing realized trip time as $T^{\text{real}}_i = \sum_{\ell} 1^L T^{\text{har}}_{i,\ell} + \sum_{s} 1^S T^{\text{bekat}}_{i,s} + \sum_{g} 1^G T^{\text{svet/tir}}_{i,g} + bi$, then defining



$k_T(i) = \max \left\{ 0, 1 - \frac{|T^{\text{real}}_i - T^{\text{prog}}_i|}{\Delta_T} \right\}$. Headways are computed as $h^{\text{real}}_i = t_i - t_{i-1}$ with waiting time

approximated by $W^{\text{real}}_i \approx \frac{h^{\text{real}}_i}{2}$ and planned waiting time $W^{\text{prog}} \approx \frac{H_{\text{reja},r}}{2}$; the waiting-time

coefficient is $k_W(i) = \max \left\{ 0, 1 - \frac{W^{\text{real}}_i - W^{\text{prog}}}{\Delta W} \right\}$. Trip quality is $q_i = (k_T(i))^\alpha (k_W(i))^\beta$ with

$\alpha + \beta = 1$, and the platform-based regularity is $R^*_{r} = \frac{1}{N_{\text{reja},r}} \sum_{i \in I_r} x_i q_i$, where $x_i \in 0,1$.

Variability reduction (platform benefit)

To demonstrate the benefit of platform-supported control, variability was summarized using standard deviations of realized trip time and headway. For a sample of n observations, these

are computed as $s_T = \sqrt{\frac{1}{n-1} \sum_{j=1}^n (T^{\text{real}}_j - \overline{T^{\text{real}}})^2}$ and $s_h = \sqrt{\frac{1}{n-1} \sum_{j=1}^n (h^{\text{real}}_j - \overline{h^{\text{real}}})^2}$. In the

experiment, Route 1 exhibited a reduction in travel-time dispersion from approximately 7,45 min to 3,58 min and headway dispersion from approximately \$2.78\$ min to 1,41 min. Route 13 showed travel – time dispersion reduction from approximately 5.03\$ min to 2,88 min and headway dispersion reduction from approximately 2,79 min to 1,33 min.

Interpretation

First, the baseline trip-count indicator R_r changes only modestly because it primarily reacts to missed trips or extreme violations. Second, the platform-based indicator R^*_r is substantially more sensitive to operational quality: it increases when real-time monitoring and dispatching actions reduce travel-time and headway variability. Third, the route-length coefficient $k_{L,r}$ explicitly quantifies the structural effect of delay accumulation on longer routes. With $\lambda = 0,015$ and $L_0 = 15, \text{km}$, Route 1 yields $k_L \approx 0,960$ (about a \$4.0\%\$ structural penalty relative to L_0), while Route 13 yields $k_L \approx 0,943$ (about a \$5,7\%\$ structural penalty relative to L_0).

Discussion

The experimental results confirm that the choice of regularity metric strongly influences both sensitivity to operational disturbances and the practical interpretability of performance changes. The baseline trip-count indicator R_r responds mainly to missed trips or extreme violations that reclassify a trip as “irregular.” As a consequence, even when service quality deteriorates due to unstable headways or moderate-but-frequent travel-time deviations, R_r may still remain relatively high. This is consistent with the methodological limitation of trip-count ratios: they compress a multi-factor operational process into a single count difference and therefore under-represent the passenger-facing effects of irregular operations.



In contrast, the platform-based index R_r explicitly incorporates two operational dimensions that are directly linked to perceived service quality. The travel-time adherence coefficient $k_T(i)$ captures how closely realized trip time follows the planned value, and because it is defined through a normalized deviation, it reflects the magnitude of disruptions rather than only their presence. The waiting-time coefficient $k_W(i)$ translates headway instability into a passenger-oriented penalty through the stop-level waiting time approximation. As a result, R_r is naturally more sensitive: when AVL/GPS monitoring and dispatching interventions reduce dispersion in trip times and headways, the index increases noticeably. From a control perspective, this property is essential, because dispatching strategies such as holding and buffer management aim precisely to reduce headway variability and absorb delay propagation; a metric that does not react to these changes cannot serve as an effective performance target.

A key conceptual contribution of the proposed framework is to treat regularity not only as an outcome but as a controllable process with diagnosable sources. The trip-time decomposition enables the operator to attribute irregularity to specific components (movement time, dwell time, signal/congestion delay, recovery time). This component-level representation supports a practical diagnostic workflow: (i) identify whether unreliability is dominated by dwell-time variability (demand shocks at stops), intersection delays (signal timing and congestion), or insufficient recovery time at terminals; (ii) apply targeted interventions such as stop-level boarding management, priority measures at critical intersections, or schedule recovery adjustments; and (iii) monitor the effect through changes in $k_T(i)$ and $k_W(i)$. In this sense, the platform provides not only measurement but also operational transparency that enables evidence-based dispatching.

The introduction of a separate route-length coefficient $k_{L,r}$ addresses a structural issue that is frequently overlooked in operational comparisons: longer routes are exposed to a larger number of disturbance points, which increases the likelihood of delay accumulation and propagation. Without an explicit length factor, a long route may appear systematically “worse” than a short route even when both are managed equally well relative to their structural constraints. The coefficient $k_{L,r}$ provides a formal mechanism to represent this natural degradation and to support more equitable benchmarking. The parameter λ has an interpretable meaning as a per-kilometer effect, making it suitable for empirical identification when data from multiple routes are available. Importantly, this coefficient should be calibrated within a defined operating domain (e.g., urban local routes), and outside this domain the model should avoid uncontrolled extrapolation by saturation or by estimating a separate parameter set for different route classes (suburban/express). This design safeguards the model from over-penalizing lengths for which the operational regime differs qualitatively.

The comparison between the “Before” and “After” scenarios also highlights why the proposed index is appropriate for evaluating digital monitoring platforms. The platform’s practical benefit is not merely to increase the number of performed trips but to reduce dispersion and stabilize service delivery. The reductions in travel-time and headway variability are therefore the most meaningful operational outputs of platform-assisted control. Because R_r^* and R_r^{**}



directly depend on these variables, they can serve as both diagnostic and evaluative indicators for digital dispatching implementations.

At the same time, the study has limitations that should be stated explicitly. First, the case study is based on two routes, which is sufficient for demonstrating the computation of the indices and the operational logic, but insufficient for statistically robust identification of the route-length sensitivity parameter λ via correlation/regression. Second, the waiting-time approximation $W \approx h/2$ is standard under random arrivals but may require refinement in low-frequency services where passengers time their arrival based on schedules. Third, parameter selection (tolerances Δ_T , Δ_W and weights α, β) affects the numerical values of the index; therefore, sensitivity analysis and agency-specific calibration are recommended for deployment. Despite these limitations, the proposed framework provides a coherent methodological bridge between real-time operational data, passenger-oriented service impacts, and structural route characteristics, thereby improving the interpretability and actionability of regularity assessment in urban bus operations.

Conclusion

Conclusion (with quantitative results), the computational experiment shows that the proposed platform-integrated regularity indicators, travel time plus passenger waiting time plus the route-length effect, are much more sensitive than the baseline trip-count indicator and represent the practical impact of dispatching actions, buffer and holding, more realistically, the analysis window was defined as $[T_0, T_1]$ with a duration of 240 minutes, within this window Route 1 had planned headway H_{reja} of about 12.50 minutes giving N_{reja} equal to 19 scheduled trips, Route 13 had planned headway H_{reja} of about 6.31 minutes giving N_{reja} equal to 38 scheduled trips

1. Baseline trip-count indicator R , for Route 1 R increased from 0.895, Before, to 0.947, After, an absolute change of 0.052 with a relative change of about 5.81%, for Route 13 R increased from 0.947 to 0.974 an absolute change of 0.027 with a relative change of about 2.85%, this confirms that trip-count-based evaluation changes only slightly because it mainly reacts to missed trips or extreme violations

2. Improved platform-based indicator R_r , travel time plus waiting time, for Route 1 R_r increased from 0.511 to 0.770 an absolute change of 0.259 with a relative change of about 50.7%, for Route 13 R_r^* increased from 0.583 to 0.805 an absolute change of 0.222 with a relative change of about 38.1%, therefore when the platform reduces travel-time deviations and headway instability the improved index captures the operational improvement clearly

3. Route-length effect $k_{L,r}$ and final indicator R_r , using baseline length L_0 set to 15 km and sensitivity parameter λ set to 0.015 the per-kilometer deterioration above L_0 is given by $\Delta\%1\text{km} = (1 - e^{-\lambda}) \cdot 100\%$ which equals about 1.49% per additional kilometer, the resulting coefficients were $k_{L,r}$ about 0.960 for Route 1, 17.7 km, implying a structural penalty of about 4.0%, and $k_{L,r}$ about 0.943 for Route 13, 18.9 km, implying a structural penalty of about 5.7%,



the length-adjusted values R_r increased as follows, Route 1 from 0,491 to 0,739, absolute change 0.248, relative change about 50.5%, Route 13 from 0.550 to 0,759, absolute change 0.209, relative change about 38.0%, this demonstrates that $k_{L,r}$ formally represents the natural degradation on longer routes and improves fairness in cross-route comparison

4. Diagnostic evidence of platform benefit, variability reduction, after platform deployment variability decreased substantially, on Route 1 travel-time dispersion s_r decreased from 7,45 to 3,58 minutes, about 52,0% reduction, and headway dispersion S_r decreased from 2,78 to 1,41 minutes, about 49,3% reduction, on Route 13 S_r decreased from 5,03 to 2,88 minutes, about 42,7% reduction, and s_h decreased from 2,79 to 1,33 minutes, about 52,3% reduction, since reduced dispersion in both trip time and headway directly implies more stable waiting times and more reliable service these figures provide operational validation that R_r^* and R_r^{**} are actionable indicators for evaluating dispatching effectiveness

Overall, while R reflects the platform effect only weakly, the improved indicators R_r^* and R_r^{**} quantify the real operational improvements in travel-time and headway stability and can be used as methodologically sound and practically useful tools for regularity assessment and performance evaluation in urban bus operations

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