Detecting Structural Changes in Urban Road Network Performance: A Kernel-Based Hierarchical Change Point Detection Framework

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Short summary

Urban road networks generate increasingly rich long-term traffic datasets, yet their full temporal depth remains underexploited. Most retrospective studies either aggregate data over long periods or perform before–after comparisons tied to pre-identified events, missing any unanticipated change. This paper proposes a general unsupervised framework for automatically detecting all dates at which a structural or relevant change occurred in urban traffic performance. The method combines a set of MFD-based macroscopic indicators and microscopic indicators — capturing the distribution of speed, flow, and density across individual road segments — with a hierarchical kernel-based change point detection algorithm operating at two complementary spatial scales. Applied to seven years of loop detector data in Rotterdam (2016–2023), the framework identifies both major network-wide disruptions — including the COVID-19 mobility collapse — and subtler, spatially localized reorganizations invisible to global aggregation, each assigned an objective impact score. The resulting dated and impact-scored record of network behavioral shifts offers urban practitioners a systematic tool to audit their traffic data, evaluate the effect of past interventions, and identify stable periods suitable for further modelling.
Keywords: change point detection, macroscopic fundamental diagram, road network performance, traffic indicators, urban traffic analysis

1 Introduction

The growing availability of long-term traffic datasets — from loop detectors and probe vehicles — creates new opportunities for retrospective performance analysis of urban road networks. Yet, systematic exploitation of this temporal richness remains rare. Most studies either aggregate data over long periods (EU-JRC 2023), losing fine temporal structure, or perform discrete before–after comparisons anchored on pre-identified events (Li and Guo 2016; Liu et al. 2008; Currie and Delbosc 2011). Fine temporal granularity is essential for detecting complex behavioral shifts beyond simple changes in the mean — for instance, weekday and weekend traffic patterns may diverge significantly over time while their average remains unchanged, a shift invisible to coarse aggregations.

A few studies have begun to exploit this granularity. Ambühl et al. (2021) summarized year-long MFD (Geroliminis and Daganzo 2008) variability into representative daily profiles, but without first verifying that the network remained in a stable behavioral regime throughout the studied period — a prerequisite for unbiased clustering. Fang et al. (2022) applied change detection to travel delay indicators, but focused only on pre-identified dates rather than offering a fully data-driven, unsupervised approach.

To our knowledge, no general methodology exists that automatically detects all dates at which a measurable structural change occurred in urban traffic performance, at fine temporal granularity and across multiple spatial scales. This paper addresses that gap, with a framework that yields three directly actionable outputs:

1. Identify stable periods in network performance;
2. Detect dates at which events significantly impacted network performance;

3. Operate at two complementary spatial scales, in order to capture both major network-wide disruptions and more localized changes that would remain undetectable through global aggregation alone.

2 Methodology

We propose a two-stage framework. First, speed and flow data are processed into performance indicators. Second, a hierarchical kernel-based change point detection algorithm (*KernelCPD* (Truong, Oudre, and Vayatis 2020)) is applied to these time series.

Performance indicators

Indicators are computed at two complementary scales :

Macroscopic indicators aggregate measurements across all selected loop detectors to characterize the global network state via daily MFD parameters: free-flow speed (v_f), maximum flow ($Q_{\max}$), critical density (K_c), and the curvature index (Δs). The curvature index (Δs), defined as the difference between the slope of a linear regression fitted to all data points and the slope of a linear regression restricted to low-density observations — where the MFD is expected to follow a straight line of slope v_f. A large discrepancy between the two slopes indicates that the overall speed–density relationship deviates from linearity, which is interpreted as evidence of a congested regime within the daily MFD. The free-flow slope S_1, the congested slope S_2, and the breakpoint density K_{break} are derived from a two-piece linear fit of the MFD shape, which approximates the fundamental diagram as two distinct linear regimes separated by a breakpoint corresponding to the onset of congestion.

Microscopic indicators characterize the spatial distribution of traffic to capture localized changes masked by network-wide averaging. Three indicators capture the network's most constrained conditions: v_{10}^{peak}, the speed below which the 10% slowest links fall during peak hours; q_{90}, the flow exceeded by only the 10% highest-flow links; and k_{90}, the density exceeded by only the 10% most congested links.

Hierarchical change point detection

The *KernelCPD* algorithm (Truong, Oudre, and Vayatis 2020) is non-parametric and multivariate, making no assumptions about the data distribution. It maps observations into a Reproducing Kernel Hilbert Space via an RBF kernel, and detects change points by minimizing a segmentation cost C — a measure of the statistical heterogeneity within each segment. Changes in mean, variance, or distribution shape are all captured. A minimum segment length constraint filters transient noise and focuses detection on lasting structural shifts. The optimal number of change points is selected automatically via the Kneedle algorithm (Arvai et al. 2020) applied to the segmentation cost curve.
Rather than processing all indicators simultaneously, we adopt a hierarchical, top-down strategy proceeding in four sequential steps: (1) **joint macroscopic** - simultaneous analysis of macroscopic indicators - isolating major network-wide disruptions;(2) **individual macroscopic** - individual analysis of macroscopic indicators- capturing dimension-specific shifts smoothed out in the joint analysis; (3) **joint microscopic**, targeting widespread spatial reorganizations; (4) **individual microscopic**, capturing the most granular and localized events. Change points identified at each step are imposed as fixed boundaries in all subsequent steps, preventing redundant detections. The joint analysis is performed first, as it captures two types of major events: those with a massive intensity — drastically reducing the segmentation cost even if driven by only a few indicators — and those with

a broad scope, where a subtle but simultaneous shift occurs across the majority of indicators. The individual analysis follows, targeting weaker, dimension-specific shifts that were mathematically smoothed out or overshadowed during the joint step.
Every detected change point is assigned an impact score — the relative reduction in cost compared to C_0, the cost of the unsegmented signal:

$$\text{Impact}(t) = \frac{C_0 - C(t)}{C_0} \tag{1}$$

This normalized score provides an objective, cross-comparable measure of event severity across all scales and indicators.

3 Results and discussion

Data and preprocessing

The framework is applied to the road network of Rotterdam, instrumented with approximately 180 loop detectors over October 2016 to December 2023 (30-second resolution), complemented by one month of probe data (1-minute intervals, 200 m spatial resolution). Loop detector speeds are corrected for positional bias via the Random Forest-based methodology of Maiti and Leclercq (2025), with separate models for peak and off-peak periods. Sensors are then filtered through a three-step procedure based on signal variance and Wasserstein distance (Weng 2017) clustering to retain a homogeneous, continuously operational subset of approximately 30 loops per during the 7 years of analysis.

Detected change points

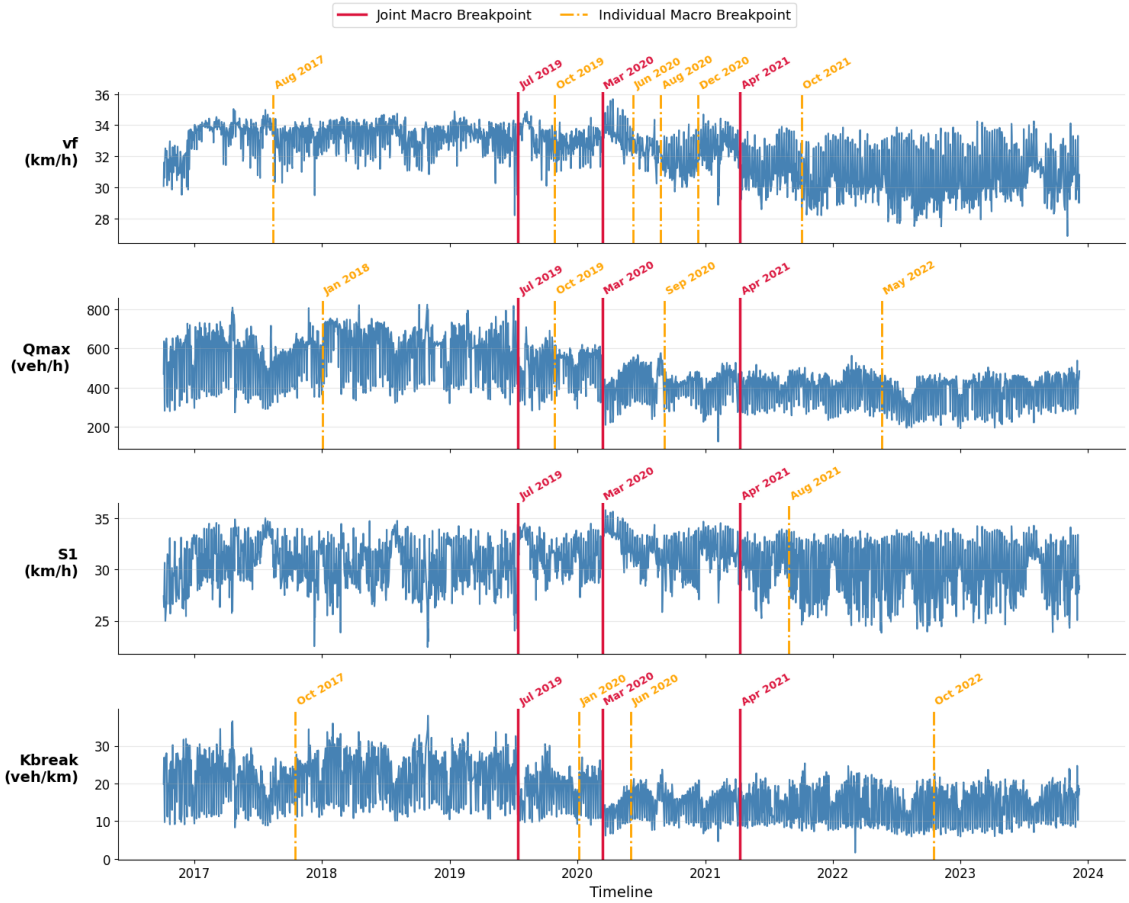


Figure 1: Hierarchical change-point detection algorithm applied to macroscopic indicators (Steps 1–2). Red lines: major joint breakpoints where 4 signals are processed simultaneously. Dashed orange lines: secondary individual breakpoints for each individual signal. Only changes with an impact score greater than 1% are shown.

Figure 1 presents the output of Steps 1 and 2. The most prominent structural shift occurs around March 2020 (impact: 16.29%), consistent with the COVID-19-related mobility collapse, detected simultaneously across all MFD parameters. Additional major breakpoints are identified in July 2019 and April 2021. The July 2019 breakpoint coincides with the final reopening phase of the Maastunnel, Rotterdam's oldest and most central river crossing, which had been closed in the southbound direction since July 2017 for a two-year structural renovation ("Rotterdam's Maas tunnel fully open after years-long renovations" 2019). The April 2021 breakpoint coincides with the official reopening of the Coolsingel on 10 April 2021, Rotterdam's main central boulevard, after three years of reconstruction (*Coolsingel* n.d.). The redesign permanently reduced motor traffic from four lanes to two, reallocating the freed space to a two-way cycle path and a widened pedestrian esplanade. This structural reduction in road capacity on one of the city's primary arterials is consistent with the decrease in free-flow speed v_f and maximum flow $Q_{\max}$ observed simultaneously across the network at that date, reflecting a permanent, city-scale change in traffic supply.

The individual macroscopic analysis (Step 2) further surfaces subtler, dimension-specific changes, particularly concentrated around late 2019 and the second half of 2020. Among these, the change detected in Q_{max} in January 2018 (impact: 4.09% can be interpreted in light of two simultaneous urban construction projects that began to affect the road network

at that time. First, the Maastunnel had been closed in the southbound direction since July 2017 ("Rotterdam's Maas tunnel fully open after years-long renovations" 2019), rerouting a large share of north–south cross-river traffic onto the ring road and the Erasmus Bridge. Second, the physical reconstruction of the Coolsingel began in January 2018 on its eastern side, closing half of the available car lanes along the city's main central thoroughfare for the duration of the works (*Coolsingel* n.d.). The simultaneous restriction of capacity on both a major river crossing and the central urban artery provides a plausible explanation for the reduction in Q_{max} detected at this date: the network's ability to sustain high flow levels was structurally constrained, even if free-flow speed and other MFD parameters remained largely unaffected — consistent with a capacity-driven rather than a speed-driven regime change.

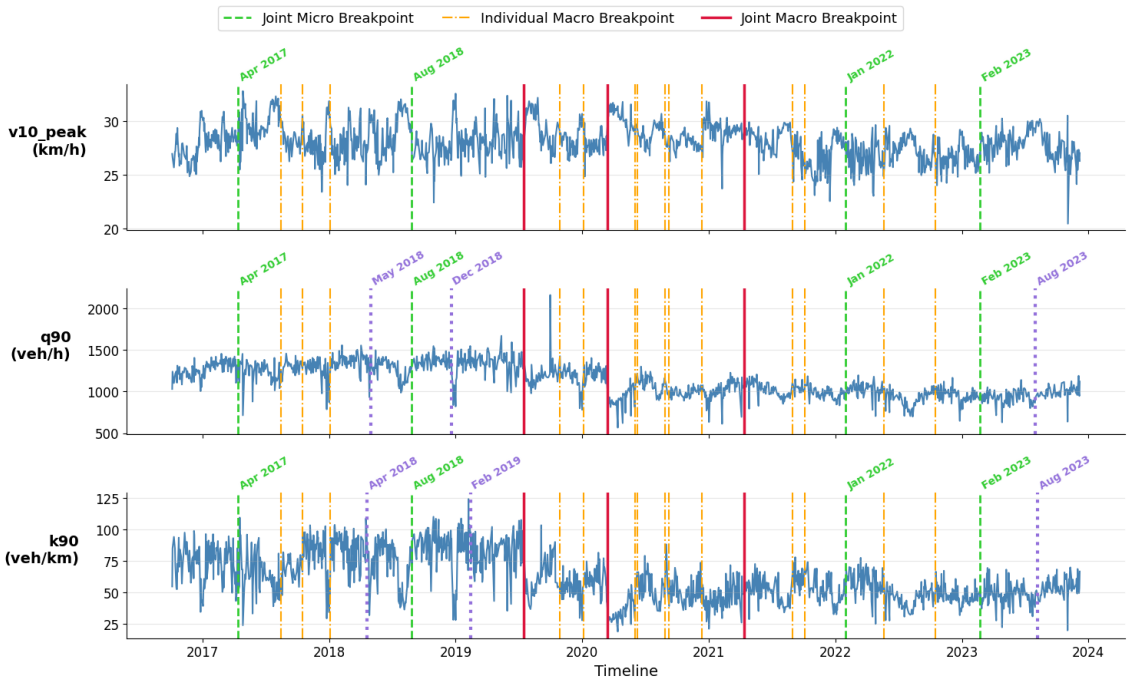


Figure 2: Hierarchical change-point detection algorithm extended to microscopic indicators (Steps 3–4). Macro breakpoints from Figure 1 are preserved as fixed boundaries. Dashed green lines: new joint microscopic breakpoints. Dashed purple lines: new individual microscopic breakpoints. Only changes with an impact score greater than 1% are shown.

Figure 2 extends the analysis to the microscopic scale. The algorithm identifies additional change points specific to localized traffic conditions that do not correspond to any macroscopic breakpoint, demonstrating that some spatial reorganizations are entirely invisible to network-wide aggregation. The joint microscopic breakpoint detected on 27 August 2018 (impact: 11.08%), for example, likely corresponds to the onset of maintenance works on the Van Brienenoord Bridge on the A16 motorway — the busiest highway in the Netherlands, carrying over 230,000 vehicles daily — whose partial closures would have redistributed traffic onto alternative urban corridors, altering local flow and density distributions without measurably disrupting the global network state.
At the microscopic scale, the individual breakpoint detected on q_{90} in May 2018 (impact: 15.03%) is among the highest-scoring changes identified across all individual analyses, and provides an illustrative example of a spatially localised event invisible to macroscopic aggregation. This date falls within an active period of concurrent infrastructure works in Rotterdam, including the ongoing Coolsingel reconstruction and the preparation works associated with the A16 Rotterdam project (Voorn n.d.), whose financing agreement was finalised in June 2018 and whose preliminary civil works began in the surrounding area

shortly before. These works would have induced localised traffic redistribution on specific high-flow corridors, driving up flow concentrations on alternative routes — precisely the type of spatial reorganisation that q_{90}, which captures the flow level exceeded by only the 10 % highest-flow links, is designed to detect. The absence of any corresponding macroscopic breakpoint at this date confirms that the underlying event, while significant at the level of individual road segments, did not produce a measurable shift in the network's global performance.

Not all urban interventions produce a detectable signal in the framework. The renovation of the Roseknoop junction in Rotterdam-Zuid, which began in January 2023 ("Renovatie Roseknoop in 2023" 2023) and was planned to last approximately 18 months, constitutes a relevant example of an event that falls below the detection threshold at both spatial scales. This junction serves as a convergence point for several major roads in the southern part of the city, including Laan op Zuid, the Varkenoordse viaduct, Putselaan and Beijerlandselaan, and its renovation caused sustained traffic diversions for both private vehicles and public transport throughout the construction period. Despite its operational significance, no breakpoint is identified in the vicinity of this date in either the macroscopic or microscopic results. This absence is informative: the disruption was sufficiently localised and sufficiently gradual in its onset that it did not generate a statistically dominant change in the segmentation cost at either scale.
Tables 1 and 2 report all detected change points with an impact score above 1%. A notable feature of the individual analyses (Steps 2 and 4) is the detection of temporally clustered breakpoints across different indicators. This is particularly visible around late 2019 in the case of secondary macroscopic breakpoints, where change points are detected independently for v_f, $Q_{\max}$, K_{break}, and S_1 within a narrow time window. These clustered detections most likely reflect a single underlying event whose impact, while significant at the level of individual indicators, was insufficient to emerge during the joint analysis — where the signal must simultaneously dominate the multivariate cost function. This illustrates a key property of the hierarchical workflow: the individual step acts as a refinement layer, surfacing events that are real but dimension-specific.

Table 1: Macroscopic change points with impact score above 1% ordered by impact score.

Step 1 — Joint macro		**Step 2 — Individual macro**		
Date	**Impact**	**Indicator**	**Date**	**Impact**
2020-03-13	16.29 %	v_f	2020-08-27	19.13 %
2021-04-11	14.95 %	v_f	2020-06-08	18.57 %
2019-07-16	12.75 %	$Q_{\max}$	2020-09-06	17.87 %
		$Q_{\max}$	2019-10-28	17.39 %
		v_f	2020-12-12	16.82 %
		v_f	2021-10-03	15.51 %
		v_f	2019-10-28	13.75 %
		K_{break}	2020-01-05	10.61 %
		K_{break}	2020-06-01	9.73 %
		$Q_{\max}$	2022-05-20	6.44 %
		$Q_{\max}$	2018-01-03	4.09 %
		v_f	2017-08-14	2.54 %
		K_{break}	2022-10-16	1.86 %
		K_{break}	2017-10-16	1.55 %
		S_1	2021-08-28	1.53 %

Table 2: Microscopic change points ordered by impact score (impact > 1%).

Step 3 — Joint micro		Step 4 — Individual micro		
Date	**Impact**	**Indicator**	**Date**	**Impact**
2022-01-31	12.22 %	q_{90}	2018-12-19	23.76 %
2018-08-27	11.08 %	k_{90}	2019-02-13	16.97 %
2023-02-23	3.26 %	q_{90}	2018-05-02	15.03 %
2017-04-13	2.64 %	k_{90}	2018-04-20	8.67 %
		q_{90}	2023-08-01	2.16 %
		k_{90}	2023-08-08	1.09 %

4 Conclusions

This paper presented a general, unsupervised framework for detecting structural change points in urban traffic performance at fine temporal granularity and across two complementary spatial scales. Applied to seven years of loop detector data in Rotterdam, the method produces two directly actionable outputs: stable periods suitable for MFD clustering or policy evaluation, and a dated, impact-scored record of all events that measurably affected network performance. The hierarchical structure ensures that both major network-wide disruptions and subtle, spatially localized changes are captured — the latter being invisible to conventional global aggregation. Future work will focus on cross-city validation and on systematically linking detected change points to their causal events through external event databases.

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